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RESEARCH ARTICLE

Dynamic relationship among agriculture-energy-forestry and carbon dioxide (CO_2) emissions: empirical evidence from China

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Abstract

This study aims to explore the dynamic association among crop production, livestock production, power consumption in agriculture, forest area, and carbon dioxide (CO_2) emissions. Based on the annual data of China, spanning the period 1990 to 2016, the study applied the auto-regressive distributed lag (ARDL) bounds testing approach. In addition, the fully modified ordinary least squares (FMOLS) canonical cointegration regression (CCR) and the Granger causality tests are employed to check the robustness of the ARDL estimations. The ARDL-bounds testing approach indicated that all variables share a long-run connection. The long- and short-run ARDL estimations confirmed that crop production, as well as livestock production, has a significant positive effect on CO_2 emissions in both cases. However, power consumption in agriculture and forest area has a negative effect on it, indicating that both variables reduce CO_2 emissions in the long and short run. These results stood robust under various regression estimators and confirmed the findings of the ARDL method. Additionally, the results of the causality approach specified that a unidirectional causality is running from crop production, power consumption in agriculture, and forest area to CO_2 emissions. The causality between livestock production and CO_2 emissions is bidirectional. Therefore, the directions of this connection also validate the outcomes under various techniques used for robustness. These findings suggest that the government must reconsider its policies related to agricultural and livestock production and adopt environment-friendly practices in the agriculture sector that may reduce the carbon footprints in the long run.

Keywords CO_2 emissions · Agricultural production · Cointegration approach · China

Introduction

An exponential increase in population in the twentieth century increased the demand for food consumption, which resulted in the intensified and mechanized agricultural production and energy use (Adom et al. 2012; Asumadu-Sarkodie and Owusu 2016; McAusland 2010). China is among those countries that increased its production capacity on a larger scale to cater to the growing needs of food to feed the population. For instance, from 1990 to 2016, the crop production index of China has surged from 55.8 to 144.2 (FAO 2020a). Similarly, during the same period, the livestock production index rose from 40.11 to 130.43 (FAO 2020b). At the same time, energy use in China has also increased from 766.995 thousand kilograms in 1990 to 2236.73 thousand kilograms in 2016. China surpassed the USA in 2009, becoming the top energy consumer in the world (IEA 2012). When it comes to the agricultural sector, it heavily relies on conventional energy sources in comparison with other developed countries. For instance, it used 75 metric tons carbon equivalent (Mtce) energy in 2011, which is 3.75 times more than the energy consumption of Israel (20 Mtce), 2.7 times more than Switzerland (27 Mtce), 1.6 times more than of Sweden (46 Mtce), and 1.2 times more than Belgium (61 Mtce) (NBS 2016, 2017; Yang et al. 2018). The natural resources are also under stress, for example, the global forest level has decreased by 0.32 percent (1990–2016) that naturally plays the role of an air purifier, as it accumulates CO_2 and converts it into carbon and oxygen

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(Harris and Feriz 2011). In opposite to this, in China, the forest area has increased from 1.571 million km^2 in 1990 to 2.098 km^2 in 2016 (WDI 2018), which still occupies the significant chunk of energy providers in China. As per the study of food agricultural organization (1998), nearly 50 percent of the total energy is derived from wood in China. In addition, the use of wood as fuel is insignificant outside the rural household sector (Luo 1998). However, China is the top CO_2 emitter in the world, which has produced 10.3 million kt in 2014 (WDI 2018). It has been recently narrated that approximately 18 percent of the Chinese population resides in 35 megacities, which consume an estimated amount of about 40 percent of national energy consumption and hence produce a considerable share of CO_2 emissions. In the same vein, the global scenario is not much different from it. In light of this, global CO_2 emissions have skyrocketed. China's agricultural sector is producing approximately 17 percent of the total nationwide CO_2 emissions. It is because of the increasing population, which has boosted the demand for agricultural production, the need for energy, and economic growth to attain food security (Adom et al. 2012; Asumadu-Sarkodie and Owusu 2016; Hongmin et al. 2008; McAusland 2010; Xiong et al. 2016). As a consequence, they are adversely affecting human beings through their diverse impact on economic and social development, and environmental quality. In view of this situation, there is a need to rethink and redevelop the policies to introduce reforms in the agriculture sector to counter the adverse impacts of CO_2 emissions. It has been noted the availability of immense literature on the nexus between energy consumption, greenhouse gas emission, CO_2 emissions, and agricultural production. However, there is a dire need to incorporate the condition of forest production as well as crop and livestock production indexes in China. It provides the foundations to develop and test the hypotheses whether there exists dynamic interaction among crop and livestock production indexes, energy use for the agricultural machinery, level of the forest, and CO_2 emissions by undertaking the data of China from 1990 to 2016. These hypotheses will be tested by using the auto-regressive distributed lag (ARDL) approach and Granger causality test. Therefore, this study not only considers the energy use and emissions but also incorporates livestock and forestory in this nexus. This is the novel study of its kind for China using the aforementioned variables with a fresh data range and variety of econometric methods to check the robustness. Thus, this paper will provide interesting results and solid ground for all stakeholders.

Literature and hypothesis

This study empirically investigates the dynamic interaction between crop production, livestock production, power consumption in agriculture, forest, and CO_2 emissions in China from 1990 to 2016. The review of literature section is divided into the following segments: (i) firstly, we discuss the previous studies on the association among crop production, livestock production, and CO_2 emissions; (ii) secondly, we study the earlier works on the interaction between energy consumption in agriculture and CO_2 emissions; (iii) in last, we review the prior studies on the linkage between forest and CO_2 emissions. In addition, we developed hypotheses based on previous studies.

