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RESEARCH ARTICLE

Causal relationship between agricultural production and carbon dioxide emissions in selected emerging economies

Kingsley Appiah [1,2] · Jianguo Du [1] · John Poku [2]

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Abstract

Continuous threat posed by climate change caused by carbon dioxide emission has reignited global advocacy to confront its negative ramification with the greatest possible firmness. Global food security and agriculture face major challenges under climate change as a result of the potential negative effect of production and implementation of sectoral action to limit global warming. Overall, agricultural greenhouse emissions continue to rise and the analysis of superior data on emissions from farming, livestock, and fisheries can help countries identify opportunities to contemporaneously reduce emissions and address their food security. This study seeks to contribute to the recent literature by examining the causal relationship between agriculture production and carbon dioxide emissions in selected emerging economies for the period 1971 to 2013. The study, therefore, disaggregated agriculture production into crop production index and livestock production index to explicate the distinct and to find individual variable contribution to carbon dioxide emissions. By using FMOLS and DOLS, empirical results indicate that 1% increase in economic growth, crop production index, and livestock production index will cause a proportional increase in carbon dioxide emission by 17%, 28%, and 28% correspondingly, while 1% increase in energy consumption and population improves the environment of emerging economies. The direction of causality among the variables was, accordingly, examined using PMG estimator. Potentially, for emerging countries to achieve Sustainable Development Goal of ensuring zero hunger for their citizenry requires the need to alter their farming production techniques and also adopt agricultural technology method, which is more environmentally friendly.

Keywords Carbon dioxide emissions · Economic growth · Energy consumption · Agriculture production · Pool Mean Group estimator · Population · Emerging economies

Introduction

The effect of greenhouse gas emissions on environment is becoming a pressing reality. One of the key contributors to global warming is carbon dioxide (CO_2) emission and continues to receive academic attention (Tunç et al. 2009; Sarkar et al. 2015; Appiah et al. 2017a, b). Among pollutants, carbon dioxide emission accounts for the highest share of the total greenhouse gases in emerging economies (Khan et al. 2011). Carbon dioxide emission has increased over the years due to increasing population, increasing energy demand, increasing economic growth, and increasing agriculture production to achieve food security (McAusland 2010; Adom et al. 2012; Asumadu-Sarkodie and Owusu 2016a, b; Shahbaz et al. 2017). Most countries have pledged their support through the Kyoto Protocol 1997 to deal with global warming of which emerging economies are not exception. Emerging economies such as Brazil, Russia, India, China, and South Africa (BRICS) are considered as the main pillars for global economic growth (Zakarya et al. 2015; Oganesyan 2017). As emerging economies around the world, their contribution to carbon emission is very high compared to other countries.

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✉ Kingsley Appiah
kingsleyappiah2004@yahoo.com

Jianguo Du
jd_foreign_phd@163.com

John Poku
johnpoku59@yahoo.com

[1] School of Management, Jiangsu University, Zhenjiang 212013, People's Republic of China

[2] Accountancy Department, Kumasi Technical University, Box 854, Kumasi, Ghana

These five countries are ranked among first sixteen (16) countries with highest carbon emissions globally (European 2015). South Africa is the 16th largest emitter of carbon dioxide in the world and is responsible for nearly half the CO_2 emissions on the entire African Continent. Table 1 provides the percentage of determinants of greenhouse gases of BRICS countries. Stakeholders who have signed to the treaty are doing their best to reduce carbon emissions. During the 21st session conference of the parties (COP) held in Paris, France, participants promised to keep global warming under control maximum $2C^0$ above the level of the pre-industrial period. However, factors such as agriculture production, energy consumption, economic growth, and population still contribute largely to total carbon dioxide emissions in these emerging economies.

Agricultural production plays a critical role in ensuring food security and economic expansion of a country (Funk and Brown 2009). Farming activities discharge a significant quantity of nitrous oxide (N_2O) and methane (CH_4) gases into the atmosphere which are influenced by land management (Duxbury 1994; Paustian et al. 1998; Johnson et al. 2007). Carbon footprint of food produced and not consumed, which is termed as food loss or food waste, is estimated to generate annually 4.4 $GtCO_2$ equivalent. This amount of CO_2 equivalent is about 8% of total human greenhouse gas emissions and is ranked as third top emitter after USA and China (Food 2015). The direct economic cost of agricultural food waste is estimated globally to an amount of 750 billion USD, equivalent to the GDP of Switzerland (Food 2015). There is the need to increase global food stock by 60% to meet the demand of speedy growth of world population by 2050. Yet, one third of the world's food produced today go waste (Food 2011). The Food and Agriculture Organization explain food loss as the decrease in large quantities of edible food at the production, post-harvest, and processing stages of the food chain, while food waste is elucidated as discarded edible foods at the retail and consumer levels. The implication of this phenomenon is that food waste accounts for the opportunities missed to improve food security and at the same time with sharp environmental expense (Food 2011).

Total greenhouse gas emissions from agriculture (i.e., crops and livestock) have doubled over the past 50 years from 2.7 billion t CO_2 equivalent (1961) to more than 5.3 billion t CO_2 equivalent (2011) (Food 2014). Emitters in agriculture come from enteric fermentation—when methane is produced by livestock during digestion and released via belches. Emissions from enteric fermentation constitute 40% of the total greenhouse gas emissions, followed by manure left on pasture (16%) (Food 2014a). The application of synthetic fertilizers accounted for 13% of agricultural emissions (725 Mt. CO2 eq.) in 2011 (Food 2014a). Greenhouse gases resulting from biological processes in rice paddies also generate methane that make up 10% of total agricultural emissions, while the burning of savannahs accounts for 5%. Several studies have examined the sources of agricultural GHG emissions as well as the methods to mitigate its impact (Muller et al. 2011; Smith 2012; Alper and Onur 2016; Amuakwa-Mensah and Adom 2017). For instance, Smith conducted a study of EU 27 countries and UK on how to mitigate the impact of agricultural GHG emissions. One of the mitigation options is the changes in terrestrial carbon stock, which involves predominantly organic C stored in plants and soils. By reducing, the stocks will result in a net flux of CO_2 to the atmosphere. Contrary, increasing the standing stocks of organic C in soils and biomass removes CO_2 from the atmosphere (Paustian et al. 1998). The issues of agricultural greenhouse gas fluxes are complex and heterogeneous, but with the implementation of active management of agricultural structure provide some mitigation solutions (Smith et al. 2008). Roth et al. (2014) investigated private pig farming emissions of CH_4 and N_2O under a tropical climate Uvéa Island. They measured physiochemical soil parameter such as nitrate, total organic carbon, pH, nitrite, Kjeldahl nitrogen, and ammonium. The authors discovered that CH_4 emissions solely depended on moisture, while N_2O emissions were related to nitrate composition.

Empirical work has been conducted to find a carbon footprint of agronomic production and its effect (Druckman and Jackson 2009; Hillier et al. 2009) using traditional methods and modern econometric techniques. The idea of ensuring low carbon footprint globally will go a long way to help in agricultural production and at the same time helps in environmental sustainability. Hussain et al. (2015) scrutinized how crop management systems influence GHG emissions in rice fields. The study was based upon the fact that amendments of the conventional method of crop management hold massive potential to overcome GHG emissions in rice fields. The study further evaluated different crop management options using meta-analysis. Their study findings were that altering tillage permutations and irrigation patterns, managing organic and fertilizer inputs, picking appropriate cultivar, and cropping regime can lessen GHG emissions. Bakhtiari et al.

Table 1 Determinants of GHG emission from agriculture sector (2012)

GHG emissions	BRA	RUS	IND	CHN	ZAF
Carbon dioxide emissions	40.46%	75.03%	81.07%	69.73%	84.85%
Nitrous oxide emissions	18.47%	2.66%	4.75%	8.28%	3.80%
Methane	41.07%	22.31%	14.18%	21.99%	11.35%

From World (2017)

(2015) study in Iran analyzed the energy balance for saffron production cycle and investigated the matching greenhouse gas (GHG) emission. The study applied Cobb-Douglas production to define the functional relationship. Data of 127 randomly selected saffron growers were used, and the study findings revealed that cultivation of saffron emits 2325.5 kg CO_2 equivalent ha^{-1} of total emissions. Hagemann et al. (2012) assessed the influence of milk production to world greenhouse gas emissions. The study was conducted in 38 countries, which consist of 117 typical farms. They applied standard regression model to estimate GHG emissions from milk production. Findings indicate that estimations of milk production contribution to emissions are subject to uncertainty. That is, the results depend upon the choice of appropriate technique to estimate the emissions of individual animal. Asumadu-Sarkodie and Owusu (2016a, b) investigated the relationship between carbon dioxide and agriculture in Ghana using Vector Error Correction Model (VECM) and Autoregressive Distributed Lag (ARDL) model for period 1961 to 2012. Study findings postulate that carbon dioxide emissions affect agricultural production.

