



Does carbon dioxide, methane, nitrous oxide, and GHG emissions influence the agriculture? Evidence from China

Abdul Rehman¹ · Hengyun Ma¹ · Muhammad Irfan² · Munir Ahmad³

Received: 20 March 2020 / Accepted: 16 April 2020 / Published online: 28 April 2020
© Springer-Verlag GmbH Germany, part of Springer Nature 2020

Abstract

Carbon dioxide emission and greenhouse gas emissions are considered core issue in the world that influence agricultural production and also cause climate change. The present study seeks to investigate the linkage of methane emissions, nitrous oxide emissions, carbon dioxide emission, and greenhouse gas emissions with agricultural gross domestic product in China. The long-term association was checked by using an autoregressive distributed lag (ARDL) bounds testing approach, fully modified least squares method, and canonical cointegrating regression analysis. The results from long-run analysis exposed that carbon dioxide emission and greenhouse gas emissions have positive coefficients that demonstrate the long-run linkage with the agricultural gross domestic product having p values of 0.5709 and 0.3751, respectively. Similarly, results also revealed that agricultural methane emissions and agricultural nitrous oxide emissions have a negative association with the agricultural gross domestic product having p values of 0.1737 and 0.0559. China is a huge emitter of CO₂ emission and greenhouse gas emissions. Possible conservative policies are required to form the Chinese government to tackle this challenge to decrease CO₂ emission in order to increase agricultural production.

Keywords CO₂ emission · Agricultural production · Methane emission · Climate change · China

Introduction

The agricultural sector has key contribution to the Chinese economy and recently, China is a huge emitter of CO₂

emission. As the chief agricultural country, CO₂ emission is growing rapidly. Energy conservation, agricultural growth, and emission reduction are related to human activities and environmental sustainability (DECC 2013). At present, annual carbon dioxide emissions in China have risen dramatically and known to be a major emitter. It is under increasing pressure to reduce carbon dioxide emission. Control of domestic CO₂ emission and the achievement of CO₂ emission mitigation goals have been the top priority of the Chinese government (Li et al. 2017a). Due to climate change and its effect on the environment in the past three decades, carbon dioxide emission have drawn global attention, and careful observation of emission trends reveals that China requires a firm effort to reduce carbon emissions, and China needs to work hard to reduce and restraint the CO₂ emission from its primary energy sources. China is the cornerstone of economic development, and the value of China's transportation sector cannot be overemphasized as China continues to encourage industrialization and urbanization (Lin and Benjamin 2017; Zhao et al. 2017a).

Coal consumption is the main source of energy production in China and demand is rising over time and considered the key choice owing to its abundant resources and low prices.

Responsible editor: Nicholas Apergis

✉ Abdul Rehman
abdrehman@henau.edu.cn

Hengyun Ma
h.y.ma@163.com

Muhammad Irfan
irfan@ncepu.edu.cn

Munir Ahmad
munirahmad@zju.edu.cn

¹ College of Economics and Management, Henan Agricultural University, Zhengzhou 450002, China

² Beijing Key Laboratory of New Energy and Low Carbon Development, School of Economics and Management, North China Electric Power University, Beijing 102206, China

³ School of Economics, Zhejiang University, Hangzhou 310027, China

Coal is therefore known to be the main energy source. China is, in reality, is the most consumer of energy. The population of China is growing rapidly and it is the most populated country with limited choices in the energy structure. The main goal is to create a sustainable economic development by increasing trade and tumbling the social burden that needs to be supported by cheap energy. However, serious environmental concerns have been identified as a consequence of coal combustion (Liu et al. 2015; Ouyang and Lin 2017). The agricultural production including crops has ecological roles which generates economic importance. Carbon sink has an important role to play in the crop production in order to combat climate change. Various estimates show that CO₂ emission influences the farmland which assesses the input function to crop production. Furthermore, the carbon footprint for crops in the major agricultural areas varies from the average and the largest crop yields are carbon sinks (She et al. 2017).

The agriculture sector is known to be a significant source of carbon dioxide emission and is therefore the most vulnerable sector to climate change as it is directly related to climate change and CO₂ emission. Compared with other sectors, the agriculture sector has fewer CO₂ emissions (Hasegawa and Matsuoka 2015; Fais et al. 2016). Various studies have been conducted to highlight the issue of CO₂ emission linkage with crop production, renewable energy, urbanization, industrialization, agriculture technology, agriculture land transfer, modernization, and soil porosity (Adams and Nsiah 2019; Lin and Nelson 2019; Marescaux et al. 2018; Cillis et al. 2018; Wenbo and Yan 2018; Li et al. 2019; Rehman et al. 2019; de Souza et al. 2019), but in this study, we will investigate the association of CO₂ emission, methane, nitrous oxide, and greenhouse gas emissions to the agricultural gross domestic product in China by applying an autoregressive distributed lag (ARDL) bounds testing approach, fully modified least squares method, and canonical cointegrating regression analysis. The remaining parts of the paper, in addition to the [Introduction](#), are [Previous literature](#), [Methodology and data sources](#), [Results and discussion](#), and [Conclusion and policy recommendations](#).

Previous literature

In the agriculture sector, the mitigation of CO₂ emission is not only a technical issue but also a socio-economic issue. Carbon emission from agriculture is ultimately generated by agricultural activities. Various levels of farmland and mechanization may trigger different levels of emission and cause the agricultural output and energy consumption (Van den Berg et al. 2007; Zaman et al. 2012). Global warming is increasing and has detrimental influence; many experts have invested their time to explore the key cause. Different measures have been taken in spite of the variation in thinking to curb the negative climate impacts. Among developed and emerging economies,

an agreement of the Kyoto Protocol has been done regarding the emissions of such harmful gases (Kumazawa and Callaghan 2012; Stigson et al. 2013; Kiviyiro and Arminen 2014). The key cause of greenhouse gas emissions is fossil fuel combustion, and CO₂ emission has an effect on climate change through their effects on energy use. Climate change causes the temperature and energy requirement has been increased in the winter and summer. Environmental change and life quality have improved due to energy requirement adaptation. Finally, energy demand may generate the variation in CO₂ emission and energy consumption (Ouedraogo et al. 2012; Kagawa et al. 2015; Hao et al. 2016; Valipour et al. 2018; Wang et al. 2018).

The agricultural land accounts for about 40% of the world's land area and is used for grain production, live-stock, grassland, forestry, and bioenergy development. However, agriculture is actually considered a critical sector for food production, confronted with the need to produce more food for the growing population, but in a way that can reduce environmental pressures in terms of energy and water scarcity, climate change, and insufficient availability of new agricultural land (Godfray et al. 2010). Through food storage, pesticide processing, and manufacturing, the output of the global food system contributes to the amount of anthropogenic greenhouse gas emissions. Agricultural production accounts for a significant proportion of greenhouse gases emitted by food systems, and the production of fertilizers is at the next level. In addition, energy-related emissions compensate for more than anthropogenic greenhouse gas emissions (Taseska et al. 2011; Sefeedpari et al. 2013). Energy efficiency and agricultural production have a crucial role to play in economic growth and even in people's everyday lives (DECC 2014).