Nexus between crop production, livestock production, and CO_2 emissions

The world population has seen exponential growth and has increased from 1.6 billion in 1900 to nearly 6 billion in 2000 (Sommerfeld 1999). The increased population demands relatively more food in comparison with the past. Thus, in the last century, we also witnessed an increase in energy demand, economic growth, and agricultural production (crop and livestock) to achieve food security, which has resulted in increased CO_2 emissions (Owusu and Asumadu-Sarkodie 2016; Sarkodie and Owusu 2017). Solely, agriculture is the 2nd most significant contributor to the greenhouse gas owing to the high use of fossil fuel-driven machinery, fertilizers, and the burning of biomass (Qiao et al. 2019). It is simultaneously the victim and the cause of CO_2 emissions (Ismael et al. 2018). Many studies have been conducted to state the interrelationship among agricultural production and CO_2 emissions.

Appiah et al. (2018), in their research, found the causal interaction among agricultural production (crop production and livestock production) and CO_2 emissions during the period of 1973 to 2013 by using the fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS) in BRICS.[1] They discovered that if there is an increase of 1% in economic progression, crop, and livestock production indexes, there is a proportional increase in CO_2 emissions by 17%, 28%, and 28%, respectively. Hence, they suggested to rethink and revamp the agricultural production techniques and choose those that are environmentally friendly.

Another researcher, Luo et al. (2017), found that fertilizer consumption and livestock production add a lot to the CO_2 emissions in China. Similarly, Sarkodie and Owusu (2017) explored the interrelationship among CO_2 emissions and agricultural production (crop and livestock) in Ghana, utilizing the ARDL method and variance decomposition. They undertook the annual time series data spanning the period of 1960 to 2013. They quote that the 1% increase in both crop and livestock production indexes increases the CO_2 emissions by 0.52% and 0.81% in the long run. Besides, they explored the bidirectional causality between CO_2 emissions and crop production index, and a unidirectional causality, which is running

[1] Brazil, Russia, India, China, and South Africa

from livestock production to CO_2 emissions. Therefore, they suggested undertaking the efforts to reduce on-farm and off-farm (transportation and processing) losses, as they hamper the carbon footprint of Ghana.

Furthermore, Owusu and Asumadu-Sarkodie (2016) examined the dynamic linkages between agricultural productivity and CO_2 emissions using the ARDL model and time series data from 1960 to 2015. Their findings indicated the two-way causality between agricultural productivity and CO_2 emissions in a term that in the short run, 1% increase in copra and green coffee production tends to increase CO_2 emissions by 0.22% and 0.03%, respectively, whereas 1% increase in sorghum and millet decreases the CO_2 emissions by 0.11% and 0.13%. They also explored the one-way causality, which runs from crop production to CO_2 emission and then to palm kernel production.

More specifically, Dogan (2016) explored the determinants of CO_2 emissions in Turkey and reached on the notion that the negative yet significant impact of agriculture on CO_2 emissions in the short run as well long run prevails. Therefore, the researcher suggests rethinking the policies related to agriculture and CO_2 emissions, as policies/reforms intending to enhance agricultural production may reduce CO_2 emissions. Likewise, Mahmood et al. (2019) inspected the dynamic interaction among agriculture share, energy use and the environmental Kuznets curve, and the impact on CO_2 emissions. The findings depicted the inverted and U-shaped interrelationship between GDP and CO_2 (per capita). Besides, the significantly negative effect of the agricultural sector on CO_2 emissions was also found.

Qiao et al. (2019) explored the nexus between agriculture, economic progression, renewable energy, and CO_2 in G20 countries by undertaking the data from 1990 to 2014. The estimated results predicted the long-run interrelationship in a manner that agriculture is responsible for increasing the CO_2 emissions, and the usage of renewable energy reduces it. Ali et al. (2019) investigated the dynamic linkages among CO_2 emissions, GDP, agricultural value-added, and land under cereal crops from 1961 to 2014 in Pakistan. The outcomes portrayed the presence of a positive and insignificant relationship between agriculture value-added, land under cereal crops, and CO_2 emissions in the long run, whereas in the short run, this relationship is negative and insignificant. Based on their findings, they suggest policymakers to develop policies that are aimed to reduce the CO_2 emission.

Koondhar et al. (2020) undertook air pollution, energy use, and agricultural value-added to GDP to examine the underlying relationship. The estimated outcomes revealed that these variables are correlated at the level. Hence, they suggested the government to take measures that may improve the agricultural industry. Based on a survey of previous related studies, we propose the following hypotheses:

H1: Crop production has a positive association with CO_2 emissions in China.

H2: Livestock production has a positive interaction with CO_2 emissions in China.

Nexus between energy use in agriculture production and CO_2 emissions

Since the energy use in agricultural production has intensified, the CO_2 emission has also increased (Filipovic et al. 2006). Robertson et al. (2000) suggested that the energy consumption is high in those areas where the mechanization is high for soil tillage, thus resulting in more CO_2 emissions. Therefore, the global concern is to produce the food which can ensure food security as well as can meet the sustainable development goals of using modern energy for all agricultural processes (Ghosh 2018).

Ghosh (2018), in his study, used the VECM and Granger causality and investigated the linkages between CO_2 emissions, energy used, value-added agriculture, trade liberalization, and financial expansion by undertaking the data from 1971 to 2013 in India. His findings have depicted the short-term bidirectional causality between value-added agriculture and CO_2 emissions, and energy use and CO_2 emissions, whereas trade, financial expansion, energy used, and value-added agriculture affect CO_2 emissions in the long term. Therefore, he suggested increasing the utilization of energy-efficient technologies in agricultural production and mechanization to reduce environmental impact.

Another study conducted by Agboola and Bekun (2019) examined the environment Kuznets curves (EKC) in agriculture by using the annual data of the period 1981 to 2014. The outcomes illustrated the validation of the long-run interrelationship among gross domestic product, agricultural value-added, foreign direct investment, CO_2 emissions, energy use, and trade openness. Owing to these results, they recommended developing the environment-compatible agricultural processes and energy utilization in Nigeria. Likewise, Chandio et al. (2019) investigated the dynamic interaction between energy use and agricultural economic progression from the time span of 1984 to 2016 in Pakistan. Their results, which employed the ARDL method and showed the positive interrelationship between gas consumption and electricity, and agricultural development. Thus, the linkage between power consumption in agriculture and CO_2 emissions was hypothesize as follows:

H3: Power consumption in agriculture has a negative/positive association with CO_2 emissions in China.