In relations to our current study, quite a number of studies have examined the causal relationship between agriculture production, energy consumption, economic growth, population, and carbon dioxide emissions. Typical among them is the study of Asumadu-Sarkodie and Owusu (2017) who looked at the causal nexus between carbon dioxide emissions and agricultural ecosystem—an econometric approach by employing data spanning from 1961 to 2012. Their findings indicate that an increase of rice paddy harvest, biomass-burned crop residues, and cereal production causes an increase in carbon dioxide emissions. The study also found that increase in agricultural machinery causes a decrease in carbon dioxide emissions. These studies add to agriculture-carbon dioxide emissions nexus but, however, failed to disaggregate the agriculture production system into various indexes to look at their distinct impact or contribution to CO_2 emissions. Our interest sprouts from this gap identified. Estimation of various agriculture production index effects on carbon emissions of the emerging economies will help to evaluate all possible mitigation approaches with respect to ecological efficacy and economic feasibility. Mitigation approaches involve directing agricultural practices or activities toward a more sustainable environmental practice.

Other issues of concern are energy consumption, economic growth, and population contribution to carbon emission. Provision of energy and availability of food plays a significant role in the socio-economic development of every country. Energy uses worldwide increased more than 55% between 1990 and 2014, to 13.3 billion metric tons of oil equivalent (World 2017). Report of Dudley (2017) shows that China and India account for 50% of the world's incremental energy demand. It is expected that world atmospheric CO_2 emissions are to rise by 6.13% annually as a result of high level of energy consumption due to the economic growth (Global 2017). Previous researchers have looked at carbon dioxide emissions relation with energy consumption (Chen and Huang 2013; Ozturk and Al-Mulali 2015; Ahmada et al. 2016; Azam et al. 2016; Dogan and Turkekul 2016; Li et al. 2016; Lorente and Álvarez-Herranz 2016). Since agriculture production activities take a vast share of emerging economies gross domestic product, the study also introduces economic growth into the nexus. Economic growth-related CO_2 emissions (Du et al. 2012; Kasman and Duman 2015; Ozturk and Al-Mulali 2015; Charfeddine and Khediri 2016; Dogan and Turkekul 2016; Ramakrishnan et al. 2016; Wang et al. 2016; Zou et al. 2016).

In this paper, we focused on the agriculture-related CO_2 emissions. Our motivation in this study follows the food loss campaign by International Congress Save Food Initiative. Global effort to fight hunger, raise income, and improve food security has been derailed by high level of food losses. Food losses have an impact on food security for living species, on food quality and safety, on economic development and on the environment in general (Food 2011). Even though exact causes of food losses are unknown and are also not peculiar to the individual country, however, in general terms, food losses are influenced by crop production choices and patterns, food use practice, and internal infrastructure (Food 2011). Food losses epitomize waste of resources used in the production process. According to Food (2011), food produced that is not consumed creates unnecessary CO_2 emissions together with the losses attributable to economic value. This paper seeks to answer the following questions: (i) Do agriculture production indexes have effects on CO_2 emission? (ii) To what extent agriculture production indexes impact CO_2 emission for emerging economies? And (iii) do energy consumption, population, and economic growth have effects on CO_2 emissions in emerging economies? To get answers to these questions, there is the need to look at the causal relationship between energy consumption, population, economic growth, agriculture production, and environmental pollution. The study would provide some policy guidance on how crop and livestock production can be improved. The findings would also bring to light key strategies that emerging countries can adopt toward achieving agricultural sustainability and at the same time mitigate the agricultural activity's negative effects on environment.

The rest of the study entails section "Literature Review", section "Materials and method", section "Results and Discussions", and lastly section "Conclusions".

Literature review

Agricultural production—carbon dioxide emissions nexus

The influence of livestock as a farming sector on the ecosystem is very large growing at a faster rate with dynamic constantly changing patterns and environment (Leip et al. 2015). This is due to increasing worldwide demand for meat, milk, and eggs. Livestock serves as a livelihood for many people, and it contributes significantly to the emerging country's gross domestic product (GDP). Livestock is seen as major contributors to greenhouse gas emissions, which constitute 18% of the total anthropogenic emissions (Henning et al. 2006). The link between livestock and environmental contaminants has been established by many research findings (Chauhan and Johnston 2003; Trasande and Thurston 2005; Smit et al. 2017). Other empirical findings also provided evidence to the theory that livestock such as cattle, chicken, and goats have an impact on the health of living species as results of changes in air quality (Smit et al. 2013). Livestock keeping is believed to have both positive and negative effects at the ecosystem (Thornton 2010). The positive effect is that livestock helps vulnerable communities by providing them nutrients, which reduce their health risk (Thornton 2010). However, negative effect of livestock possession if not properly managed can cause ecological toxins (Cambra-López et al. 2010). Among the ruminants, especially cattle, produce a lot of methane gas and thus contribute considerably to universal heating up (Tisdell 2005; Van Haarlem et al. 2008; Desjardins et al. 2012).

Vast empirical studies have been undertaken by researchers to find the relationship between agriculture production and carbon dioxide. Luo et al.'s (2017) study found that the use of fertilizer and cattle rearing contributes a lot of carbon dioxide emissions in China. Ben Jebli and Ben Youssef (2017) as well found that a farming value increase causes an increase in emissions in Tunisia in the long run. However, study by Zhen et al. (2017) found no positive correlation between crop production and energy consumption. Waheed et al. (2018) investigated the effects of renewable-energy consumption, agriculture production, and forest on carbon dioxide emissions in Pakistan for the period 1990 to 2014. Using Autoregressive Distributed lag model, the study found agricultural production as a major source of carbon dioxide emissions in Pakistan in the long-term. Sarkodie and Owusu (2017) conducted a study in Ghana on the relationship between carbon dioxide, crop, and livestock production index using Autoregressive Distributed Lags (ARDL) and variance decomposition. They found that increase in crop production index and livestock production index causes an increase in carbon dioxide emissions. The study further revealed bidirectional causality between carbon dioxide emissions and crop production index. In the same vein, bi-directional causality runs from the livestock production index to carbon dioxide emissions. Owusu and Asumadu-Sarkodie (2016) analyzed whether there is a causal effect between agricultural production and carbon dioxide emission in Ghana. Autoregressive Distributed Lag (ARDL) technique was applied using time-series data over the period from 1960 to 2015. The study findings indicate bidirectional causality between milled rice production and carbon dioxide emissions; millet production and carbon dioxide; and between sorghum production and carbon dioxide emissions. On the other hand, the study also found unidirectional causality running from corn production to carbon dioxide emissions and carbon dioxide emissions to palm kernel production.

Energy consumption—carbon dioxide emissions nexus

The effect of energy consumption on CO_2 emissions has been a controversial issue. A quite number of studies have explored the causal relationship between energy consumption and carbon dioxide emissions. Some empirical findings indicate that energy consumption influences carbon dioxide emission (Acaravci and Ozturk 2010; Hatzigeorgiou et al. 2011; Jayanthakumaran et al. 2012; Hwang and Yoo 2014). Others also found the reverse of the case whereby energy consumption and economic growth have been influenced by carbon dioxide emission (Hatzigeorgiou et al. 2011; Alam et al. 2012; Saboori and Sulaiman 2013). A study by Alam et al. (2012) in Bangladesh found energy consumption and carbon dioxide emissions to be bidirectional. Hamit-Haggar's (2012) study of the Canadian industrial sector also found bidirectional causality between energy consumption and carbon dioxide emissions. Various studies have proven different effects both positive (Pao et al. 2011) and negative (Apergis et al. 2010; Menyah and Wolde-Rufael 2010) of energy consumption on CO_2 emissions. Lozano and Gutierrez (2008) studied the causal relationship between energy consumption, economic growth, population, and carbon dioxide in USA using the non-parametric method. Huang et al. (2008) also examined the relationship between energy consumption and economic growth of 82 countries between the periods 1972 to 2002 using generalized method of moments. Findings of the study indicate that more efficient energy use improves the environment by means of a reduction in carbon dioxide emissions. Soytas and Sari (2009) explored the relationship between economic growth, carbon dioxide emissions, and energy consumption in Turkey. The study found that carbon dioxide emissions Granger causes energy consumption. However, the reverse of it does not hold. Adom and Bekoe (2012) investigated the factors that affect aggregate electricity demand in Ghana in both short- and long-term. The study employed Partial Adjustment Model (PAM) and Autoregressive Distributed Lag (ARDL) to forecast Ghana's electricity energy requirement for 2020. Their study revealed that electricity consumption in Ghana is explained by positive output, urbanization, and income factors.