CO₂ emission rarely decouples the production in China and numerous significant changes in the reduction of CO₂ emission in different areas of China due to the accumulation of problems as an agricultural region. Work on spatiotemporal variability of CO₂ emissions from agricultural decoupling in various areas of China has proposed separate strategies for the reduction of carbon dioxide emission (Zhou et al. 2017; Nayak et al. 2015; Luo et al. 2017). Environmental change is becoming the biggest global threat to human life. Greenhouse gas emissions and CO₂ emission have risen significantly in recent decades (Sari and Soytas 2009; Chang 2010). The urban green economy and emission growth allure extensively recognized. As a massive emitter of CO₂ emission and the largest consumer of energy, China is struggling to reduce emissions from fossil fuels (Chen et al. 2018; Zhao et al. 2017b). As we all know, carbon dioxide triggers global warming, environmental issues, and climate change. As the world's biggest emitter of CO₂, an

increasing pressure has come from the world to force China to decrease its CO₂ emission. The manufacturing sector has a rich contribution to the increasing carbon dioxide emissions in China relative to other sectors. Extensive development in the agriculture sector has provided substantial attention in recent years to reduce carbon dioxide (Xu and Lin 2017; Zhou et al. 2015).

In the mid of the twentieth century, the rise in greenhouse gases was believed to be the primary cause of global warming, and the key factor was the CO₂ emission from fossil fuels. Growing population and economic intensification utilizing fossil fuels are both the key factors of rising CO₂ emission. The income effects and demographic changes on CO₂ emissions are crucial for an effective climate change strategy (Sumabat et al. 2016; Liddle 2015; Liu et al. 2013; Wang and Zhao 2015; Zhou and Liu 2016). The government of China has adopted a range of environmental policies to meet the carbon dioxide emission goal, such as eliminating redundant manufacturing facilities and promoting energy storage technologies. Big contaminated factories have gradually moved from one area to another viable region that will play a role in regional economic growth (Yang et al. 2016; Green and Stern 2017; Li et al. 2017b).

Methodology and data sources

Data sources

This empirical study examined the linkage of methane emissions, nitrous oxide emissions, carbon dioxide emission, greenhouse gas emissions, and agricultural gross domestic product in China. We used time-series data ranging from 1978 to 2017 and it is taken from WDI (World Development Indicators). Explanations for variables are provided in Table 1 with descriptions.

Table 1 provides the description of all variables and trends of the variables are depicted in Fig. 1.

All study variable trends are illustrated in Fig. 1 in the logarithmic form.

Specification of econometric model

In order to test the linkage of variables, the following model was specified as:

$$AGDP_t = f(AMe_t, ANOe_t, CO_2e_t, GHGe_t) \quad (1)$$

In Eq. (1), AGDP_{*t*} presents the agricultural gross domestic product, AMe_{*t*} shows the methane emissions from agriculture, variable ANOe_{*t*} specifies the nitrous oxide emissions from agriculture, variable CO₂e_{*t*} presents the carbon dioxide emission in China, and GHGe_{*t*} indicates the greenhouse gas emissions. We can write Eq. (1) also as:

$$AGDP_t = \vartheta_0 + \vartheta_1 AMe_t + \vartheta_2 ANOe_t + \vartheta_3 CO_2e_t + \vartheta_4 GHGe_t + \varepsilon_t \quad (2)$$

The logarithmic form of variables can be specified as:

$$\ln AGDP_t = \vartheta_0 + \vartheta_1 \ln AMe_t + \vartheta_2 \ln ANOe_t + \vartheta_3 \ln CO_2e_t + \vartheta_4 \ln GHGe_t + \varepsilon_t \quad (3)$$

Equation (3) indicates the logarithmic form of agricultural gross domestic product, methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, and greenhouse gas emissions. *t* indicates the time dimension, ε_{*t*} signifies error term, ϑ₀ is the constant intercept, and coefficients of the models ϑ₁ to ϑ₄ demonstrate the long-run elasticity.

ARDL model specification and cointegration test

In 1998, Pesaran and Shin (1998) developed an ARDL model to test the relation between various variables. The long-run and short-run linkages between agricultural gross domestic product, methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, and greenhouse gas emissions were explored in the integration order at *I*(0) and *I*(1). The long-run and short-run associations of variables can be determined with UECM (unrestricted error correction model) and specified as:

Table 1 Explanation of variables and sources

Study variables	Explanations with units	Sources
LnAGDP	Agricultural gross domestic product (USD)	WDI
LnAMe	Methane emissions from agriculture (%)	WDI
LnANOe	Nitrous oxide emissions from agriculture (%)	WDI
LnCO ₂ e	Carbon dioxide emission (in kt)	WDI
LnGHGe	Greenhouse gas emissions (kt of CO ₂ equivalent)	WDI