Nexus between forest and CO_2 emissions

As the CO_2 emission has increased for a few decades, the human solely held responsible for this increase, and this emission is more than the capacity to be absorbed by the forests, oceans, and living and dead biomass. Currently, there are likely only two options to balance this emission: (a) reduction in CO_2 emission and (b) an increase in the CO_2 absorbents. Forests play the role of natural absorbents, as they accumulate CO_2 and convert it into carbon and oxygen (Harris and Feriz 2011).

Khan et al. (2018) worked on finding the interrelationship among coal electricity, hydroelectricity, renewable energy, agriculture value-added, forestry, vegetable area, and greenhouse gas (GHG) emissions in Pakistan by undertaking the time series data from the period of 1981 to 2015. They used the Toda and Yamamoto method to investigate the causality. They found the unidirectional causality passing from hydroelectricity to GHG emissions, renewable energy to GHG emissions, forestry to GHG emissions, forestry to coal electricity, hydropower to forestry, and vegetable area to forestry. They also found the bidirectional causality between value-added in agriculture and forestry. Contrasting this, the FMOLS and CCR tests depicted that the decrease in GHG emissions resulted from the increase in agricultural value-added (0.124%), renewable energy (1.086%), vegetable area (0.153%), and forestry (0.240%), respectively. In last, they have suggested the government to raise the agricultural value assed, renewable energy, vegetables, and forestry to reduce the GHG emissions.

Waheed et al. (2018) analyzed how agricultural production, renewable energy used, and forest affects CO_2 emissions in Pakistan by employing the data from 1990 to 2014. Their findings have shown that CO_2 emission is negatively affected by renewable energy consumption and forest, while positively affected by agricultural production.

Similarly, Farooq et al. (2019) examined the impacts of greenhouse gas on the health and suggested to increase the afforestation, as it assists in the mitigation of CO_2 emissions and alternatively improves the health conditions. Aziz et al. (2020) explored the role of forest, agricultural value-added, and renewable energy in accessing the environmental Kuznets curve in Pakistan. Their findings depicted the negative impacts of renewable energy and forest area on carbon footprints. Besides, it was also found that carbon footprints from agriculture can be reduced by undertaking environmentally friendly technologies. Therefore, following these previous studies, we hypothesize that:

H4: Forest has a negative relationship with CO_2 emissions in China.

Data and methodology

The present empirical study is utilizing the time series data for the period of 1990 to 2016. Data for CO_2 eq. (carbon dioxide equivalent emissions) was extracted from the Food Agriculture Organization[2] (2020c). The data of crop production index (2004–2006 = 100), livestock production index (2004–2006 = 100), and forest area (% of land area) are extracted from the World Development Indicators[3] (2018). Furthermore, the total power of agricultural machinery (10,000 kW) was gathered from the National Bureau of Statistics of China[4] (2017).

To investigate the dynamic interaction between crop production, livestock production, forest, power consumption in agriculture, and carbon emissions, we considered the following multivariate model:

$$\mathrm{CO}_{2t}\mathrm{eq} = \beta_0 + \beta_1 \mathrm{CRP}_t + \beta_2 \mathrm{LSP}_t + \beta_3 \mathrm{PC}_t + \beta_4 FA_t + \varepsilon_t \tag{1}$$

In order to ensure that the estimated outcomes of the study are efficient, reliable, and consistent, we transformed the data into their natural log-transform. Equation 1 can be expressed as follows:

$$\mathrm{lnCO}_{2t}\mathrm{eq} = \beta_0 + \beta_1 \mathrm{lnCRP}_t + \beta_2 \mathrm{lnLSP}_t + \beta_3 \mathrm{lnPC}_t + \beta_4 \mathrm{lnFA}_t + \varepsilon_t \tag{2}$$

where $\mathrm{lnCO}_{2t}\mathrm{eq}$, $ln\ \mathrm{CRP}_t$, lnLSP_t, lnPC_t and lnFA_t denote the natural logarithm of CO_2 emissions, crop production, livestock production, power consumption in agriculture, and forest, respectively.

We applied the Phillips and Perron (1988); the augmented Dickey and Fuller (1981); and the Kwiatkowski-Phillips-Schmidt-Shin (1999) unit root tests to check the order of integration of the selected variables. To explore the long-run linkages among the selected variables, we employed the ARDL approach. This technique is appropriate for the small size in contrast to the traditional techniques, i.e., Engle and Granger (1987), and Johansen and Juselius (1990) approaches. Furthermore, an ARDL approach can be applied with a combination of I(0) and I(1) order of integration in the series, while it cannot be applied when one of the study variables is integrated at I(2). (Pesaran et al. 2001).

[2] www.fao.org
[3] http://data.worldbank.org
[4] http://data.stats.gov.cn/english/

The ARDL equation is expressed as follows:

$$
\begin{aligned}
\Delta \mathrm{LogCO}_{t2}\mathrm{eq} = {} & \beta_0 + \beta_1 \mathrm{LogCO}_{2t-1}\mathrm{eq} + \beta_2 \mathrm{LogCRP}_{t-1} \\
& + \beta_3 \mathrm{LogCRP}_{t=1} + \beta_4 \mathrm{LogLSP}_{t-1} \\
& + \beta_5 \mathrm{LogPC}_{t-1} + \beta_6 \mathrm{LogFA}_{t-1} \\
& + \sum_{i}^{p} \gamma_i \Delta \mathrm{LogCO}_{2t-i}\mathrm{eq} \\
& + \sum_{j}^{q} \delta_j \Delta \mathrm{LongCRP}_{t-j} \\
& + \sum_{l}^{q} \varphi_l \Delta \mathrm{LongLSP}_{t-l} \\
& + \sum_{m}^{q} \omega_m \Delta \mathrm{LongPC}_{t-m} + \sum_{n}^{q} \eta_n \Delta \mathrm{LongFA}_{t-n} \\
& + \epsilon_t
\end{aligned} \tag{3}
$$

To check the joint significance of the coefficients of lagged selected variables with a view to notice if long-term equilibrium interrelationship among the selected variables exists, this study estimated Eq. (3) based on OLS, followed by analyzing F-test. We used the F-stat in order to inspect the presence of a long-term interrelationship among the study variables. The null hypothesis $H_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$, which displays that there is no long-term cointegration interrelationship against alternate $H_1 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq 0$, which indicates that there is a long-term cointegration interaction among the variables. We can reject the null hypothesis of no cointegration among the study variables if the computed F-stat is larger than the (upper bounds I 1) value. Likewise, we cannot reject the null hypothesis of no cointegration. If the calculated F-stat is less than the (lower bounds I 0) value. However, if the calculated F-stat lies between both bound values, then the outcomes are inconclusive.