Paramati et al. (2018) examined the impact of renewable and non-renewable energy consumption on the agriculture, industry, services, and overall economic activities (GDP) across a panel of G20 nations. The study made use of annual data from 1980 to 2012 on 17 countries of the G20. Using an econometric model, the study found long-run elasticities that showed that renewable energy has a significant positive impact on the economic output across the sectors (i.e., agriculture, industry, services, and economic activities).

Economic growth—carbon dioxide emissions nexus

Most studies on economic growth-environment pollution nexus indicate that economic growth is detrimental to the ecosystem, particularly at the early stage of economic development within a country. However, Environment Kuznet Curve (EKC) hypothesis postulates that at the later stage, the negative effect of the environment is reverse due to high level of economic growth, which provides enough resources to deal with the environmental degradation. Several empirical works suggest that colossal economic growth adds to the upsurge in carbon dioxide emissions (Elliott et al. 2017). Some studies found that carbon dioxide emission has been influenced by economic growth (Saboori and Sulaiman 2013; Kasman and Duman 2015; Azam et al. 2016). That is, economic growth leads to increased energy consumption and CO_2 emissions, with negative effects on global climate (Yue et al. 2013). A comparative analysis study by Jayanthakumaran et al. (2012) of China and India found unidirectional causality of CO_2 emissions in China influenced by economic growth and energy consumption, while similar connection could not be established in India. Related result in Greece was found by Hatzigeorgiou et al. (2011), Pao and Tsai (2010) in Brazil, Wang et al. (2011) in China, Acaravci and Ozturk (2010), Hossain (2011), and Pao et al. (2011) in Russia of the relationship between economic growth, energy consumption, and carbon dioxide emissions, whereby CO_2 emissions are influenced by economic growth and energy consumption. On the other hand, other researchers also found the relationship between the variables to be bi-directional (Adom et al. 2012). Hussain et al. (2012) investigated the relationship between environmental pollution, economic growth, and energy consumption in Pakistan. The study applied vector error correction model (VECM) and conventional Granger's causality tests, and findings revealed unidirectional relationship between $CO_2$and GDP. Similar study by Ahmada et al. (2016) in Malaysia from 1980 to 2011 using STATA software, to find the impact of economic activities on CO_2 emissions also found momentous relationship between GDP and CO_2.

Hossain (2011) conducted a study on carbon dioxide emission, energy consumption, economic growth, trade openness, and urbanization of newly industrialized countries. The study findings showed that long-term relationship between the variables does not exist, even though the study findings suggest unidirectional relationship from economic growth and trade openness to CO_2 emissions in the short-term. Chen and Huang (2013) investigated the nexus between carbon dioxide emissions per capita and economic growth in Next Eleven (N-11)1 for the period 1981–2009. Cointegrating test was performed using heterogeneous panels. The study found positive relationship between CO_2 emission, energy consumption, GDP, and electric power consumption. Zhang and Cheng (2009) analyzed the relationship between energy consumption, carbon emissions, and economic in China over the period 1960–2007. They applied multivariate model and empirical results that suggest that neither energy consumption nor carbon emissions lead to economic growth. Li et al. (2014) analyzed the driving forces of agricultural CO_2 emissions in China from 1994 to 2011. The purpose to the study was to determine the driving forces which are fundamental for low-carbo agricultural policy formulation and decomposition analysis. The study, therefore, applied Logarithmic Mean Divisia Index (LMDI) as the decomposition method. Findings indicate that economic development turns to escalate CO_2 emissions considerably.

Population–carbon dioxide emission relationship

Empirical studies proposed that population growth had been one of the major factors that cause emissions in both developing and developed countries around the world (Lutz et al. 2001). Most of the findings from the previous studies show that population growth has a negative effect on emissions (Özokcu and Özdemir 2017). Other researchers also found positive association between population growth and emissions (Shi 2001; Bargaoui et al. 2014; Feng et al. 2015; Yeh and Liao 2017; Yu et al. 2017). Martin and Saikawa (2017) thus posit that larger populations call for an increase in demand on energy and other essentials of life such as food, water, clothing, shelter, and so on. Özokcu and Özdemir (2017) reiterated that emissions is directly linked to human activities which result in increased demand for energy for power, industry, and transportation, hence increasing fossil fuel emissions. An upsurge of population growth also contributes significantly to greenhouse gas emissions through its effect on deforestation. That is, destruction to the forests, use of fuel wood, and drastic change in land use contribute momentously to greenhouse gas emissions.

Materials and method

It is palpable that the use of panel data comes with its own merits and demerits, even though panel models may suffer from the issues of heterogeneity and cross-sectional dependence. However, the application of panel model is able to deal with complexity of behavior of the variables. Panel model also takes into account more degrees of freedom and more sample variation than single-country time-series data. Even with respect to the problem of heterogeneity and cross-sectional dependence, advent of econometric technique considers those issues and therefore is eliminated in the analysis. Based on the identified problem, we first examined whether or not the panel data used for this study suffer from the aforementioned issues and then use appropriate panel models accordingly. We investigated the relationship between agriculture production, energy consumption, population, economic growth, and carbon dioxide emissions of four emerging economies. The study selected four emerging economies: Brazil, India, China, and South Africa (BICS) out of five that formed BRICS (i.e., Brazil, Russia, India, China, and South Africa) in order to cover a lengthy period to make relevant conclusions. The study excluded Russia from the analysis since available data starts from 1992, which would make analysis and comparison difficult if not impossible. To accomplish the study objectives, panel data set for the four emerging economies were procured from the World Development Indicators (http://data.worldbank.org) and FAOSTATS (www.fao.org). The period of interest was from 1971 to 2013 using DOLS and FMOLS estimators to test for long-run elasticities. While current data points for the World Development Indicators are available up to the year 2016, we truncated the data in 2013 since data on the variables of interest in the designated countries of study are only available up to 2013. Our study disaggregated agriculture production into crop production and livestock production in order to determine individual distinct contribution to CO_2 emissions.

Data collection and variable definitions

Variables used throughout the analysis as explanatory variables include EC (Energy Consumption) (kg of oil equivalent per capita), GDP (gross domestic product per capita) (current US $) as proxy of economic growth, CRP (crop production index) (2004–2006 = 100), LVP (livestock production index) (2004–2006 = 100), POP (population) (total), and CO_2 eq. (carbon dioxide equivalent emissions) (gigram) as the dependent variable. Crop production index includes all crop's output with the exception of forage, while livestock production index is the index of livestock product's output (meat, milk, cheese, eggs, wool, honey, etc.). Carbon dioxide equivalent is a conversion of the various gases into equivalent amounts of CO_2 based on Global Warming Potential (GWP) standard ratios. Our study made use of potential CO_2 (i.e., CO_2 eq.) instead of actual CO_2 (example, CO_2 (kt)). The use of potential CO_2 emissions is supported by the findings of Amuakwa-Mensah and Adom (2017) and Adom et al.'s (2018) study, which confirms that the usage of potential CO_2 emissions improves the efficiency of model and also provides a better approximation of the long-term elasticities of the variables. Additionally, the use of potential CO_2 emissions is empty of short-run cyclicality, and therefore, the issue of reverse causality is minimized. Table 2 provides data and variable definition (i.e., abbreviation used, variable name, unit of measurement, and source of data).

Descriptive statistics

The volatility, mean, coefficient of variation, skew ness, kurtosis, and normality of distribution over the variables were performed under descriptive analysis. To measure the thickness or immensity of the tails of the distribution, the kurtosis in Table 3 shows that all the variables exhibit platykurtic distribution. Evidence from the analysis clearly shows that all the variables exhibit negative skewness (long-left tail). Results of Jarque-Bera test statistic show that all the variables are generally distributed and therefore accepted the null hypothesis that the series are normally distributed at 5% significance. The means and standard deviation (SD) of the analysis showed that population gave the highest mean of 19.42, which makes it a critical variable in the emerging countries under discussion. Notwithstanding that, our standard deviation also exposed population (i.e., POP) as the most explosive variable with the highest deviation of 1.41 followed by gross domestic product. The coefficient of variation (CV) for the panel variables indicates the existence of differential between the variables, with economic growth showing the highest differential of 17.80% among the variables.