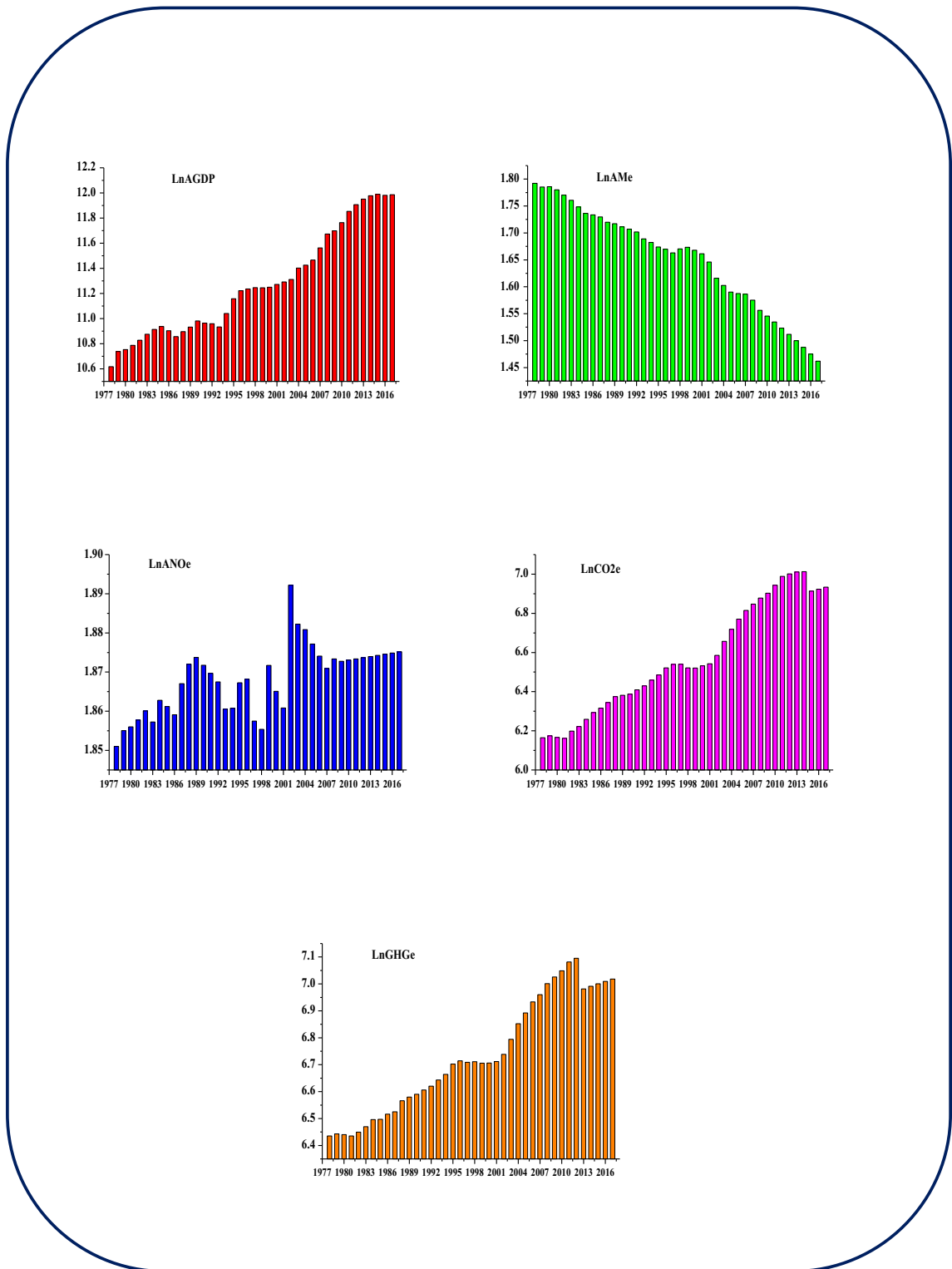


Fig. 1 Variables trends

$$\begin{aligned} \Delta \text{LnAGDP}_t &= \rho_0 + \sum_{i=1}^g \rho_{1j} \Delta \text{LnAGDP}_{t-k} \\ &+ \sum_{i=1}^g \rho_{2j} \Delta \text{LnAME}_{t-k} \\ &+ \sum_{i=1}^g \rho_{3j} \Delta \text{LnANO}_{t-k} \\ &+ \sum_{i=1}^g \rho_{4j} \Delta \text{LnCO}_2e_{t-k} \\ &+ \sum_{i=1}^g \rho_{5j} \Delta \text{LnGHGe}_{t-k} + \rho_6 \text{LnAGDP}e_{t-1} \\ &+ \rho_7 \text{LnAME}_{t-1} + \rho_8 \text{LnANO}_{t-1} \\ &+ \rho_9 \text{LnCO}_2e_{t-1} + \rho_{10} \text{LnGHGe}_{t-1} + \varepsilon_{1t} \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta \text{LnAME}_t &= \psi_0 + \sum_{i=1}^g \psi_{1j} \Delta \text{LnAME}_{t-k} \\ &+ \sum_{i=1}^g \psi_{2j} \Delta \text{LnAGDP}_{t-k} \\ &+ \sum_{i=1}^g \psi_{3j} \Delta \text{LnANO}_{t-k} \\ &+ \sum_{i=1}^g \psi_{4j} \Delta \text{LnCO}_2e_{t-k} \\ &+ \sum_{i=1}^g \psi_{5j} \Delta \text{LnGHGe}_{t-k} + \psi_6 \text{LnAME}_{t-1} \\ &+ \psi_7 \text{LnAGDP}_{t-1} + \psi_8 \text{LnANO}_{t-1} \\ &+ \psi_9 \text{LnCO}_2e_{t-1} + \psi_{10} \text{LnGHGe}_{t-1} + \varepsilon_{2t} \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta \text{LnANO}_t &= \zeta_0 + \sum_{i=1}^g \zeta_{1j} \Delta \text{LnANO}_{t-k} \\ &+ \sum_{i=1}^g \zeta_{2j} \Delta \text{LnAME}_{t-k} \\ &+ \sum_{i=1}^g \zeta_{3j} \Delta \text{LnAGDP}_{t-k} \\ &+ \sum_{i=1}^g \zeta_{4j} \Delta \text{LnCO}_2e_{t-k} \\ &+ \sum_{i=1}^g \zeta_{5j} \Delta \text{LnGHGe}_{t-k} + \zeta_6 \text{LnANO}_{t-1} \\ &+ \zeta_7 \text{LnAME}_{t-1} + \zeta_8 \text{LnAGDP}_{t-1} \\ &+ \zeta_9 \text{LnCO}_2e_{t-1} + \zeta_{10} \text{LnGHGe}_{t-1} + \varepsilon_{3t} \end{aligned} \tag{6}$$

$$\begin{aligned} \Delta \text{LnCO}_2e_t &= \eta_0 + \sum_{i=1}^g \eta_{1j} \Delta \text{LnCO}_2e_{t-k} \\ &+ \sum_{i=1}^g \eta_{2j} \Delta \text{LnANO}_{t-k} + \sum_{i=1}^g \eta_{3j} \Delta \text{LnAME}_{t-k} \\ &+ \sum_{i=1}^g \eta_{4j} \Delta \text{LnAGDP}_{t-k} \\ &+ \sum_{i=1}^g \eta_{5j} \Delta \text{LnGHGe}_{t-k} + \eta_6 \text{LnCO}_2e_{t-1} \\ &+ \eta_7 \text{LnANO}_{t-1} + \eta_8 \text{LnAME}_{t-1} \\ &+ \eta_9 \text{LnAGDP}_{t-1} + \eta_{10} \text{LnGHGe}_{t-1} + \varepsilon_{4t} \end{aligned} \tag{7}$$

$$\begin{aligned} \Delta \text{LnGHGe}_t &= \partial_0 + \sum_{i=1}^g \partial_{1j} \Delta \text{LnGHGe}_{t-k} \\ &+ \sum_{i=1}^g \partial_{2j} \Delta \text{LnCO}_2e_{t-k} \\ &+ \sum_{i=1}^g \partial_{3j} \Delta \text{LnANO}_{t-k} \\ &+ \sum_{i=1}^g \partial_{4j} \Delta \text{LnAME}_{t-k} \\ &+ \sum_{i=1}^g \partial_{5j} \Delta \text{LnAGDP}_{t-k} + \partial_6 \text{LnGHGe}_{t-1} \\ &+ \partial_7 \text{LnCO}_2e_{t-1} + \partial_8 \text{LnANO}_{t-1} \\ &+ \partial_9 \text{LnAME}_{t-1} + \partial_{10} \text{LnAGDP}_{t-1} + \varepsilon_{5t} \end{aligned} \tag{8}$$