The long-run coefficients of the ARDL model will be estimated based on Eq. (4):

$$
\begin{aligned}
& \mathrm{LogCO}_{2t}\mathrm{eq} + \theta_0 + \sum_{i=1}^{p} \theta_1 \mathrm{LogCO}_{2t-i}\mathrm{eq} \\
& + \sum_{i=1}^{q} \theta_2 \mathrm{LongCRP}_{t-i} + \sum_{i=1}^{q} \theta_3 \mathrm{LongLSP}_{t-i} \\
& + \sum_{i=1}^{q} \theta_4 \mathrm{LongPC}_{t-i} + \sum_{i=1}^{q} \theta_5 \mathrm{LongFA}_{t-i} + \epsilon_t
\end{aligned} \tag{4}
$$

In Eq. (4), θ denotes the long-run elasticities of the ARDL model.

We applied the Akaike information criterion (AIC) to select the lag length of the model and applied the error correction model (ECM) in order to calculate the short-run interrelationships between the selected variables.

The short-run coefficients of the ARDL model will be estimated based on Eq. (5):

$$
\begin{aligned}
& \Delta \mathrm{LogCO}_{2t}\mathrm{eq} + \gamma_0 + \sum_{i=1}^{p} \gamma_1 \Delta \mathrm{LogCO}_{2t-i}\mathrm{eq} \\
& + \sum_{i=1}^{q} \gamma_2 \Delta \mathrm{LongCRP}_{t-i} + \sum_{i=1}^{q} \gamma_3 \Delta \mathrm{LongLSP}_{t-i} \\
& + \sum_{i=1}^{q} \gamma_4 \Delta \mathrm{LongPC}_{t-i} + \sum_{i=1}^{q} \gamma_5 \Delta \mathrm{LongFA}_{t-i} + \delta \mathrm{ECM}_{t-1} \\
& + \epsilon_t
\end{aligned} \tag{5}
$$

In Eq. (5), ECM_{t-1} represents the lagged error correction term, Δ denotes the first difference, γ denotes the short-run elasticities of the ARDL model, and ϵ indicates the disturbance term.

Empirical results and discussions

The mean, skewness, kurtosis, and normality of distribution over the series were performed under the descriptive statistics analysis. Table 1 (panel A) reported that all the series reveal negative skewness. Furthermore, all the series are normally distributed, as indicated by using the Jarque-Bera test statistic. The estimated outcomes of correlation analysis are also presented in Table 1 (panel B), indicating that crop production, livestock production, power consumption in agriculture, and forest area are positively and significantly associated with CO_2 emissions. The trend of the variables is shown in Fig. 1.

Mostly in the annual time series data analysis, as it is a common practice to inspect the long-run interaction between the study variables in the model, this study applied the Phillips-Perron (PP), Augmented Dickey-Fuller (ADF), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests to evaluate the stationarity of the series to confirm that none of the study variables is stationary or integrated at I(2). If the series is stationary or integrated at I(1), it suggests the existence of cointegration or presumes a long-run connection among the variables. The outcomes of the PP, ADF, and KPSS are demonstrated in Table 2, showing that livestock production and forest area are integrated or stationary at level I(0). In contrast, crop production, power consumption in agriculture, and CO_2 emissions are integrated or stationary at I(1).

The estimated outcomes of the ARDL-bounds test are exhibited in Table 3. The F-statistics are 10.59, 11.47, 20.99, and 19.26 exceed (upper bounds I1) at 1% when the CO_2 emissions ($LnCO_2$ eq), crop production (LnCRP), livestock production (LnLSP), power consumption in agriculture (LnPC), and forest area (LnFA) are used as dependent variables. The outcomes of the ARDL-bounds test confirmed the

Table 1 Descriptive statistics and correlation analysis

	$LnCO_2$ eq	LnCRP	LnLSP	LnPC	LnFA
Panel A					
Mean	13.351	4.523	4.460	10.988	2.976
Median	13.367	4.508	4.532	11.008	2.989
Maximum	13.440	4.971	4.870	11.623	3.107
Minimum	13.207	4.008	3.691	10.264	2.817
Std. Dev.	0.070	0.303	0.350	0.452	0.093
Skewness	− 0.845	− 0.171	− 0.687	− 0.182	− 0.215
Kurtosis	2.614	1.844	2.404	1.690	1.647
Jarque-Bera	3.386	1.633	2.527	2.077	2.268
Probability	0.183	0.441	0.282	0.353	0.321
Sum	360.479	122.129	120.425	296.701	80.371
Sum Sq. Dev.	0.128	2.387	3.196	5.314	0.226
Observations	27	27	27	27	27
Panel B	Correlation analysis				
$LnCO_2$ eq	1				
t-statistic	-				
P value	-				
LnCRP	0.903***	1			
t-statistic	10.557	-			
P value	0.000	-			
LnLSP	0.922***	0.981***	1		
t-statistic	11.948	25.439	-		
P value	0.000	0.000	-		
LnPC	0.882***	0.994***	0.977***	1	
t-statistic	9.400	47.639	23.094	-	
P value	0.000	0.000	0.000	-	
LnFA	0.878***	0.993***	0.978***	0.993***	1
t-statistic	9.204	42.710	23.966	44.300	-
P value	0.000	0.000	0.000	0.000	-

***1% statistical significance level

long-run interaction among the variables. In addition, this study also employed the Johansen and Juselius (1990) cointegration testing to evaluate the long-term linkages among the study variables. The computed values of both trace statistic and Max-Eigen statistic of J-J cointegration testing are demonstrated in Table 4, showing that there are three cointegration vectors between CO_2 emissions, crop production, livestock production, power consumption in agriculture, and forest area, which means the presence of a long-term interrelationships.