Empirical model

The theoretical framework of the study was coined based on the endogenous growth model of which the expected

Table 2 Data and variable definition

Abbreviation	Variable name	Unit	Source
CO_2 eq.	Carbon dioxide emissions	Gigram	FAOSTAT (2017)
CRP	Crop production index	Crop production index (2004–2006 = 100)	WDI (2017)
LVP	Livestock production index	Livestock production index (2004–2006 = 100)	WDI (2017)
POP	Population	Population, total	WDI (2017)
GDP	Gross domestic product per capita	Gross domestic product per capita (current US $)	WDI (2017)
EC	Energy consumption	Kilogram of oil equivalent per capita	WDI (2017)

undesirable output depends on agricultural production, energy consumption, economic growth, and population.

$$CO2eq_{it} = f(A, EC, GDP, POP)_{it} \tag{1}$$

where A is the agricultural production, EC is the energy consumption, and GDP is the gross domestic product, while POP is for population. Equation (1) can also be expressed as Eq. (2) after disaggregation of agricultural production into crop and livestock production indexes.

$$CO2eq_{it} = f(CRP, LVP, EC, GDP, POP)_{it} \tag{2}$$

Our study follows the work of Amuakwa-Mensah and Adom (2017) who examined the quality of institution and the FEG (forest, energy intensity, and globalization)–environment relationships in sub-Saharan Africa. To determine the marginal effects of significant variables, especially the agricultural production indexes on environment, the study applied Cobb Douglas (1928) Production Function in its stochastic form as

$$CO2eq_{it} = a_0 CRP_{it}{}^{\beta_1} LVP_{it}{}^{\beta_2} EC_{it}{}^{\beta_3} GDP_{it}{}^{\beta_4} POP_{it}{}^{\beta_5} \tag{3}$$

Clearly, the relationships between CO_2eq and the predictors are nonlinear. Using the log-linear model, we log-transform the model to have linear regression model expressed as

$$\log_e(CO2eq) = a + \sum a \log_e(X_{kth}) \tag{4}$$

where CO_2eq = Environmental Impact (i.e., carbon dioxide equivalent emissions) and X_{kth} represents the explanatory variables, while a represents the model coefficients. Therefore, the model can also be written as

$$\log_e(CO2eq) = a + \sum a \log_e(CRP, LVP, EC, GDP, POP) \tag{5}$$

To test the long-run relationship between variables as expressed in Eq. (1), the study transformed variables value in their natural logarithm as expressed in Eq. (4). The transformation of the data into their natural logarithm is to ensure that results are efficient, reliable, and consistent. Hence, the log-transform of the model as expressed in Eq. (5) can also be expressed in a functional model as follows:

$$\begin{aligned} InCO2eq_{it} = a + \beta_1 InCRP_{it} + \beta_2 InLVP_{it} + \beta_3 InEC_{it} \\ + \beta_4 InGDP_{it} + \beta_5 InPOP_{it} + \mu_{it} \end{aligned} \tag{6}$$

where $InCO2eq_{it}$, $InEC_{it}$, $InGDP_{it}$, $InCRP_{it}$, $InLVP_{it}$, and $InPOP_{it}$ depict the natural logarithm of carbon dioxide equivalent emissions, energy consumption, economic growth, crop production index, livestock production index, and population, respectively. The $i = 1, \ldots., N$ denotes the countries, $t = 1, \ldots\ldots., T$ denotes the time period and μ_{it} is the error term. The μ_{it} is assumed to be serial uncorrelated. Non-zero assumption is imposed on the explanatory variables, and therefore, we assumed that elasticity of CO_2 equivalent emissions real output remains the same across countries but, however, may vary across economies at any given level of real output (Stern 2004). It is also assumed that increase in economic growth, energy consumption, population, and agriculture activities will increase emissions.

Methodology

It is generally expected that disturbances in panel data models are cross-sectionally independent, particularly when the cross-section dimension (N) is large. There is, however, considerable evidence that cross-sectional dependence is often present in the panel regression setting. Ignoring cross-sectional dependence in estimation can have serious consequences with unaccounted for residual dependence resulting in estimation efficiency loss and invalid test statistics. Performance of cross-sectional dependence or independence among the variables also provides relevant ideas for the selection of econometric technique to undertake to ensure that the study does not provide statistical results that are misleading and inefficient. Therefore, we first tested for cross-sectional dependence or independence among the variables using Pesaran CD (Pesaran 2004) instead of Breusch-Pagan Lagrange Multiplier (LM) test because LM test use requires that the researchers identify previous model specifications used. Pesaran CD provides robust means to deal with any unobserved common factors or spillover effects in the countries due to factors such as having reached the same economic development, similar economic indicators, and other common features.

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} P'ij\right) \Rightarrow N(0,1) \tag{7}$$

where T is the time period, N is the sample size, and $P'ij$ is the sample estimate of cross-sectional correlation of errors of country i and j given as

$$P'ij = P'ij = \frac{\sum_{t=1}^{T} u_{it}u_{jt}}{\left(\sum_{t=1}^{T} u_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T} u_{jt}^2\right)^{1/2}} \tag{8}$$

where the number of possible pairings (u_{it}, u_{jt}) rises with N and therefore can state our null hypothesis of cross-sectional independence, $H_0: p_{ij} = p_{ji} = cor(u_{it}, u_{it}) = 0$ for $i \neq j$, against the alternative hypothesis of cross-sectional dependence, $H_1: p_{ij} = p_{ji} \neq 0$ for some $i \neq j$.

Subsequent to cross-sectional dependence test, we scrutinized stationarity and non-stationarity of the variables. Once our results from the cross-sectional dependence test confirm the presence of cross section dependence in the series; the use of conventional (i.e., first generation) unit root tests method become invalid as they rely on the assumption of cross section independence in the series. Our study, therefore, applied second-generation unit root test such as cross-sectionally augmented Dicker-Fuller (CADF) and cross-sectional augmented IPS (CIPS) to perform panel unit root test. That is, CADF and CIPS tests produce results, which are reliable in the presence of cross-section dependence and heterogeneity across the countries under study. The applications of the two methods of unit root tests are the same except that CIPS uses the average of the cross section of the CADF test expressed mathematically as

$$\varDelta y_{it} = a_i + p_i y_{i,t-1} + \gamma_1 \overline{y}_{t-1} + \sum_{j}^{k} \gamma_{ij} \varDelta \overline{y}_{i,t-j} + \sum_{j=0}^{k} \varDelta y_{i,t-j} + \varepsilon_{it} \tag{9}$$

where $\overline{y}_{t-1} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} y_{i,t-1}, \varDelta\overline{y}_t = \left(\frac{1}{N}\right)\sum_{i=1}^{N} y_{it,}$ and $t_i(N, T)$ are the t-statistic of the estimate and p_i is the individual ADF statistics.

$$CIPS(N,T) = t\text{–}bar = N^{-1} \sum_{i=1}^{N} t_i(N,T) \tag{10}$$

where $t_i(N, T)$ is the cross-sectional augmented Dickey–Fuller statistic for the ith cross section unit given by the t-ratio of the coefficient of the model in Eq. (3).

To search for possible cointegrating relationship between our variables, the study applied both Kao and Pedroni cointegration test. Subsequent to the cointegrating findings would be to estimate the long-run effects or elasticity of the predicting variables using Pooled (weighted) Dynamic Ordinary Least Square (DOLS) and Fully Modified Ordinary Least Square (FMOLS) for the entire countries. To find the direction of cause and effect relationship between the variables, our study employed Pool Mean Group (PMG) estimator.

Table 3 Descriptive analysis

	CO_2 eq	EC	GDP	CRP	LVP	POP
Mean	11.45	6.85	7.08	4.25	4.06	19.42
Std. Dev.	1.19	0.73	1.26	0.40	0.61	1.41
Min	9.37	5.59	4.77	3.28	2.41	16.96
Max	12.56	7.99	9.49	4.95	4.92	21.03
Skewness	− 0.98	− 0.03	− 0.15	− 0.41	− 0.82	− 0.34
Kurtosis	2.19	1.85	1.83	2.36	2.93	1.55
Jarque-Bera	32.38	9.44	10.47	7.72	19.20	18.52
Probability	0.00*	0.01*	0.01*	0.02*	0.00*	0.00*
CV	10.39	10.66	17.80	9.41	15.02	7.26

In order to check the convergence among the emerging countries, the coefficients of variation (CV) are calculated as (std. dev./mean × 100)

*p value of statistical significance at 5% level

Cointegration analysis

To search for possible cointegrating relationship between our variables as stated in the model of Eq. (1), the study, firstly, applied Kao cointegrating test. Our ADF t-statistics is therefore calculated as

$$ADF = \frac{{}^{t}ADF + \left(\frac{\sqrt{6N\vartheta_q}}{2\vartheta_{0q}}\right)}{\sqrt{\left(\frac{\vartheta_{0q}^2}{2\vartheta_q^2}\right) + \left(10\vartheta_{0q}^2\right)}} \tag{11}$$

where $\vartheta_q^2 = \sum_{u\varepsilon} - \sum_{u\varepsilon}\sum_{\varepsilon}^{-1}, \vartheta_{0q}^2 = \Omega_u - \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1}, \Omega$ is the long run covariance matrix and ${}^{t}ADF$is the t-statistic in ADF regression for cointegration.