The parameters of the equations $\rho_1, \rho_2, \rho_3, \rho_4,$ and $\rho_5; \psi_1, \psi_2, \psi_3, \psi_4,$ and $\psi_5; \zeta_1, \zeta_2, \zeta_3, \zeta_4,$ and $\zeta_5; \eta_1, \eta_2, \eta_3, \eta_4,$ and $\eta_5;$ and $\zeta_1, \zeta_2, \zeta_3, \zeta_4,$ and ζ_5 display the short-run coefficients, and $\rho_6, \rho_7, \rho_8, \rho_9,$ and $\rho_{10}; \psi_6, \psi_7, \psi_8, \psi_9,$ and $\psi_{10}; \zeta_6, \zeta_7, \zeta_8, \zeta_9,$ and $\zeta_{10}; \eta_6, \eta_7, \eta_8, \eta_9,$ and $\eta_{10};$ and $\zeta_6, \zeta_7, \zeta_8, \zeta_9,$ and ζ_{10} show the long-run coefficients in the model. Equations (4)–(8) illustrate the null hypothesis with no cointegration between the variables ($H_0: \rho_6 = \rho_7 = \rho_8 = \rho_9 = \rho_{10} = 0, \psi_6 = \psi_7 = \psi_8 = \psi_9 = \psi_{10} = 0, \zeta_6 = \zeta_7 = \zeta_8 = \zeta_9 = \zeta_{10} = 0, \eta_6 = \eta_7 = \eta_8 = \eta_9 = \eta_{10} = 0, \zeta_6 = \zeta_7 = \zeta_8 = \zeta_9 = \zeta_{10} = 0$ against $H_1: \rho_6 \neq \rho_7 \neq \rho_8 \neq \rho_9 \neq \rho_{10} \neq 0, \psi_6 \neq \psi_7 \neq \psi_8 \neq \psi_9 \neq \psi_{10} \neq 0, \zeta_6 \neq \zeta_7 \neq \zeta_8 \neq \zeta_9 \neq \zeta_{10} \neq 0, \eta_6 \neq \eta_7 \neq \eta_8 \neq \eta_9 \neq \eta_{10} \neq 0, \zeta_6 \neq \zeta_7 \neq \zeta_8 \neq \zeta_9 \neq \zeta_{10} \neq 0,$ respectively).

The autoregressive distributed lag bounds testing approach was used in this analysis to demonstrate the dynamic linkage between agricultural gross domestic product, methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, and greenhouse gas emissions. The acceptance and rejection

of H0 are accompanied by the measured value of *F*-statistics, which should be less than the critical boundary values in the upper case. The cointegration is denied without the zero hypotheses, demonstrating that there are a co-integrated relation dependency and invaders amid the variables.

Results and discussion

Descriptive analysis and covariance relation amid variables

Analysis of descriptive statistics and covariance relation between variables are depicted in Tables 2 and 3 and concluded that all variables including methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, greenhouse gas emissions, and agricultural gross domestic product are correlated each other.

Stationarity of variable test results

The stationarity was tested using two unit root tests including Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979) and Phillips-Perron (P-P) (Phillips and Perron 1988) unit root test. Both tests demonstrate that no variables were integrated through *I*(2). Table 4 displays the results of the unit root tests between methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, greenhouse gas emissions, and agricultural gross domestic product which confirmed that all are integrated at the level and at first difference.

Table 3 Covariance relation among variables

Correlation						
<i>t</i> -statistic						
Probability	LnAGDP	LnAMe	LnANOe	LnCO ₂ e	LnGHGe	
	LnAGDP	1.000000				

	LnAMe	-0.985924	1.000000			
		-36.35108	----			
		[0.0000]	----			
	LnANOe	0.613354	-0.659416	1.000000		
		4.787199	-5.407071	----		
		[0.0000]	[0.0000]	----		
	LnCO ₂ e	0.973704	-0.979944	0.665128	1.000000	
		26.34694	-30.31426	5.490784	----	
		[0.0000]	[0.0000]	[0.0000]	----	
	LnGHGe	0.965661	-0.970119	0.651327	0.993292	1.000000
		22.91234	-24.64763	5.291329	52.95443	----
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	----

ARDL bounds test to cointegration results

An autoregressive distributed lag approach was employed to demonstrate the variable long-run linkage and equilibrium through bounds test to cointegration at 1%, 2.5%, 5%, and 10% levels of significance. Table 5 interprets the results of ARDL bounds test to cointegration.

The *F*-statistic value is 4.034113 which is exposed in Table 5 and surpassed the higher critical bound. In addition, the cointegration test shows the linkage amid methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, greenhouse gas emissions, and agricultural gross domestic product. Moreover, we have used

Table 2 Descriptive analysis

	LnAGDP	LnAMe	LnANOe	LnCO ₂ e	LnGHGe
Mean	11.26984	1.650790	1.868146	6.571229	6.734057
Median	11.24031	1.670161	1.870313	6.526923	6.707399
Maximum	11.99003	1.792194	1.892183	7.012496	7.095334
Minimum	10.61701	1.462039	1.851012	6.161818	6.435256
SD	0.418155	0.095929	0.008759	0.280052	0.215935
Skewness	0.455286	-0.375875	0.165003	0.176725	0.199243
Kurtosis	1.946683	2.036165	2.891091	1.737302	1.680526
J-B	3.231029	2.490175	0.201274	2.865557	3.166339
Probability	0.198788	0.287916	0.904261	0.238645	0.205323
Sum	450.7934	66.03161	74.72583	262.8492	269.3623
Sum SD	6.819278	0.358896	0.002992	3.058732	1.818494

Table 4 Unit root test results

Variables	ADF <i>t</i> -statistic		P-P <i>t</i> -statistic	
	At level	First difference	At level	First difference
LnAGDP	−2.298473	−4.496569***	−1.319118	−4.413385***
LnAMe	−1.448705	−3.899955**	−0.496177	−3.902028**
LnANoe	−3.942101**	−6.930631***	−3.953873**	−7.836809***
LnCO ₂ e	−2.418038	−3.647935**	−1.969548	−3.627423**
LnGHGe	−2.253816	−4.508279***	−2.099617	−4.497956***

Note: ** and *** denotes the significance level at 1% and 5% by rejecting the null hypothesis

the Johansen cointegration test (Johansen and Juselius 1990) and the findings are seen in Table 6. It supports the robustness of the variables through long-run interaction.

Evidence from long-run and short-run estimations

Estimated long-run and short-run analysis results are depicted in Table 7 which clarifies the linkage between methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, greenhouse gas emissions, and agricultural gross domestic product. Subsequently, the ARDL approach was used to validate the cointegration test, which investigated the dynamic association of variables via long-run and short-run estimates.

