RESEARCH ARTICLE

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Coupling and decoupling effects of agricultural carbon emissions in China and their driving factors

Haibin Han[1] · Zhangqi Zhong[2] · Yu Guo[3] · Feng Xi[1] · Shuangliang Liu[1]

Abstract

The relationship between agricultural carbon emissions and agricultural economic growth has attracted a significant research attention. A key issue to address in the development of agriculture is the reduction of agricultural carbon emissions while maintaining agricultural economic growth. This study investigated the interactions between agricultural carbon emissions and agricultural economic growth from multiple perspectives based on agricultural carbon emission data from 30 provinces in China measured from 1997 to 2015. Using this dataset, the coupling and decoupling effects of agricultural carbon emissions and the underlying driving factors were explored using a coupling development degree model, the Tapio decoupling assessment model, and a logarithmic mean Divisia index (LMDI) decomposition model. The results were as follows: (1) at the regional scale, the degree of coupling development between agricultural carbon emissions and agricultural economic growth is high in the central region of China and low in the western region. At the provincial scale, the coupling effects of agricultural carbon emissions exhibited four levels: minimal, low, moderate, and high coupling. (2) With the exceptions of Beijing, Zhejiang, Fujian, Guangdong, Inner Mongolia, and Shanghai, the relationships between agricultural carbon emissions and agricultural economic growth in the other 24 provinces were in a weak decoupling state. (3) The effects of agricultural development scale and agricultural technical progress were the major driving factors associated with increases and decreases in agricultural carbon emissions, respectively.

Keywords Agricultural carbon emissions · Coupling effect · Decoupling effect · LMDI decomposition model

Introduction

China's rapid economic growth has resulted in high carbon dioxide emissions that poses many risks to the ecological balance of the area (Li and Jin 2018; Liu et al. 2018). Indeed, China has surpassed the USA as the world's largest producer of carbon dioxide emissions (Li et al. 2016a). In an effort to mitigate rising carbon dioxide emissions, the Chinese

government has promised that carbon dioxide emissions per unit GDP will be reduced to 40–45% of 2005 levels by 2020 (Li et al. 2016b). The promise reflects the determination and confidence of the Chinese government to substantially reduce carbon emissions and to manage economic growth responsibly. As a developing country, economic development is always the primary goal for China. The 17th National Congress of the Communist Party of China indicated that fourfold growth of the per capita GDP in 2000 by the year 2020 was one of the country's economic development goals (Zhou and Li 2013). Consequently, the Chinese government faces conflicting pressures from carbon emission reduction and increased economic growth during the country's current development, and in the foreseeable future.

Transforming the pattern of economic growth is key to resolving the conflict between growth and environmental concerns. It is integral to adopt advanced carbon emission reduction measures, with particular focus on the often-overlooked emissions of agricultural carbon. An excessive use of agricultural production inputs such as chemical fertilizers and pesticides results in large increases of greenhouse gas (GHG)

✉ Haibin Han
  hshore@tjcu.edu.cn

[1] School of Public Administration, Tianjin University of Commerce, No. 409 Guangrong Rd., Beichen District, Tianjin 300134, People's Republic of China

[2] School of Economics, Zhejiang University of Finance and Economics, Hangzhou 310018, China

[3] College of Land and Environment, Shenyang Agricultural University, Shenyang 110866, China

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emissions (Tian et al. 2015). For example, GHG emissions from agriculture account for approximately 17% of the total emissions of China (Lu 2013). Although the proportion of agricultural GHG emissions is not as high as that of other industries, emission reduction and energy conservation in agriculture are still important and have a significantly positive externality (Wu et al. 2015). A key issue to address in agricultural development is reducing agricultural carbon emissions while simultaneously developing the agricultural economy. To accomplish a "win–win" outcome with respect to the reduction of agricultural carbon emissions and the maintenance of agricultural economic growth, it is necessary to clarify the relationship between the two properties. In theory, a long-term relationship between agricultural carbon emissions (environmental degradation) and agricultural economic growth generally exhibits an inverted U-shaped curve (Liang 2017). The curve is often referred to as an "environmental mountain" (Fig. 1; Sheng et al. 2015). In the early agricultural development phase, a large amount of GHGs are produced because agricultural economic growth strongly relies on the consumption of agricultural production inputs. During the period when agricultural carbon emissions increase with the growth of the agricultural economy, agricultural carbon emissions and agricultural economic growth exhibit a coupling relationship. After agricultural economic growth reaches a critical point (inflection point A), i.e., after agricultural carbon emissions peak, emissions continuously decline with the growth of the agricultural economy. These variables then exhibit opposite trends, i.e., a decoupling relationship.