Our study further applied (Pedroni 2004) cointegrating technique to confirm the results of Kao cointegration test. Panel unit root test such as a Pedroni cointegrating test is based on within-dimension and between-dimension with lag lengths in parentheses. The within-dimension approach (i.e., panel test) of cointegration includes v-statistic, rho-statistic, PP-statistic, and ADF-statistic. These tests of unit root are done on estimated residuals, which pool the auto-regressive coefficients across the four countries under study. Within-dimension approach test of cointegration considers the common time factor and heterogeneity across the four countries. On the other hand, between-dimension approach (i.e., group test) deals with the average of the individual auto-regressive coefficient for the unit root based on estimated residuals. Between dimension tests of cointegration include rho-statistic, PP-statistic, and ADF-statistic. Pedroni panel cointegration test can be expressed as

$$CO2eq_{it} = \alpha_i + \delta_{1i}X_{it} + \delta_{2i}X_{2it} + \ldots\ldots\delta_{pi}X_{pit} + \varepsilon_{it} \tag{12}$$

where α_i and δ_i are the intercepts and slope coefficients that can vary across cross-sections, $t = 1, \ldots, T, i = 1, \ldots, N, p = 1, \ldots, CO2eq, x$ and p are assumed to be integrated of the same order ($I(1)$). Under the null hypothesis of no cointegration, the residuals ε_{it} will be $I(1)$. The general approach is to obtain the residuals from Eq. (12) and test whether the residuals are $I(1)$ by estimating the auxiliary regression.

Long-run estimates

Subsequent to the findings of both Kao and Pedroni cointegrating test that variables are cointegrated, we proceeded further to generate individual long-run estimates or the elasticity of the predicting variables. Using Dynamic Ordinary Least Square (DOLS) and Fully Modified Ordinary Least Square (FMOLS) as estimators for elasticity instead of the first-generation estimator such as Ordinary Least Square (OLS), the FMOLS estimation modifies the Ordinary Least Square. It overcomes the inherent problem of the serial correlation in the cointegrating residuals as well as the endogeneity bias predominant in most analysis involving the causal influence from the endogenous to the exogenous variables. FMOLS is quite effective in getting away the problem of endogeneity and sequential correlation of the regressors and the error term using the non-parametric approach (Dogan and Seker 2016), while DOLS estimator uses a parametric approach, lags, and leads. Besides that, OLS estimator produces results which are biased and inconsistent estimates when used on the cointegrated panel. The adoption of FMOLS approaches by (Pedroni 2001) to measure the long-run relationship between the variables can be expressed as

$$CO2eq_{it} = \omega_0 + \beta X_{it} - i + \sum_{j=i}^{j} \gamma_j \Delta X_{it-j} + \mu_{it} \tag{13}$$

where $CO2eq_{it}$ denotes the dependent variable carbon dioxide equivalent emissions. The X_{it} denotes the independent variables in this study. The long-run covariance is presented as Ω_t=limT→∞ F [($^1/_T$) ($\sum_t^T = 1^{\mu_{it}}$) ($\sum_t^T = 1^{\mu_{it}}$)’].

Then, the FMOLS estimator is extended to Eq. (13) below.

$$\beta = \frac{1}{n} \sum_{i=1}^{n} \left[\sum_{t=1}^{T} \left(X_{it} - \overline{X}_t \right)^2 \right)^{-1} \left(\sum_{t=1}^{T} \left(X_{it} - \overline{X}_{it} \right) \right) (CO2eq_{it}) - \Gamma_{\hat{\gamma}} \right]$$

where $CO2eq_{it} = CO2eq_{it} - \overline{CO2eq} - \left({}^{\hat{\Omega}_{1,0}}/_{\hat{\Omega}_{1,1}} \right) \Delta X_{it};$

and

$$\hat{\gamma} = \hat{\Gamma}_{1,0} + \hat{\Omega}_{1,0} - \left({}^{\hat{\Omega}_{1,0}}/_{\hat{\Omega}_{1,1}} \right) \left(\hat{\Gamma}_{1,1} + \hat{\Omega}_{1,1} \right)$$

Results and discussions

Results of Table 4 of cross-section dependence test rejected the null hypothesis and therefore accepted the alternative hypothesis of cross section dependence on the variables. Our findings on homogeneity tests using (Pesaran and Yamagata 2008) revealed a rejection of the null hypothesis and that coefficients were found to be heterogeneous.

Table 4 Cross-section dependence and homogeneity test results

Cross-sectional dependency tests (H_0: there is cross-sectional independency)		
Test	Statistic	*P* value
CO_2eq	9.55	0.00*
EC	13.71	0.00*
GDP	14.94	0.00*
CRP	14.74	0.00*
LVP	15.36	0.00*
POP	16.03	0.00*
Homogeneity tests (H_0: slope coefficients are homogeneous)		
Test	Stastistic	*P* value
Delta_tilde	3.588	0.003*
Delta_tilde_adj	− 2.797	0.005*

*Rejection of CD test and homogeneity test of the null hypothesis at 5% significance level

Our findings in Table 5 indicate that data series confirms the presence of non-stationary of all the variables at level. However, variables became stationary at their first difference and therefore rejected the null hypothesis that unit root exists at first difference. Results in the Table 5, therefore, settled that the variables are integrated at the same order.

Results of Kao cointegration in Table 6 show that our variables are cointegrated and therefore have a long-run association. This, therefore, provides us the basis to reject the null hypothesis of no cointegration at 5% significance level.

With the 11 tests as shown in Table 7, the panel rho-statistic shows one-sided test of positive values that accept the null hypothesis of no cointegrating among the variables, while the remaining test of the panel (i.e., *v*-statistics, PP-statistic, and ADF-statistic) shows gloomy values. However, Panel PP and ADF statistics were found to be significant and therefore rejected the null hypothesis of no cointegration. Group test, on the other hand, shows the negative value for ADF, while rho

Table 5 Results from panel unit root test

	CIPS		CADF	
	Level	Δ	Level	Δ
CO_2eq	[− 2.51]	[− 4.35]**	[− 2.51]	[− 3.10]**
EC	[− 2.12]	[− 5.06]**	[− 1.93]	[− 3.27]**
GDP	[− 1.49]	[− 5.58]**	[− 1.59]	[− 3.45]**
CRP	[− 2.77]	[− 6.19]**	[− 2.25]	[− 3.99]**
LVP	[− 1.29]	[− 4.63]**	[− 1.91]	[− 3.06]**
POP	[− 2.45]	[− 2.25]**	[− 2.45]	[− 2.22]**

[ ] and Δ represent the value of *t*-statistics and the first difference of the variables, respectively. Critical values are not provided for the sake of brevity but can be provided upon request

**The statistical significance at 5% level

Table 6 Results from the Kao Panel cointegration test

	t-statistics	p value
ADF	− 4.222	0.000**

**Reject the null hypothesis at 5% significance level

and PP has positive values of the test statistics with probability of PP-statistic (0.041), ADF-statistic (0.029), and rho-statistic (0.943). Therefore, at 5% significance level, PP and ADF-statistics group test rejected the null hypothesis of no cointegrating among the variables, while rho-statistic test results projected the reverse as the case. The results from the Pedroni panel cointegrating test, therefore, indicate an individual intercepts with no deterministic trend of variables with respect for the majority (i.e., 6 out of 11) of the test statistics which, therefore, confirm Kao cointegrating test results.

Result from the pooled (weighted) DOLS and FMOLS estimators are provided in Table 8. Pooled (weighted) panel method estimation was used to accounts for heterogeneity by using cross section-specific estimates of the long-run covariance to reweight the data prior to computing pooled FMOLS. Table 8 reports of DOLS estimator show that GDP and POP coefficients are statistically insignificant at 5% significance level. However, FMOLS estimation found all the variables to be statistically significant at 5%. Therefore, a 1% increase in economic growth, crop production index, and livestock production index will cause a proportional increase in carbon dioxide equivalent emission by 17, 28, and 28% correspondingly, while 1% increase in EC and POP will cause a decrease in CO_2 equivalent emissions by 59 and 17%, respectively. The R-squared of 99% for both DOLS and FMOLS indicates that energy consumption (EC), economic growth (GDP), crop production index (CRP), livestock production index (LVP), and population (POP) have statistically significant explanatory powers for the dependent variable. That is, variations in EC, GDP, CRP, LVP, and POP account for 99% of the variability in CO_2 equivalent emissions.