The estimated results in Table 7 indicate that CO₂ emission has a positive association with an agricultural gross domestic product with a coefficient of 0.449777 and *p* value of 0.5709. Similarly, the results also demonstrated that greenhouse gas emissions have positive and significant linkage to agriculture gross domestic product with a coefficient of 0.816959 and a *p* value of 0.3751. Furthermore, the results concluded that methane emissions from agriculture and nitrous oxide emissions from agriculture have negative linkage with an agricultural gross domestic product with coefficients of −1.886104 and

−7.560422 and *p* values of 0.1737 and 0.0559, respectively. China is known to be a huge agricultural country, with carbon dioxide emissions and energy consumption in this sector growing steadily after the industrial revolution, and a large number of fossil energy sources, such as coal, have been used extensively. Fossil fuel is considered the primary aspect of growth that creates a major competitive influence on economic development. In contrast, the excessive use of fossil fuels will produce a large amount of CO₂ emissions. Carbon dioxide is a major source of environmental problems, including extreme temperatures and climate change (Wang et al. 2020; Lin and Xu 2018; Fei and Lin 2017). The reduction of carbon dioxide emission and saving energy has a vital position to play in creating a low-carbon economy and preserving the atmosphere. Carbon dioxide emission from fossil fuel triggers a critical effect on the environment that has been affecting human wellbeing for a long time. Several nations across the world have made enormous attempts to reduce carbon dioxide emission. For economic growth, energy demand is driven by urbanization and industrialization has risen rapidly, and China's government faces significant challenges in finding various ways to mitigate carbon dioxide emissions (Fei and Lin 2016; Du et al. 2016; Xian et al. 2018; Feng et al. 2018).

The agricultural sector has a leading contribution to the economy of any country and has a vital role to reduce CO₂ emission. In addition, the estimation of CO₂ emission and the analysis to change the performance of agricultural CO₂ emission have become necessary and imperative. Agriculture can help to reduce carbon dioxide emission from plants. In other words, due to survival metabolism and energy-associated CO₂ emission, it is unavoidable to input factors in the production process, so carbon dioxide emission has also contributed (Lin and Fei 2015; Lin and Tan 2017). Increases in crop yields are likely to increase every year, due to certain influences such as adverse weather and pests and diseases. The duration of the growing season has changed due to climate change, particularly at high latitudes. There is a clear and growing human impact on the climate system. Greenhouse gases have responsibility for the usage of carbon and energy, as well as other inputs through food processing, storage, and transport.

Table 5 ARDL bounds test to cointegration results

Test statistic	Value	<i>K</i>
<i>F</i> -statistic	4.034113	5
Significance	I0 bound	II bound
At 10%	2.45	3.52
At 5%	2.86	4.01
At 2.5%	3.25	4.49
At 1%	3.74	5.06
Diagnostic tests		
<i>R</i> ²	0.390678	
Adj- <i>R</i> ²	0.279892	
<i>F</i> -statistic	3.526424	
Probability(<i>F</i> -statistic)	0.008309	

Table 6 Johansen cointegration test results

Null hypothesis	Trace test statistic	<i>p</i> value	Null hypothesis	Maximum Eigenvalue	<i>p</i> value
$r \leq 0$	89.65841	0.0433	$r \leq 0$	46.18525	0.0052
$r \leq 1$	43.47316	0.7158	$r \leq 1$	16.56665	0.8847
$r \leq 2$	26.90651	0.6865	$r \leq 2$	12.45625	0.8431
$r \leq 3$	14.45026	0.6203	$r \leq 3$	8.333568	0.7907
$r \leq 4$	6.116696	0.4456	$r \leq 4$	6.116696	0.4456
$r \leq 5$	89.65841	0.0433	$r \leq 5$	46.18525	0.0052

Note: *r* indicates the number of cointegrating equation

Enhanced agricultural production systems require increased input, but in order to reduce greenhouse gasses, food systems need to shift to lower inputs and resource quality (Litskas et al. 2020; Savary et al. 2019).

The short-run dynamic association also reveals that two variables have a positive association with the agricultural gross domestic product and two variables have negative linkage with the agricultural gross domestic product. In contrast, the diagnostic tests show that normality test, serial correlation, heteroscedasticity, and Ramsey RESET *p* values are 0.2155, 0.5343, 0.2695, and 0.3067, respectively.

Table 7 Estimated long-run and short-run analysis results

Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob.
Long-run estimation				
LnAMe	-1.886104	1.356440	-1.390481	0.1737
LnANOe	-7.560422	3.814584	-1.981978	0.0559
LnCO ₂ e	0.449777	0.785674	0.572473	0.5709
LnGHGe	0.816959	0.908699	0.899042	0.3751
<i>C</i>	20.121297	8.804613	2.285313	0.0289
Short-run dynamics				
DLnAGDP (-1)	0.698428	0.101244	6.898457	0.0000
DLnAMe	-0.568797	0.546469	-1.040859	0.3055
DLnANOe	0.241502	1.055507	0.228802	0.8204
DLnANOe (-1)	-2.521516	1.161349	-2.171196	0.0372
DLnCO ₂ e	0.135640	0.238859	0.567868	0.5740
DLnGHGe	0.246372	0.251741	0.978674	0.3349
ECM (-1)	-0.301572	0.101244	-2.978668	0.0054
Diagnostic tests				
<i>R</i> ²	0.992870			
Adj- <i>R</i> ²	0.991574			
<i>F</i> -statistic	765.9196			
Prob (<i>F</i> -statistic)	0.000000			
Normality	3.0687 (0.2155)			
Serial correlation	0.6395 (0.5343)			
ARCH	1.2569 (0.2695)			
Ramsey RESET	1.0386 (0.3067)			
CUSUM	Stable			
CUSUMSQ	Stable			

Figure 2 indicates the dynamic association amid the variables. Study findings demonstrate that carbon dioxide emission and greenhouse gas emissions have long-term association with the agricultural gross domestic product, but the coefficient of methane emissions from agriculture and nitrous oxide emissions from agriculture demonstrates a negative linkage. Moreover, long-run and short-run directions among variables are consistent, excluding methane emissions from agriculture and nitrous oxide emissions from agriculture in both long-run and short-run investigation. Overall study findings showed variability in the long run and short run.

Results of fully modified least squares method

The results of the fully modified least squares method are depicted in Table 8 which indicates that methane emissions from agriculture and nitrous oxide emissions from agriculture have non-significant linkage with the agricultural gross domestic product with coefficients of -3.311924 and -4.512624 and *p* values of 0.0000 and 0.0181, respectively. Similarly, the results also exposed during analysis that carbon dioxide emission and greenhouse gas emissions have a positive association with an agricultural gross domestic product with coefficients of 0.196049 and 0.296940 and *p* values of

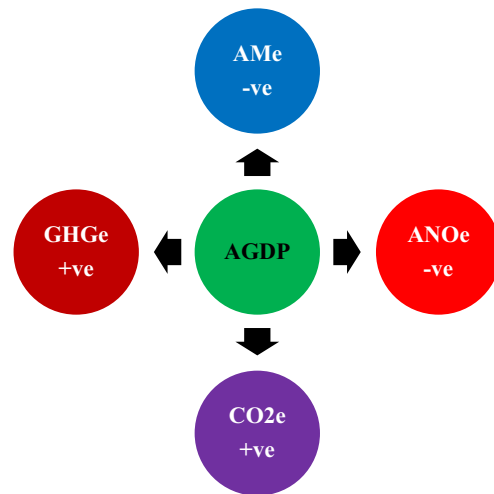


Fig. 2 Dynamic association between variables

Table 8 Results of the fully modified least squares (FMOLS) method

Variables	Coefficient	Std. Error	t-statistic	Prob.
LnAMe	-3.311924	0.625159	-5.297734	0.0000
LnANOe	-4.512624	1.819532	-2.480101	0.0181
LnCO ₂ e	0.196049	0.454129	0.431702	0.6686
LnGHGe	0.296940	0.480821	0.617569	0.5409
C	21.88036	4.126409	5.302518	0.0000
R ²	0.975649			
Adj-R ²	0.972866			

0.6686 and 0.5409, respectively. The coefficient of R² is 0.975649 and Adj-R² is 0.972866. In conclusion, the fully modified least squares (FMOLS) method also reveals the dynamic relation between the variables.