Table 5 reports the results of the ARDL model for the interrelationships among crop production, livestock production, energy consumption, forest area, and carbon emissions. Figure 2 shows a summary of the long-run nexus among the variables.

The estimated coefficient of crop production is statistically significant at the 1% significance level. This result implies that a 1% increase in crop production will cause a proportional increase in carbon dioxide equivalent emission by 1.22% in the long run. Likewise, livestock production has a positive interaction with CO_2 emissions; this means that a 1% increase in livestock production will cause a proportional increase in CO_2 emissions by 0.31% in the long run. The results of this study are consistent with the outcomes of the existing studies in the same domain (Ghosh 2018; Owusu and Asumadu-Sarkodie 2016; Sarkodie and Owusu 2017; Zandi and Haseeb 2019). Appiah et al. (2018) explored that crop production and livestock production have a significant positive interrelationship with CO_2 emissions in selected emerging countries.

Similarly, Ghosh (2018) also found that agriculture value-added has a significant positive association with CO_2 emissions in India. On the other hand, Dogan (2016) reported that agriculture has significant negative interaction with CO_2 emissions in the long run in Turkey. Furthermore, Table 5 reports that the ARDL estimator indicate that power consumption in agriculture and forest area coefficients are statistically significant at a 5% significance level. Therefore, a 1% increase in power consumption in agriculture and forest area will cause a decrease in CO_2 emissions by 0.51% and 1.35% in the long run, respectively. The results of this study are in line with the findings of previous studies (Khan et al. 2018; Liu et al. 2017; Parajuli et al. 2019; Waheed et al. 2018; Zandi and Haseeb 2019).

Additionally, compatible with Aid (2008), this finding has shown that the forestry is essential to practice in agriculture, where trees on farms improve the capability of coping of farmers to climate change risk by crops, efficient nutrient cycling conservation, and water and soil conservation. Furthermore, CO_2 and H_2O are released from the process of exploiting agriculture products. CO_2 emissions do not increase because of energy flow and material recycling in the ecosystem. Therefore, developing energy agriculture is suitable for controlling the concentration of GHGs in the atmosphere. This process is also significant for controlling the increase of surface temperature and maintaining the ecosystem carbon balance of the earth. Agriculture biomass used to provide alternative energy sources that reduce CO_2 emissions (Parajuli et al. 2019; Yang et al. 2018).

In the short run, empirical evidence reveals that crop production has a positive and significant association with CO_2 emissions. It means that with a 1% increase in crop production, CO_2 emissions will increase by 0.75%. Similarly, livestock production also has a positive relation with CO_2 emissions in the current period. This result implies that with a 1% increase in livestock production, CO_2 emissions will increase by 1.07% in the short run. The outcomes of this study are similar to the findings of earlier studies (Ghosh 2018; Khan et al. 2018; Liu et al. 2017; Mahmood et al. 2019; Sarkodie and Owusu 2017; Yang et al. 2018). In the short-run, power consumption in agriculture and forest has a negative association with CO_2 emissions, and the results are consistent with