Table 7 Results from the Pedroni cointegration test

Common AR coefficients (within-dimension)		
	Statistics	Weighted statistics
Panel v-statistic	− 0.582	− 0.753
Panel rho-statistic	0.445	0.207
Panel PP-statistic	− 0.859*	− 1.117*
Panel ADF-statistic	− 1.969*	− 1.821*
Individual AR coefficients (between-dimension)		
Group rho-statistic	1.578	
Group PP-statistic	0.453*	
Group ADF-statistic	− 0.780*	

*The statistical significance at 5% level

Table 8 Results from the pooled (weighted) DOLS and FMOLS (dependent variable: CO2eq)

	DOLS		FMOLS	
Regressors	Coefficient	P value	Coefficient	P value
EC	− 0.443	0.000**	− 0.589	0.000**
GDP	0.030	0.177	0.168	0.000**
CRP	0.432	0.000**	0.276	0.000**
LVP	0.191	0.001**	0.282	0.000**
POP	− 0.042	0.620	− 0.165	0.000**
R^2	0.99		0.99	

**The statistical significance at 5% level

The causality test using the Pooled Mean Group (PMG) estimator

Once the long-run relationship between the variable is established, the study further examined the direction of causality between the variables using the Pool Mean Group (PMG) estimator. One of the key reasons for PMG estimator use is that it allows the short-run dynamic specification to differ from country to country while making the long-run coefficients constrained to be the same for all cross sections. PMG also allowed idiosyncratic heterogeneity to be billeted by estimating individual equations for each country and averages the parameter estimates. Furthermore, PMG estimator can be used regardless of whether the variables are integrated at the same order or not. Therefore, both short and long run causality inference can be drawn irrespective of whether the cointegration was detected earlier or not.

Results of Table 9 show that in the short-run, unidirectional causality runs from energy consumption to economic growth and population, economic growth to crop production index, and population to crop production index. However, in the

Table 9 The Pooled Mean Group (PMG) estimator causality test results

Estimator	Short-run causality	Long-run causality
PMG	CO_2eq ↔ LVP	GDP ↔ CO_2eq
	EC → GDP	EC ↔ GDP
	GDP → CRP	EC ↔ CO_2eq
	EC → POP	CO2eq ↔ CRP
	LVP → EC	EC → CRP
	POP → CRP	LVP → CO_2eq
		LVP → EC
		LVP → GDP
		POP → CO_2eq

long-run, causality runs from energy consumption to crop production index, livestock production index to carbon dioxide equivalent emissions, and economic growth, while livestock production index to energy consumption was found in both short- and long-term. On the other hand, bidirectional causality was found between carbon dioxide equivalent emissions and livestock production index in the short-term. However, long-term results indicate bidirectional causality between carbon dioxide equivalent emissions and economic growth, carbon dioxide equivalent emissions and energy consumption, and crop production index and carbon dioxide equivalent emissions. Additionally, the PMG causality estimation also revealed bidirectional causality between energy consumption and economic growth in the long-run.

Conclusions

Continuous threat posed by climate change caused by carbon dioxide emission has called for world leaders to work hard to confront it with all the seriousness. This has levitated interest of researchers to find out cause and effect of various variables on global emission. In the policy-making process, associations between variables are very important. Therefore, our study on finding the causal relationship between agricultural production and carbon dioxide emissions of selected emerging economies is in the right place. That is, it has become necessary to find the elasticity of the relationship, especially with regard to emerging economies since they contribute a significant level of emissions to the global stock. Preliminary analysis shows that variables are cross-sectional dependent and heterogeneous using Pesaran (2004) CD and Pesaran and Yamagata (2008) test, respectively. Therefore, application of first-generation test will lead to spurious results, accordingly, the need to employ the second-generation techniques. Our empirical findings using second-generation method such as CADF and CIPS, which takes into account the presence of heterogeneity and cross-sectional dependence on the countries, showed that variables have unit root at their level but, however, become stationary at their first difference. Both Kao and Pedroni cointegration test shows that variables are cointegrated and hence have long run association.

Our empirical result of the long-term marginal effect of the predictors on dependent variable for the four economies was based on DOLS and FMOLS methods. Empirical analysis results indicate that 1% increase in economic growth, crop production index, and livestock production index will cause a proportional increase in carbon dioxide equivalent emission by 17%, 28%, and 28% correspondingly. This signifies that higher economic growth, crop, and livestock production contribute significantly to the growth of CO_2 equivalent emissions and, therefore, are more detrimental to emerging economies. A 1% increase in energy consumption and population, on the other hand, decreases CO_2 equivalent emissions by 59 and 17% individually. It indicates that energy consumption and population improve the environment of emerging economies. The findings suggest that both crops and livestock production causes the carbon dioxide equivalent in the emerging economies. The reason is that crops require some level of carbon dioxide for photosynthesis processes. Pre-harvest and post-harvest of crops release methane, nitrous oxide, and carbon dioxide into the atmosphere. Crop production also causes an increase in CO_2 equivalent emissions due to management model. The increase in carbon dioxide emissions resulting from a livestock production increase is due to poor grazing management, feed production, livestock processing, enteric fermentation of ruminants, and transportation of livestock in BICS countries. Increase in carbon dioxide equivalent emissions as results of economic growth indicates that emerging economies are in their early stages of economic development based on EKC hypothesis.

PMG tests unearth the direction of short- and long-run causality among variables. Results illustrate that in the short-run, unidirectional causality runs from energy consumption to economic growth and population, economic growth to crop production index, and population to crop production index. However, in the long-run, unidirectional causality runs from energy consumption to crop production index, livestock production index to carbon dioxide equivalent emissions, and economic growth, while livestock production index to energy consumption was found in both short- and long-term. On the other hand, bidirectional causality was found between carbon dioxide equivalent emissions and livestock production index in the short-term. Nonetheless, long-term results indicate bidirectional causality between carbon dioxide equivalent emissions and economic growth; carbon dioxide equivalent emissions and energy consumption; and crop production index and carbon dioxide equivalent emissions. PMG causality estimation also revealed bidirectional causality between energy consumption and economic growth in the long-run. Our long-term causality relationship test result shows that unidirectional or bidirectional exists between carbon dioxide equivalent emission and explanatory variables. This confirms findings of FMOLS test in Table 8 about the elasticities of predicting variables, which were found to be significant, although some of the results are positive in terms of improving the environment and others are detrimental to the ecosystem of BICS economies.

Policy implications

The extent literature and evidence from this study support the notion that global food security and agriculture are faced with major challenges under climate change as a result of the potential negative effect of production and implementation of sectoral action to limit global warming. Overall, agricultural greenhouse gas emissions continue to rise (albeit not rapid as emissions from other human activities); hence, the analysis of superior data on emissions from farming, livestock, and fisheries (as done in this research) can help economies identify opportunities to contemporaneously reduce emissions and address their food security, resilience, and rural development goals, and gain access to global funding to pursue them. In this way, the study potentially adds to the stock of reference points for emissions and mitigation opportunities for the sector. Results of the analysis provide an interesting finding which gives policy direction to the emerging economies to focus their attention on to reduce agricultural activity's emissions. Potentially, for emerging economies to achieve Sustainable Development of ensuring zero hunger for their citizenry requires the need to modify the method of growing crops. There is also the need to look at feeding practice and overall management techniques to cut the quantity of CH_4 resulting from enteric fermentation. That is, there is the need to ensure that optimal nitrogen is applied since high level of it creates nitrous oxide emissions, which do not necessary enhance crop production. With regard to livestock, there is the need to improve pasture quality to reduce the amount of CH_4 emission per unit of animal product. Emerging economies should also increase their research and development to provide new and improved mitigation practices to deal with emissions. BICS economies should ensure that mitigation effort is implemented as shared responsibility among key stakeholders within the economy. Emerging economies should create appropriate National Mitigation Action plans through which sectoral mitigation policies that incorporate other developmental goals could be realized. Emerging economies should make use of clean and affordable energy in order to achieve Sustainable Development Goal 7 and to protect the environment.