Results of canonical cointegrating regression analysis

Table 9 displays the results of the canonical cointegrating regression (CCR) analysis which revealed that the coefficients of the methane emissions from agriculture and nitrous oxide emissions from agriculture have a non-significant association with agricultural gross domestic product with p values of 0.0003 and 0.0366, respectively. In addition, results also indicated that carbon dioxide emission and greenhouse gas emissions have a positive influence on agricultural gross domestic product in China with p values of 0.6517 and 0.5926, respectively.

Figures 3 and 4 illustrate the long-run and short-run stability by using CUSUM (cumulative sum) and CUSUMSQ (cumulative sum of square) which indicate a 5% significance level.

Conclusion and policy recommendations

The present analysis explores the association of methane emissions from agriculture, nitrous oxide emissions from agriculture, carbon dioxide emission, and greenhouse gas emissions with agricultural gross domestic product in China. Data

Table 9 Results of canonical cointegrating regression (CCR) analysis

Variables	Coefficient	Std. error	t-statistic	Prob.
LnAMe	-3.152047	0.792691	-3.976390	0.0003
LnANOe	-4.530158	2.084402	-2.173360	0.0366
LnCO ₂ e	0.242199	0.531943	0.455310	0.6517
LnGHGe	0.298073	0.551996	0.539991	0.5926
C	21.33465	5.149868	4.142757	0.0002
R ²	0.975236			
Adj-R ²	0.972406			

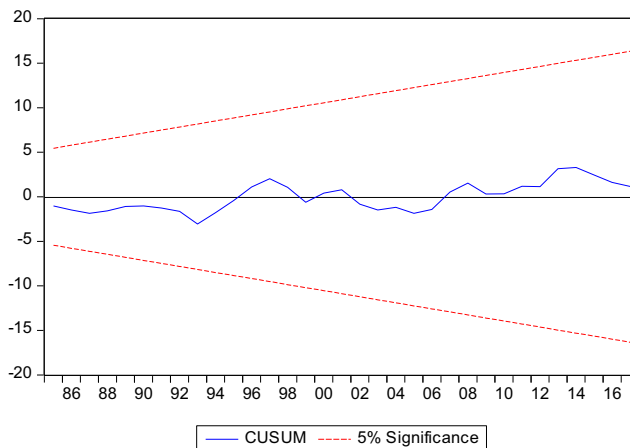


Fig. 3 Cumulative sum

stationarity was clarified by using two unit root tests including augmented Dickey-Fuller (ADF) test and Phillips-Perron (P-P) test. Furthermore, the dynamic linkage was checked by using autoregressive distributed lag (ARDL) bounds testing approach, fully modified least squares (FMOLS) method, and canonical cointegrating regression (CCR) analysis. The variables showed a long-term association as carbon dioxide emission and greenhouse gas emissions have positive influence to agricultural gross domestic product. Similarly, results also show that methane emissions from agriculture and nitrous oxide emissions from agriculture demonstrate a negative linkage with agricultural gross domestic product of China. According to the study findings, it suggests that possible conservative policies are needed from the government of China regarding the reduction of carbon dioxide emission and greenhouse gas emissions to avoid causing agricultural production as well as climate change.

Due to emission of these harmful gases, the temperature is increasing globally that causes the agricultural productivity. It is also concluded that CO₂ emission is now an emerging problem on global level, and possible conventional policies are needed from all countries to pay attention regarding the

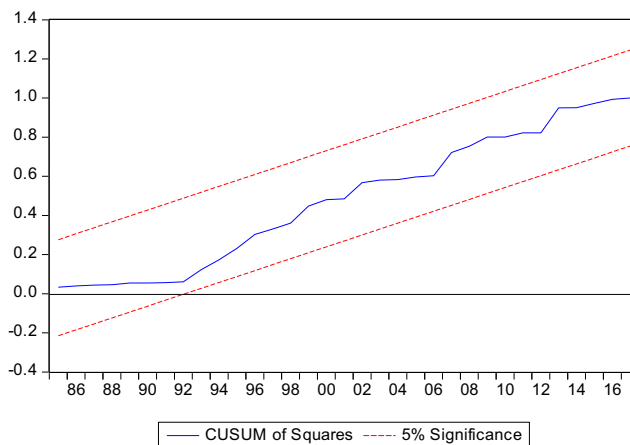


Fig. 4 Cumulative sum of square

reduction of carbon dioxide emission to avoid environmental degradation. Both in terms of production or consumption, China's greenhouse gas emissions are the largest in the world, mainly from coal. The implementation of new policies on climate change mitigation and adverse effects is intended to reduce the use of coal. The government sets targets and commits to reducing the CO₂ emission and increasing usage of non-fossil fuel energy carriers. Additionally, the consequences of greenhouse gas emissions effects almost every aspect of life and impact on agricultural production can be particularly important. The rising temperatures and decreasing precipitation have led to a decline in China's rice, wheat, and corn production. In contrast, China's cotton production has increased and the agricultural sector contribution is almost at fifth part in the entire greenhouse gas emissions. The main source of agricultural greenhouse gas emissions is the application of chemical fertilizers. Other sources include less excrement burning or pasture management than fertilizer. Another factor contributing to greenhouse gas emissions from the agricultural sector is methane and nitrous oxide emissions that come mainly from livestock carcasses and farm management. The Chinese government needs to take action as soon as possible to combat with carbon dioxide emission which is influencing the climate change and agricultural production.