Fig. 1 Trend of the selected variables

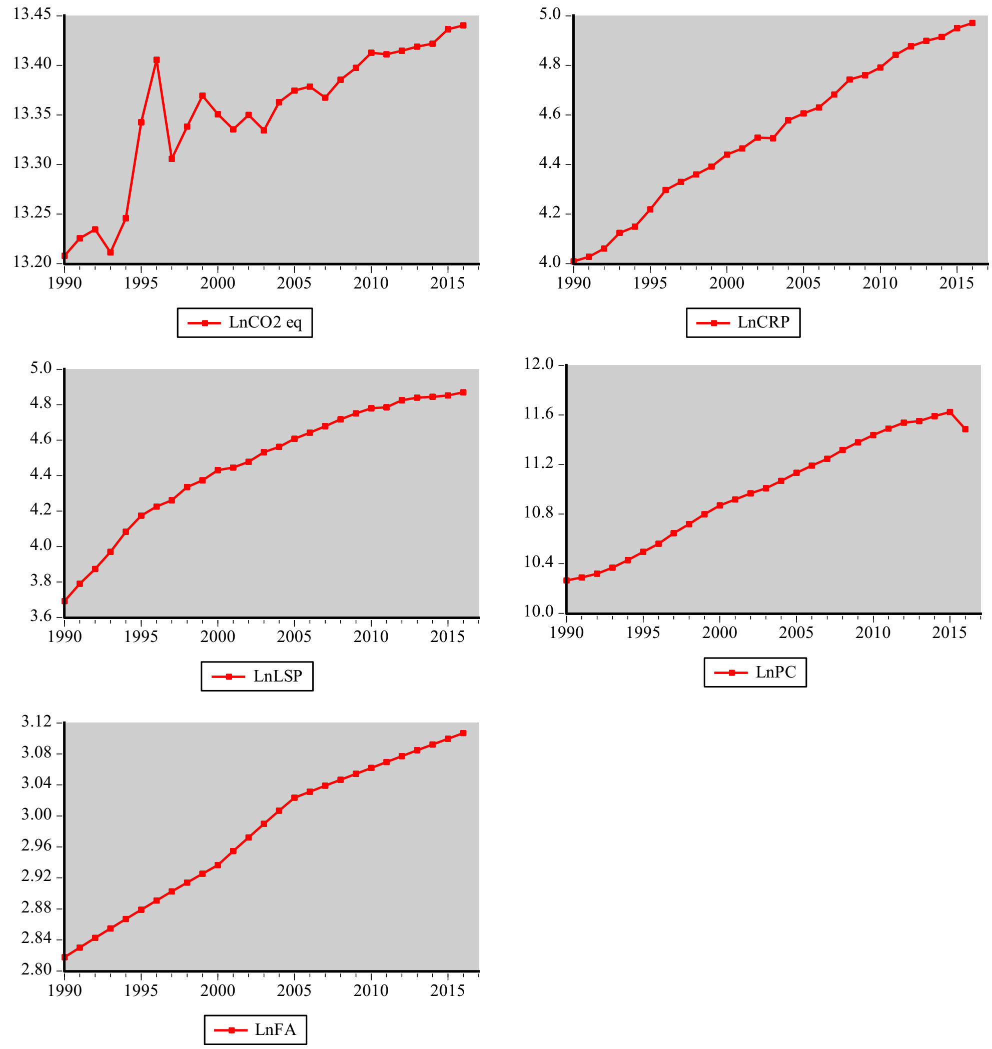

Table 2 Unit root tests results

PP test			ADF test		KPSS test	
Variables	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
$LnCO_2$ eq	− 1.951	− 2.741	− 2.776*	− 4.665***	0.693***	0.122*
LnCRP	− 2.593	− 1.339	− 1.997	− 1.565	0.777***	0.153**
LnLSP	− 9.154***	− 3.042	− 8.719***	− 2.519	0.756***	0.196**
LnPC	1.585	− 2.200	− 2.449	2.117	0.777***	0.131*
LnFA	− 4.465**	− 4.986***	− 1.486	− 1.447	0.438**	0.097
$\Delta LnCO_2$ eq	− 8.298***	− 10.281***	− 2.779*	− 2.655	0.480**	0.362***
ΔLnCRP	− 5.677***	− 7.726***	− 5.663***	− 5.032***	0.253	0.283***
ΔLnLSP	− 2.156	− 4.059***	− 3.625***	− 4.059***	0.647**	0.146**
ΔLnPC	− 6.050***	− 6.430***	− 2.650*	− 4.617***	0.275	0.131*
ΔLnFA	− 23.709***	− 25.632***	− 5.647***	− 5.532***	0.500**	0.500***

***1% statistical significance level

**5% statistical significance level

*10% statistical significance level

Table 3 The ARDL-bounds test results

Variables	$LnCO_2$ eq	LnCRP	LnLSP	LnPC	LnFA
F-statistics	10.599***	11.475***	20.996***	3.154	19.264***
Optimal lag structure	(1, 3, 3, 2, 2)	(1, 3, 3, 3, 3)	(1, 1, 1, 2, 0)	(1, 0, 0, 0, 0)	(1, 3, 2, 2, 1)
Critical value bounds	1%	5%	10%		
Upper bounds I(1)	5.06	4.01	3.52		
Lower bounds I(0)	3.74	2.86	2.45		
Diagnostic tests					
R^2	0.917	0.954	0.893	0.440	0.920
Adj-R^2	0.761	0.825	0.830	0.301	0.816
F-statistic	5.907***	7.418***	14.019***	3.154**	8.847***
Prob(F-statistic)	0.008	0.010	0.000	0.029	0.000
Serial correlation	2.221 (0.203)	1.269 (0.374)	2.557 (0.189)	0.424 (0.660)	0.312 (0.740)
Heteroskedasticity	0.240 (0.788)	0.113 (0.739)	1.588 (0.220)	2.561 (0.155)	0.073 (0.789)

***1% statistical significance level

**5% statistical significance level.

long-run findings. The evidence of the short-run interrelationship demonstrates that a 1% increase in power consumption in agriculture and forest will cause a decrease in CO_2 emissions by 0.11% and 3.13%, respectively. This is consistent with the findings of Parajuli et al. (2019) and Waheed et al. (2018).

The value of R-squared 0.96% shows that crop production (LnCRP), livestock production (LnSP), power consumption (LnPC), and forest area (LnFA) have greater significant explanatory influences for the dependent variable in the model. That is, variations in LnCRP, LnLSP, LnPC, and LnFA account for 96% of the variability in CO_2 emissions. Figures 3 and 4 exhibit plots of the CUSUM and CUSUMSQ tests for the ARDL model. The plot of both stability tests includes CUSUM, and CUSUMSQ demonstrates that the estimated parameters of the ARDL model are stable at the 5% significance level.

Table 4 Johansen and Juselius cointegration testing results

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	P value
None	0.820	120.590***	69.818	0.000
At most 1	0.786	77.685***	47.856	0.000
At most 2	0.659	39.042***	29.797	0.003
At most 3	0.383	12.127	15.494	0.150
At most 4	0.001	0.048	3.841	0.825
Maximum Eigenvalue				
None	0.820	42.904***	33.876	0.003
At most 1	0.786	38.642***	27.584	0.001
At most 2	0.659	26.915***	21.131	0.006
At most 3	0.383	12.078	14.264	0.107
At most 4	0.001	0.048	3.841	0.825

***1% statistical significance level

Robustness check

This study used FMOLS, CCR, and OLS to reconfirm the outcomes. The estimated results are reported in Table 6 for the three estimators. The first column represents the outcomes of FMOLS, stating that crop production and livestock production have significant coefficients. This indicates that both variables have a significant positive impact on CO_2 emissions. This means that these variables enhance CO_2 emissions in China. Likewise, the signs of energy consumption and forest area are negative, indicating that both variables play an essential role in reducing CO_2 emissions. However, the connection of forest area is more significant than energy consumption. The second and third column represents the outcomes of CCR and OLS. The link among all variables remains the same; both crop and livestock productions increase the emissions level, and energy and forest area reduce this level. The impact is significant for all variables except energy use. The high values of R^2 in the three models indicate that results are reliable. On the same note, the findings under these methods confirm the results of the ARDL and indicate that these estimations are robust under various techniques.