In conclusion, both crop and livestock productions have the same magnitude of impact on environment of emerging economies. Our results support the view that increases in economic growth, crop, and livestock production increase environmental pollution. Additionally, our results support the findings from other researchers that increase in energy consumption and population helps to improve ecological pollution. Emerging economies should alter their agricultural production techniques and also adopt agricultural technology method, which is more environmentally friendly. Our study, therefore, revealed that agriculture production indexes affect carbon dioxide equivalent emissions and that their respective increase causes an increase in emissions of BICS economies. Therefore, there is the need to operational listed policy guidance to address the issue of rising carbon dioxide equivalent emissions in emerging economies. Lastly, the study found energy consumption and population to affect CO_2 equivalent emissions positively, while the reverse is the case for economic growth. Further study would be to look at the individual country effect on of the variables on carbon dioxide equivalent emissions.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Acaravci A, Ozturk I (2010) On the relationship between energy consumption, CO2 emissions and economic growth in Europe. Energy 35(12):5412–5420

Adom PK, Bekoe W (2012) Conditional dynamic forecast of electrical energy consumption requirements in Ghana by 2020: a comparison of ARDL and PAM. Energy 44(1):367–380

Adom PK, Bekoe W, Amuakwa-Mensah F, Mensah JT, Botchway E (2012) Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: empirical evidence from Ghana, Senegal, and Morocco on the causal dynamics. Energy 47(1):314–325

Adom PK, Kwakwa PA, Amankwaa A (2018) The long-run effects of economic, demographic, and political indices on actual and potential CO 2 emissions. J Environ Manag 218:516–526

Ahmada R, Zulkiflib SAM, Hassanc N, Yaseer WM, Abdohd M (2016) The impact of economic activities on Co2 emission. Int Academic Res J Soc Sci 2(1):81–88

Alam MJ, Begum IA, Buysse J, Van Huylenbroeck G (2012) Energy consumption, carbon emissions and economic growth nexus in Bangladesh: cointegration and dynamic causality analysis. Energy Policy 45:217–225

Alper A, Onur G (2016) Environmental Kuznets curve hypothesis for sub-elements of the carbon emissions in China. Nat Hazards 82(2):1327–1340

Amuakwa-Mensah F, Adom PK (2017) Quality of institution and the FEG (forest, energy intensity, and globalization)-environment relationships in sub-Saharan Africa. Environ Sci Pollut Res 24(21): 17455–17473

Apergis N, Payne JE, Menyah K, Wolde-Rufael Y (2010) On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. Ecol Econ 69(11):2255–2260

Appiah K, Du J, Boamah KB (2017a) The effect of environmental performance on Firm's performance—evidence from Ghana. Br J Int Res 8(1):340–348

Appiah K, Du J, Musah A-AI, Afriyie S (2017b) Investigation of the relationship between economic growth and carbon dioxide (CO 2) emissions as economic structure changes: evidence from Ghana. Resour Environ 7(6):160–167

Asumadu-Sarkodie S, Owusu PA (2016a) The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. Environ Sci Pollut Res 23(11):10968–10982

Asumadu-Sarkodie S, Owusu PA (2016b) A review of Ghana's energy sector national energy statistics and policy framework. Cogent Eng 3(1):1155274

Asumadu-Sarkodie S, Owusu PA (2017) The causal nexus between carbon dioxide emissions and agricultural ecosystem—an econometric approach. Environ Sci Pollut Res 24(2):1608–1618

Azam M, Khan AQ, Abdullah HB, Qureshi ME (2016) The impact of CO 2 emissions on economic growth: evidence from selected higher CO 2 emissions economies. Environ Sci Pollut Res 23(7):6376–6389

Bakhtiari AA, Hematian A, Sharifi A (2015) Energy analyses and greenhouse gas emissions assessment for saffron production cycle. Environ Sci Pollut Res 22(20):16184–16201

Bargaoui SA, Liouane N, Nouri FZ (2014) Environmental impact determinants: an empirical analysis based on the STIRPAT model. Procedia Soc Behav Sci 109:449–458

Ben Jebli M, Ben Youssef S (2017) Renewable energy consumption and agriculture: evidence for cointegration and granger causality for Tunisian economy. Int J Sust Dev World Ecology 24(2):149–158

Cambra-López M, Aarnink AJ, Zhao Y, Calvet S, Torres AG (2010) Airborne particulate matter from livestock production systems: a review of an air pollution problem. Environ Pollut 158(1):1–17

Charfeddine L, Khediri KB (2016) Financial development and environmental quality in UAE: cointegration with structural breaks. Renew Sust Energ Rev 55:1322–1335

Chauhan AJ, Johnston SL (2003) Air pollution and infection in respiratory illness. Br Med Bull 68(1):95–112

Chen J-H, Huang Y-F (2013) The study of the relationship between carbon dioxide (CO2) emission and economic growth. J Int Glob Econ Stud 6(2):45–61

Desjardins RL, Worth DE, Vergé XP, Maxime D, Dyer J, Cerkowniak D (2012) Carbon footprint of beef cattle. Sustainability 4(12):3279–3301

Dogan E, Seker F (2016) The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. Renew Sust Energ Rev 60:1074–1085

Dogan E, Turkekul B (2016) CO 2 emissions, real output, energy consumption, trade, urbanization and financial development: testing the EKC hypothesis for the USA. Environ Sci Pollut Res 23(2):1203–1213

Druckman A, Jackson T (2009) The carbon footprint of UK households 1990–2004: a socio-economically disaggregated, quasi-multiregional input–output model. Ecol Econ 68(7):2066–2077

Du L, Wei C, Cai S (2012) Economic development and carbon dioxide emissions in China: provincial panel data analysis. China Econ Rev 23(2):371–384

Dudley B (2017) BP statistical review of world energy. London. In: UK

Duxbury JM (1994) The significance of agricultural sources of greenhouse gases. Fertil Res 38(2):151–163

Elliott RJ, Sun P, Zhu T (2017) The direct and indirect effect of urbanization on energy intensity: a province-level study for China. Energy 123:677–692

European Environment Agency (2015) Available: www.eea.europa.eu

Feng K, Davis SJ, Sun L, Hubacek K (2015) Drivers of the US CO 2 emissions 1997–2013. Nat Commun 6:7714

Food and Agriculture Organisation (2011) Food wastage footprint: sustainability pathways. Available: www.fao.org

Food and Agriculture Organisation (2014) Agriculture's greenhouse gas emissions on the rise. Available: www.fao.org

Food and Agriculture Organisation (2014a) Greenhouse gas emissions from Agriculture, forestry and other land use. Available: www.fao.org

Food and Agriculture Organisation (2015) Food wastage footprint & climate change. Available: www.fao.org

Funk CC, Brown ME (2009) Declining global per capita agricultural production and warming oceans threaten food security. Food Secur 1(3):271–289

Global Carbon Project (2017) Available: www.globalcarbonproject.org/

Hagemann M, Ndambi A, Hemme T, Latacz-Lohmann U (2012) Contribution of milk production to global greenhouse gas emissions. Environ Sci Pollut Res 19(2):390–402

Hamit-Haggar M (2012) Greenhouse gas emissions, energy consumption and economic growth: a panel cointegration analysis from Canadian industrial sector perspective. Energy Econ 34(1):358–364

Hatzigeorgiou E, Polatidis H, Haralambopoulos D (2011) CO2 emissions, GDP and energy intensity: a multivariate cointegration and causality analysis for Greece, 1977–2007. Appl Energy 88(4):1377–1385

Henning S, Gerber P, Wassenaar T, Castel V, Rosales M, Haan C (2006) Livestock's long shadow–environmental issues and options. FAO, Roma

Hillier J, Hawes C, Squire G, Hilton A, Wale S, Smith P (2009) The carbon footprints of food crop production. Int J Agric Sustain 7(2): 107–118

Hossain MS (2011) Panel estimation for CO2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. Energy Policy 39(11):6991–6999

Huang B-N, Hwang MJ, Yang CW (2008) Causal relationship between energy consumption and GDP growth revisited: a dynamic panel data approach. Ecol Econ 67(1):41–54

Hussain M, Irfan Javaid M, Drake PR (2012) An econometric study of carbon dioxide (CO2) emissions, energy consumption, and economic growth of Pakistan. Int J Energy Sector Manage 6(4):518–533

Hussain S, Peng S, Fahad S, Khaliq A, Huang J, Cui K, Nie L (2015) Rice management interventions to mitigate greenhouse gas emissions: a review. Environ Sci Pollut Res 22(5):3342–3360

Hwang J-H, Yoo S-H (2014) Energy consumption, CO 2 emissions, and economic growth: evidence from Indonesia. Qual Quant 48(1):63–73

Jayanthakumaran K, Verma R, Liu Y (2012) CO2 emissions, energy consumption, trade and income: a comparative analysis of China and India. Energy Policy 42:450–460

Johnson JM-F, Franzluebbers AJ, Weyers SL, Reicosky DC (2007) Agricultural opportunities to mitigate greenhouse gas emissions. Environ Pollut 150(1):107–124

Kasman A, Duman YS (2015) CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. Econ Model 44:97–103

Khan AN, Ghauri B, Jilani R, Rahman S (2011) Climate change: emissions and sinks of greenhouse gases in Pakistan. Proceedings of the Symposium on Changing Environmental Pattern and its impact with Special Focus on Pakistan

Leip A, Billen G, Garnier J, Grizzetti B, Lassaletta L, Reis S, Simpson D, Sutton MA, De Vries W, Weiss F (2015) Impacts of European livestock production: nitrogen, sulphur, phosphorus and greenhouse gas emissions, land-use, water eutrophication and biodiversity. Environ Res Lett 10(11):115004

Li W, Ou Q, Chen Y (2014) Decomposition of China's CO 2 emissions from agriculture utilizing an improved Kaya identity. Environ Sci Pollut Res 21(22):13000–13006