References

- Adams S, Nsiah C (2019) Reducing carbon dioxide emissions: does renewable energy matter? *Sci Total Environ* 693:133288. <https://doi.org/10.1016/j.scitotenv.2019.07.094>
- Chang CC (2010) A multivariate causality test of carbon dioxide emissions, energy consumption and economic growth in China. *Appl Energy* 87(11):3533–3537. <https://doi.org/10.1016/j.apenergy.2010.05.004>
- Chen J, Cheng S, Song M (2018) Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2005 to 2013. *Renew Sust Energ Rev* 94:748–761. <https://doi.org/10.1016/j.rser.2018.06.050>
- Collis D, Maestrini B, Pezzuolo A, Marinello F, Sartori L (2018) Modeling soil organic carbon and carbon dioxide emissions in different tillage systems supported by precision agriculture technologies under current climatic conditions. *Soil Tillage Res* 183:51–59. <https://doi.org/10.1016/j.still.2018.06.001>
- Department of Energy and Climate Change (DECC) (2013) Final UK greenhouse gas emissions. Available from: <https://www.gov.uk/government/publications/final-uk-emissions-estimate>. Accessed 20 Feb 2020
- Department of Energy and Climate Change (DECC) (2014) Final UK greenhouse gas emissions. Available from: <https://www.gov.uk/government/publications/final-uk-emissions-estimate>. Accessed 15 Jan 2020
- de Souza LC, Fernandes C, Moitinho MR, da Silva Bicalho E, La Scala N (2019) Soil carbon dioxide emission associated with soil porosity after sugarcane field reform. *Mitig Adapt Strateg Glob Chang* 24(1): 113–127. <https://doi.org/10.1007/s11027-018-9800-5>
- Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. *J Am Stat Assoc* 74(366a):427–431. <https://doi.org/10.1080/01621459.1979.10482531>
- Du L, Hanley A, Zhang N (2016) Environmental technical efficiency, technology gap and shadow price of coal-fuelled power plants in China: a parametric meta-frontier analysis. *Resour Energy Econ* 43: 14–32. <https://doi.org/10.1016/j.reseneeco.2015.11.001>
- Fais B, Sabio N, Strachan N (2016) The critical role of the industrial sector in reaching long-term emission reduction, energy efficiency and renewable targets. *Appl Energy* 162:699–712. <https://doi.org/10.1016/j.apenergy.2015.10.112>
- Fei R, Lin B (2016) Energy efficiency and production technology heterogeneity in China's agricultural sector: a meta-frontier approach. *Technol Forecast Soc Chang* 109:25–34. <https://doi.org/10.1016/j.techfore.2016.05.012>
- Fei R, Lin B (2017) Technology gap and CO₂ emission reduction potential by technical efficiency measures: a meta-frontier modeling for the Chinese agricultural sector. *Ecol Indic* 73:653–661. <https://doi.org/10.1016/j.ecolind.2016.10.021>
- Feng C, Huang JB, Wang M (2018) Analysis of green total-factor productivity in China's regional metal industry: a meta-frontier approach. *Resources Policy* 58:219–229. <https://doi.org/10.1016/j.resourpol.2018.05.008>
- Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM, Toulmin C (2010) Food security: the challenge of feeding 9 billion people. *Science* 327(5967):812–818. <https://doi.org/10.1126/science.1185383>
- Green F, Stern N (2017) China's changing economy: implications for its carbon dioxide emissions. *Clim Pol* 17(4):423–442. <https://doi.org/10.1080/14693062.2016.1156515>
- Hao Y, Chen H, Wei YM, Li YM (2016) The influence of climate change on CO₂ (carbon dioxide) emissions: an empirical estimation based on Chinese provincial panel data. *J Clean Prod* 131:667–677. <https://doi.org/10.1016/j.jclepro.2016.04.117>
- Hasegawa T, Matsuoka Y (2015) Climate change mitigation strategies in agriculture and land use in Indonesia. *Mitig Adapt Strateg Glob Chang* 20(3):409–424. <https://doi.org/10.1007/s11027-013-9498-3>
- Johansen S, Juselius K (1990) Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxf Bull Econ Stat* 52(2):169–210. <https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x>
- Kagawa S, Suh S, Hubacek K, Wiedmann T, Nansai K, Minx J (2015) CO₂ emission clusters within global supply chain networks: implications for climate change mitigation. *Glob Environ Chang* 35:486–496. <https://doi.org/10.1016/j.gloenvcha.2015.04.003>
- Kiviyro P, Arminen H (2014) Carbon dioxide emissions, energy consumption, economic growth, and foreign direct investment: causality analysis for sub-Saharan Africa. *Energy* 74:595–606. <https://doi.org/10.1016/j.energy.2014.07.025>
- Kumazawa R, Callaghan MS (2012) The effect of the Kyoto Protocol on carbon dioxide emissions. *J Econ Financ* 36(1):201–210
- Li A, Zhang A, Zhou Y, Yao X (2017a) Decomposition analysis of factors affecting carbon dioxide emissions across provinces in China. *J Clean Prod* 141:1428–1444
- Li H, Li B, Lu H (2017b) Carbon dioxide emissions, economic growth, and selected types of fossil energy consumption in China: empirical evidence from 1965 to 2015. *Sustainability* 9(5):697. <https://doi.org/10.3390/su9050697>
- Li S, Zhou C, Wang S (2019) Does modernization affect carbon dioxide emissions? A panel data analysis. *Sci Total Environ* 663:426–435. <https://doi.org/10.1016/j.scitotenv.2019.01.373>
- Liddle B (2015) What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. *Glob Environ Chang* 31:62–73. <https://doi.org/10.1016/j.gloenvcha.2014.10.016>
- Lin B, Benjamin NI (2017) Influencing factors on carbon emissions in China transport industry. A new evidence from quantile regression