After the confirmation of the impact and significance of all variables towards CO_2 emissions, this study explores the direction of this relationship with the help of the Granger causality test. The results are presented in Table 7, which indicated a significant causal link running from crop production to CO_2 emissions. The causality connection is significant and running in both ways between livestock and CO_2 emissions. However, the causal link among energy, forest area, and CO_2 emissions is unidirectional, stating that both energy use and forest have a significant connection with emission level. The results of the causality approach confirm the significant connection among all variables. Additionally, the directions of this connection also validate previous outcomes under various techniques used for

Table 5 Long-run and short-run results based on the ARDL model

Variables	Coefficient	SE	*t*-statistic	*P* value
Long-run estimation				
LnCRP	1.220***	0.418	2.919	0.019
LnLSP	0.316	0.180	1.751	0.118
LnPC	− 0.511**	0.227	− 2.251	0.054
LnFA	− 1.351**	0.610	− 2.211	0.057
Constant	15.942***	0.893	17.848	0.000
Short-run dynamics				
ΔLnCO_2 eq(− 1)	− 0.252	0.286	− 0.880	0.404
ΔLnCRP	0.757***	0.330	2.291	0.051
ΔLnCRP(− 1)	0.185	0.312	0.593	0.569
ΔLnCRP(− 2)	0.023	0.358	0.064	0.950
DΔLnCRP(− 3)	0.562*	0.272	2.065	0.072
ΔLnLSP	0.278	0.456	0.609	0.558
ΔLnLSP(− 1)	1.072**	0.411	2.604	0.031
ΔLnLSP(− 2)	− 0.204	0.449	− 0.455	0.661
ΔLnLSP(− 3)	− 0.749	0.353	− 2.119	0.066
ΔLnPC	− 0.117	0.134	− 0.871	0.409
ΔLnPC(− 1)	0.212	0.527	0.402	0.697
ΔLnPC(-2)	− 0.735	0.516	− 1.423	0.192
ΔLnFA	− 3.135	3.158	− 0.992	0.349
ΔLnFA(− 1)	8.039	4.651	1.728	0.122
ΔLnFA(− 2)	− 6.595**	2.513	− 2.624	0.030
ECM(− 1)	− 1.252***	0.286	− 4.373	0.002
ARDL diagnostic tests				
R^2	0.967			
Adj-R^2	0.906			
F-statistic	15.781***			
Prob(*F*-statistic)	0.000			
Normality	0.097 (0.952)			
Serial correlation	2.195 (0.181)			
Heteroscedasticity	0.330 (0.571)			
Functional form	0.498 (0.633)			
CUSUM	Stable			
CUSUMSQ	Stable			

1%, statistical significance level

**5% statistical significance level

*10% statistical significance level

robustness. Thus, causality results also support the significant impact of studied variables on CO_2 emissions.

Conclusion and policy implications

Worldwide population growth increased food demand, and agriculture production has been increasing simultaneously to meet this demand. However, this massive scale production is polluting the environment. Therefore, this study examined the links among crop production, livestock, energy use and forest area with CO_2 emissions for China. This study utilized the time series data from 1990 to 2016 for China to test the long-run association of these variables with unit root to the cointegration method. This study applied the PP, ADF, and KPSS unit root tests to evaluate the stationary features of the series to confirm that none of the studied variables is stationary or integrated at I(2). The outcomes of the PP, ADF, and KPSS indicated that livestock production and forest area are integrated or stationary at the level I(0) while crop production, power consumption in agriculture, and CO_2 emissions are integrated or stationary at I(1). These results have validated the use of the ARDL approach. The results of the ARDL-bounds testing confirm a long-run interrelationship among the study variables. Furthermore, this study also employed the Johansen cointegration approach for robustness check, and the outcomes supported a long-run link among all variables.

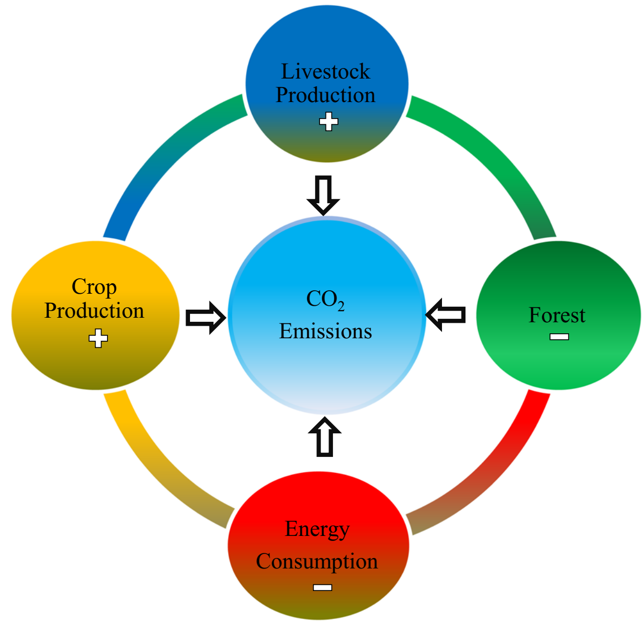

Fig. 2 Summary of the long-run nexus between the variables

After checking the long run connection, this study explored the long-run and short-run dynamics of all variables towards CO_2 emissions. The long-run results indicated that the coefficient of crop production is statistically significant at the 1% significance level. Likewise, livestock production has a positive interaction with CO_2 emissions. However, power consumption in agriculture and forest area coefficients are statistically significant at a 5% significance level, and negative relationships confirmed that power consumption in agriculture and forest area reduced CO_2 emissions in the long run. On the same note, the short-run estimated values of the ARDL also confirmed this relationship, indicating a positive connection of crop production and livestock and a negative impact of energy and forest area on CO_2 emissions.