Li T, Wang Y, Zhao D (2016) Environmental Kuznets curve in China: new evidence from dynamic panel analysis. Energy Policy 91:138–147

Lorente DB, Álvarez-Herranz A (2016) Economic growth and energy regulation in the environmental Kuznets curve. Environ Sci Pollut Res 23(16):16478–16494

Lozano S, Gutierrez E (2008) Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO2 emissions. Ecol Econ 66(4):687–699

Luo Y, Long X, Wu C, Zhang J (2017) Decoupling CO2 emissions from economic growth in agricultural sector across 30 Chinese provinces from 1997 to 2014. J Clean Prod 159:220–228

Lutz W, O'Neill F, MacKellar L (2001) Population and climate change. International Institute for Applied Systems Analysis (IIASA) Cambridge University Press, Cambridge

Martin G, Saikawa E (2017) Effectiveness of state climate and energy policies in reducing power-sector CO 2 emissions. Nat Clim Chang 7(12):912–919

McAusland C (2010) Globalisation's direct and indirect effects on the environment. Glob Transp Environ :31–53. https://doi.org/10.1787/9789264072916-4-en

Menyah K, Wolde-Rufael Y (2010) CO2 emissions, nuclear energy, renewable energy and economic growth in the US. Energy Policy 38(6):2911–2915

Muller A, Jawtusch J, Gattinger A (2011) Mitigating greenhouse gases in agriculture–a challenge and opportunity for agricultural policies. Diakonisches Werk der Evangelischen Kirche in Deutschland e. V., Stuttgart. Abrufbar unter http://orgprints.org/19989

Oganesyan M (2017) Carbon emissions, energy consumption and economic growth in the BRICS

Owusu PA, Asumadu-Sarkodie S (2016) Is there a causal effect between agricultural production and carbon dioxide emissions in Ghana? Environ Eng Res 22(1):40–54

Özokcu S, Özdemir Ö (2017) Economic growth, energy, and environmental Kuznets curve. Renew Sust Energ Rev 72:639–647

Ozturk I, Al-Mulali U (2015) Investigating the validity of the environmental Kuznets curve hypothesis in Cambodia. Ecol Indic 57:324–330

Pao H-T, Tsai C-M (2010) CO2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy 38(12):7850–7860

Pao H-T, Yu H-C, Yang Y-H (2011) Modeling the CO2 emissions, energy use, and economic growth in Russia. Energy 36(8):5094–5100

Paramati SR, Apergis N, Ummalla M (2018) Dynamics of renewable energy consumption and economic activities across the agriculture, industry, and service sectors: evidence in the perspective of sustainable development. Environ Sci Pollut Res 25(2):1375–1387

Paustian K, Cole CV, Sauerbeck D, Sampson N (1998) CO2 mitigation by agriculture: an overview. Clim Chang 40(1):135–162

Pedroni P (2001) Fully modified OLS for heterogeneous cointegrated panels. Nonstationary panels, panel cointegration, and dynamic panels. Emerald Group Publishing Limited, pp 93–130

Pedroni P (2004) Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econometric theory 20(3):597–625

Pesaran MH (2004) General diagnostic tests for cross section dependence in panels.

Pesaran MH, Yamagata T (2008) Testing slope homogeneity in large panels. J Econ 142(1):50–93

Ramakrishnan S, Hishan SS, Nabi AA, Arshad Z, Kanjanapathy M, Zaman K, Khan F (2016) An interactive environmental model for economic growth: evidence from a panel of countries. Environ Sci Pollut Res 23(14):14567–14579

Roth E, Gunkel-Grillon P, Joly L, Thomas X, Decarpenterie T, Mappe-Fogaing I, Laporte-Magoni C, Dumelié N, Durry G (2014) Impact of raw pig slurry and pig farming practices on physicochemical parameters and on atmospheric N 2 O and CH 4 emissions of tropical soils, Uvéa Island (South Pacific). Environ Sci Pollut Res 21(17):10022–10035

Saboori B, Sulaiman J (2013) Environmental degradation, economic growth and energy consumption: evidence of the environmental Kuznets curve in Malaysia. Energy Policy 60:892–905

Sarkar MSK, Sadeka S, Sikdar MMH, Zaman B (2015) Energy consumption and CO2 emission in Bangladesh: trends and policy implications. Asia Pac J Energy Environ 2(3):175–182

Sarkodie SA, Owusu PA (2017) The relationship between carbon dioxide, crop and food production index in Ghana: by estimating the long-run elasticities and variance decomposition. Environ Eng Res 22(2):193–202

Shahbaz M, Khan S, Ali A, Bhattacharya M (2017) The impact of globalization on CO2 emissions in China. Singap Econ Rev 62(04):929–957

Shi A (2001) Population growth and global carbon dioxide emissions. IUSSP Conference in Brazil/session-s09

Smit LA, Hooiveld M, van der Sman-de Beer F, Opstal-van Winden AW, Beekhuizen J, Wouters IM, Yzermans CJ, Heederik D (2013) Air pollution from livestock farms, and asthma, allergic rhinitis and COPD among neighbouring residents. Occup environ med: oemed-2013-101485

Smit LA, Boender GJ, de Steenhuijsen Piters WA, Hagenaars TJ, Huijskens EG, Rossen JW, Koopmans M, Nodelijk G, Sanders EA, Yzermans J (2017) Increased risk of pneumonia in residents living near poultry farms: does the upper respiratory tract microbiota play a role? Pneumonia 9(1):3

Smith P (2012) Agricultural greenhouse gas mitigation potential globally, in Europe and in the UK: what have we learnt in the last 20 years? Glob Chang Biol 18(1):35–43

Smith P, Martino D, Cai Z, Gwary D, Janzen H, Kumar P, McCarl B, Ogle S, O'Mara F, Rice C (2008) Greenhouse gas mitigation in agriculture. Philos Trans R Soc B Biol Sci 363(1492):789–813

Soytas U, Sari R (2009) Energy consumption, economic growth, and carbon emissions: challenges faced by an EU candidate member. Ecol Econ 68(6):1667–1675

Stern DI (2004) The rise and fall of the environmental Kuznets curve. World Dev 32(8):1419–1439

Thornton PK (2010) Livestock production: recent trends, future prospects. Philos Trans R Soc B Biol Sci 365(1554):2853–2867

Tisdell C (2005) Economics, ecology and the environment

Trasande L, Thurston GD (2005) The role of air pollution in asthma and other pediatric morbidities. J Allergy Clin Immunol 115(4):689–699

Tunç GI, Türüt-Aşık S, Akbostancı E (2009) A decomposition analysis of CO2 emissions from energy use: Turkish case. Energy Policy 37(11):4689–4699

Van Haarlem R, Desjardins R, Gao Z, Flesch T, Li X (2008) Methane and ammonia emissions from a beef feedlot in western Canada for a twelve-day period in the fall. Can J Anim Sci 88(4):641–649

Waheed R, Chang D, Sarwar S, Chen W (2018) Forest, agriculture, renewable energy, and CO2 emission. J Clean Prod 172:4231–4238

Wang S, Zhou D, Zhou P, Wang Q (2011) CO2 emissions, energy consumption and economic growth in China: a panel data analysis. Energy Policy 39(9):4870–4875

Wang S, Fang C, Wang Y (2016) Spatiotemporal variations of energy-related CO2 emissions in China and its influencing factors: an empirical analysis based on provincial panel data. Renew Sust Energ Rev 55:505–515

World Bank (2017) World Development Indicator. Available: http:data.worldbank.org/

Yeh J-C, Liao C-H (2017) Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT. Sust Environ Res 27(1):41–48

Yu Y, Y-r Deng, F-f Chen (2017) Impact of population aging and industrial structure on CO_2 emissions and emissions trend prediction in China. Atmos Pollut Res 9(3):446–454

Yue T, Long R, Chen H, Zhao X (2013) The optimal CO2 emissions reduction path in Jiangsu province: an expanded IPAT approach. Appl Energy 112:1510–1517

Zakarya GY, Mostefa B, Abbes SM, Seghir GM (2015) Factors affecting CO2 emissions in the BRICS countries: a panel data analysis. Procedia Econ Fin 26:114–125

Zhang X-P, Cheng X-M (2009) Energy consumption, carbon emissions, and economic growth in China. Ecol Econ 68(10):2706–2712

Zhen W, Qin Q, Wei Y-M (2017) Spatio-temporal patterns of energy consumption-related GHG emissions in China's crop production systems. Energy Policy 104:274–284

Zou X, Azam M, Islam T, Zaman K (2016) Environment and air pollution like gun and bullet for low-income countries: war for better health and wealth. Environ Sci Pollut Res 23(4):3641–3657