- analysis. *J Clean Prod* 150:175–187. <https://doi.org/10.1016/j.jclepro.2016.09.115>
- Lin B, Fei R (2015) Regional differences of CO₂ emissions performance in China's agricultural sector: a Malmquist index approach. *Eur J Agron* 70:33–40. <https://doi.org/10.1016/j.eja.2015.06.009>
- Lin B, Nelson BI (2019) Determinants of industrial carbon dioxide emissions growth in Shanghai: a quantile analysis. *J Clean Prod*. <https://doi.org/10.1016/j.jclepro.2019.01.208>
- Lin B, Tan R (2017) China's CO₂ emissions of a critical sector: evidence from energy intensive industries. *J Clean Prod* 142:4270–4281. <https://doi.org/10.1016/j.jclepro.2016.11.186>
- Lin B, Xu B (2018) Factors affecting CO₂ emissions in China's agriculture sector: a quantile regression. *Renew Sust Energy Rev* 94:15–27. <https://doi.org/10.1016/j.rser.2018.05.065>
- Litskas VD, Platis DP, Anagnostopoulos CD, Tسابoula AC, Menexes GC, Kalburtji KL, Stavrinides MC, Mamolos AP (2020) Climate change and agriculture: carbon footprint estimation for agricultural products and labeling for emissions mitigation. In sustainability of the food system (pp. 33–49). Academic press. <https://doi.org/10.1016/B978-0-12-818293-2.00003-3>
- Liu Z, Guan D, Crawford-Brown D, Zhang Q, He K, Liu J (2013) A low-carbon road map for China. *Nature* 500(7461):143–145. <https://doi.org/10.1038/500143a>
- Liu Z, Guan D, Wei W, Davis SJ, Ciais P, Bai J, Peng S, Zhang Q, Hubacek K, Marland G, Andres RJ (2015) Reduced carbon emission estimates from fossil fuel combustion and cement production in China. *Nature* 524(7565):335–338. <https://doi.org/10.1038/nature14677>
- 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. <https://doi.org/10.1016/j.jclepro.2017.05.076>
- Marescaux A, Thieu V, Garnier J (2018) Carbon dioxide, methane and nitrous oxide emissions from the human-impacted Seine watershed in France. *Sci Total Environ* 643:247–259. <https://doi.org/10.1016/j.scitotenv.2018.06.151>
- Nayak D, Saetnan E, Cheng K, Wang W, Koslowski F, Cheng YF, Zhu WY, Wang JK, Liu JX, Moran D, Yan X (2015) Management opportunities to mitigate greenhouse gas emissions from Chinese agriculture. *Agric Ecosyst Environ* 209:108–124. <https://doi.org/10.1016/j.agee.2015.04.035>
- Ouedraogo BI, Levermore GJ, Parkinson JB (2012) Future energy demand for public buildings in the context of climate change for Burkina Faso. *Build Environ* 49:270–282. <https://doi.org/10.1016/j.buildenv.2011.10.003>
- Ouyang X, Lin B (2017) Carbon dioxide (CO₂) emissions during urbanization: a comparative study between China and Japan. *J Clean Prod* 143:356–368. <https://doi.org/10.1016/j.jclepro.2016.12.102>
- Pesaran MH, Shin Y (1998) An autoregressive distributed-lag modelling approach to cointegration analysis. *Econom So Monogr* 31:371–413
- Phillips PC, Perron P (1988) Testing for a unit root in time series regression. *Biometrika* 75(2):335–346. <https://doi.org/10.1093/biomet/75.2.335>
- Rehman A, Ozturk I, Zhang D (2019) The causal connection between CO₂ emissions and agricultural productivity in Pakistan: empirical evidence from an autoregressive distributed lag bounds testing approach. *Appl Sci* 9(8):1692. <https://doi.org/10.3390/app9081692>
- Sari R, Soytas U (2009) Are global warming and economic growth compatible? Evidence from five OPEC countries? *Appl Energy* 86(10):1887–1893. <https://doi.org/10.1016/j.apenergy.2008.12.007>
- Savary S, Willocquet L, Pethybridge SJ, Esker P, McRoberts N, Nelson A (2019) The global burden of pathogens and pests on major food crops. *Nat Ecol Evol* 3(3):430–439. <https://doi.org/10.1038/s41559-018-0793-y>
- Sefeedpari P, Ghahderjani M, Pishgar-Komleh SH (2013) Assessment the effect of wheat farm sizes on energy consumption and CO₂ emission. *J Renewable Sustainable Energy* 5(2):023131. <https://doi.org/10.1063/1.4800207>
- She W, Wu Y, Huang H, Chen Z, Cui G, Zheng H, Guan C, Chen F (2017) Integrative analysis of carbon structure and carbon sink function for major crop production in China's typical agriculture regions. *J Clean Prod* 162:702–708. <https://doi.org/10.1016/j.jclepro.2017.05.108>
- Stigson P, Buhr K, Roth S (2013) The ambitions in Copenhagen Pledges: country case studies of drivers and barriers. *Gree Gas Meas Mana* 3(1–2):21–36
- Sumabat AK, Lopez NS, Yu KD, Hao H, Li R, Geng Y, Chiu AS (2016) Decomposition analysis of Philippine CO₂ emissions from fuel combustion and electricity generation. *Appl Energy* 164:795–804. <https://doi.org/10.1016/j.apenergy.2015.12.023>
- Taseska V, Markovska N, Causevski A, Bosevski T, Pop-Jordanov J (2011) Greenhouse gases (GHG) emissions reduction in a power system predominantly based on lignite. *Energy* 36(4):2266–2270. <https://doi.org/10.1016/j.energy.2010.04.010>
- Valipour M, Raeini-Sarjaz M, Sefidkouhi MAG (2018) Optimisation of cropping pattern considering stomatal response to elevated CO₂ emission and climate change. *Int J Glob Warm* 15(2):227–255. <https://doi.org/10.1504/IJGW.2018.092897>
- Van den Berg MM, Hengsdijk H, Wolf J, Van Ittersum MK, Guanghuo W, Roetter RP (2007) The impact of increasing farm size and mechanization on rural income and rice production in Zhejiang province, China. *Agric Syst* 94(3):841–850
- Wang Y, Zhao T (2015) Impacts of energy-related CO₂ emissions: evidence from under developed, developing and highly developed regions in China. *Ecol Indic* 50:186–195. <https://doi.org/10.1016/j.ecolind.2014.11.010>
- Wang H, Ang BW, Zhou P (2018) Decomposing aggregate CO₂ emission changes with heterogeneity: an extended production-theoretical approach. *Energy J* 39(1). <https://doi.org/10.5547/01956574.39.1.hwan>
- Wang J, Song X, Chen K (2020) Which influencing factors cause CO₂ emissions differences in China's provincial construction industry: empirical analysis from a quantile regression model. *Pol J Environ Stud* 29(1). <https://doi.org/10.15244/pjoes/105239>
- Wenbo G, Yan C (2018) Assessing the efficiency of China's environmental regulation on carbon emissions based on Tapio decoupling models and GMM models. *Energy Rep* 4:713–723. <https://doi.org/10.1016/j.egy.2018.10.007>
- Xian Y, Wang K, Shi X, Zhang C, Wei YM, Huang Z (2018) Carbon emissions intensity reduction target for China's power industry: an efficiency and productivity perspective. *J Clean Prod* 197:1022–1034. <https://doi.org/10.1016/j.jclepro.2018.06.272>
- Xu B, Lin B (2017) Factors affecting CO₂ emissions in China's agriculture sector: evidence from geographically weighted regression model. *Energy Policy* 104:404–414. <https://doi.org/10.1016/j.enpol.2017.02.011>
- Yang J, Zhang T, Sheng P, Shackman JD (2016) Carbon dioxide emissions and interregional economic convergence in China. *Econ Model* 52:672–680. <https://doi.org/10.1016/j.econmod.2015.09.038>
- Zaman K, Khan MM, Ahmad M, Rustam R (2012) The relationship between agricultural technology and energy demand in Pakistan. *Energy Policy* 44:268–279
- Zhao X, Zhang X, Li N, Shao S, Geng Y (2017a) Decoupling economic growth from carbon dioxide emissions in China: a sectoral factor decomposition analysis. *J Clean Prod* 142:3500–3516. <https://doi.org/10.1016/j.jclepro.2016.10.117>
- Zhao Y, Li H, Zhang Z, Zhang Y, Wang S, Liu Y (2017b) Decomposition and scenario analysis of CO₂ emissions in China's power industry: based on LMDI method. *Nat Hazards* 86(2):645–668. <https://doi.org/10.1007/s11069-016-2710-5>
- Zhou Y, Liu Y (2016) Does population have a larger impact on carbon dioxide emissions than income? Evidence from a cross-regional

- panel analysis in China. *Appl Energy* 180:800–809. <https://doi.org/10.1016/j.apenergy.2016.08.035>
- Zhou Y, Liu Y, Wu W, Li Y (2015) Effects of rural–urban development transformation on energy consumption and CO₂ emissions: a regional analysis in China. *Renew Sust Energ Rev* 52:863–875. <https://doi.org/10.1016/j.rser.2015.07.158>
- Zhou X, Zhang M, Zhou M, Zhou M (2017) A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy–related carbon emissions. *J Clean Prod* 142:783–800. <https://doi.org/10.1016/j.jclepro.2016.09.115>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.