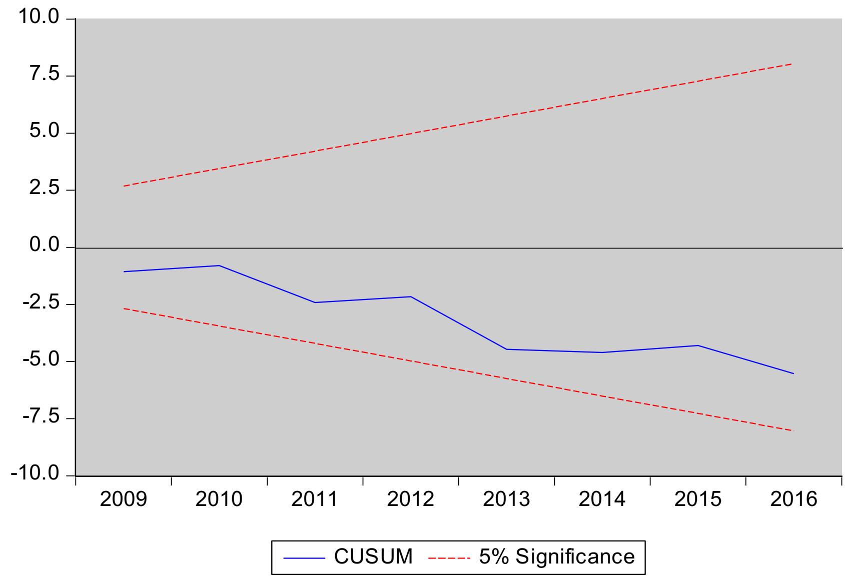

Fig. 3 Plot of CUSUM stability test

The robustness of these outcomes is checked with the FMOLS, CCR, and OLS. The results of these three methods indicated that both crop production and livestock have a significant and positive impact on CO_2 emissions. This means that these variables enhance CO_2 emissions in China. Likewise, the signs of energy consumption and forest area are negative, indicating that both variables play an essential role in reducing CO_2 emissions. However, the connection of forest area is more significant than energy consumption.

Furthermore, the direction of this relationship is confirmed with the causality test. The results of the causality approach confirm the significant connection among all variables. Additionally, the directions of this connection also validate previous outcomes under various techniques used for robustness. To summarize, the impact and significance of all variables towards CO_2 emissions stand robust under various robustness checks. The outcomes of the on-hand study have several policy implications. For instance, the government must reconsider its policies related to agricultural and livestock production and adopt environment-friendly practices in the agriculture sector that may reduce the carbon footprints in the long run. Besides, the government can aid in increasing the level of the forest at the national level that will help in tackling the CO_2 emissions. Based on the current outcomes, there is a significant potential for future research on this topic. For instance, the majority of developing countries are basically agriculture-based economies. The livestock is also a crucial component of their economic structure. Thus, both play an important role in the overall progress. Further investigations can be conducted to examine the interaction among the

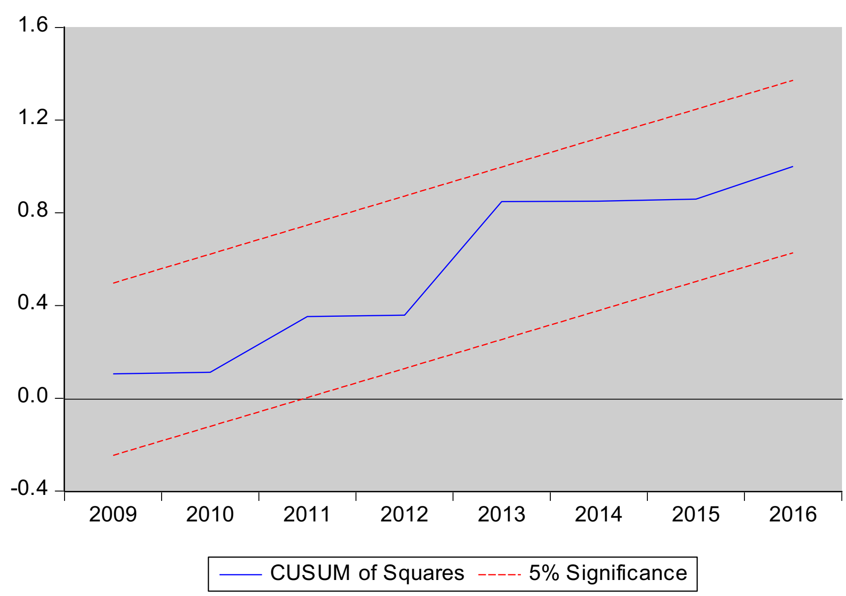

Fig. 4 Plot of CUSUM of squares stability test

Table 6 Results of the robustness analysis

Variables	FMOLS	CCR	OLS
LnCRP	0.492 (0.001)	0.561(0.019)	0.466 (0.014)
LnLSP	0.208 (0.006)	0.210 (0.002)	0.231 (0.003)
LnPC	− 0.165 (0.085)	− 0.222 (0.168)	− 0.134 (0.257)
LnFA	− 0.925 (0.028)	− 0.869 (0.051)	− 1.047 (0.052)
Constant	14.764 (0.000)	14.903 (0.000)	14.804 (0.000)
R^2	0.875	0.874	0.898
Adjusted-R^2	0.851	0.850	0.879

Values in parentheses denote the probability value

Table 7 Granger causality test

Causality relationship	*F*-statistic	*P* value	Decision
LnCRP → LnCO_2 eq	5.364**	0.029	LnCRP causes LnCO_2 eq
LnCO_2 eq → LnCRP	0.381	0.542	No causal relationship
LnLSP → LnCO_2 eq	10.160***	0.004	LnLSP causes LnCO_2 eq
LnCO_2 → LNLSP	10.989***	0.003	LnCO_2 eq causes LNLSP
LnPC → LnCO_2 eq	4.792**	0.039	LnPC causes LnCO_2 eq
LnCO_2 eq → LnPC	1.229	0.278	No causal relationship
LnFA → LnCO_2	5.057**	0.034	LnFA causes LnCO_2 eq
LnCO_2 eq → LnFA	0.030	0.863	No causal relationship

*** and **denote rejection of the hypothesis at the 1% and 5% level

aforementioned variables in other developing and agriculture economies in Asia and the remaining regions with similar characteristics. This will not only help to understand the link but also guide the related authorities to make policies for carbon-friendly growth of agriculture and livestock. Further extension of this study can be directed towards the positive role of agriculture and livestock in mitigating emissions from the renewable energy produced from these sources.

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