With increased attention on agricultural effects on environments, numerous investigations have been conducted to assess agricultural carbon emissions. For instance, Bell et al. (2014) questioned the IPCC method of quantifying GHG emissions from agricultural production and presented a new approach that was subsequently adopted by the Scottish government. Machado et al. (2017) estimated agricultural carbon emissions of certain ethanol feedstocks in Brazil. Robaina-Alves and Moutinho (2014) identified the specific effects of decomposition on the intensity of GHG emissions in agriculture for certain European countries. Further, Xu and Lin (2017) investigated the forces driving CO_2 emissions in China's agriculture sector using a geographically weighted regression model. Yan et al. (2017) analyzed the main drivers of GHG emissions from agriculture in 17 European countries using the Generalized Divisia Index. Nayak et al. (2015) presented the outcomes of a bottom-up assessment of mitigation options for China's agricultural sector using a meta-analysis.

The above studies of agricultural carbon emissions focused mainly on the estimation of agricultural carbon emissions, its driving forces, and methods of its reduction. Although existing literature provides an important foundation for our research, the relationship between agricultural carbon emissions and agricultural economic growth is still unclear. Some
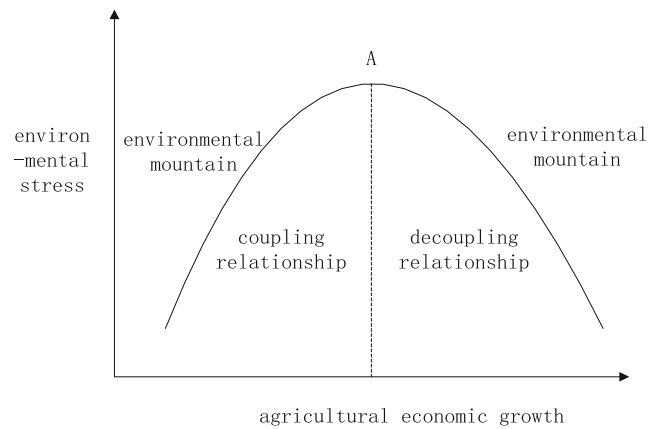

Fig. 1 The environmental mountain curve

studies have investigated whether agricultural carbon emissions and agricultural economic growth were compatible using the environmental Kuznets curve (EKC) hypothesis. For example, Managi (2006) examined the EKC hypothesis as it pertains to pesticide use. Using the EKC theory, Yan et al. (2014) explored the relationship between the intensity of agricultural carbon emissions and the strength of the agricultural economy in China. The authors discovered that the EKCs of these variables exhibited double inflection points. Vlontzos et al. (2017) developed a synthetic Eco-(in) efficiency index and used it to examine EKC in the EU agricultural sector. Liu et al. (2017) explored the impact of agriculture on carbon dioxide emissions and examined the EKC hypothesis in four Association of Southeast Asian Nations (ASEAN) countries. These EKC-based studies focused specifically on the effect of agricultural economic growth on agricultural carbon emissions but overlooked possible interactions between them (Yang 2011). In addition, this model only describes the curve relationships between agricultural carbon emissions and agricultural economic growth. Thus, it is not able to identify and classify their specific phases effectively (Liu and Cao 2017).

The term "decoupling" originates from physics and indicates a rift in the relationship among physical quantities that initially have similar response relationships (Zhao et al. 2017). Unlike the EKC method, which only investigates the one-way relationship between two variables, the decoupling method can reveal the interactions between variables. In addition, it is also easier to understand and calculate. Consequently, the decoupling method has become widely used to investigate the relationships among the economy, energy use, and emissions (Wang et al. 2017a). For example, Zhang and Wang (2013) studied decoupling between economic growth and CO_2 emissions in Jiangsu. Wang et al. (2017b) also demonstrated a relationship between CO_2 emissions and electricity production in the Shandong province using the decoupling method. Zhang et al. (2018) examined the decoupling relationship between coal consumption and economic growth. Meng et al. (2018) used the decoupling index to evaluate the

relationship between fossil fuel consumption and industrial outputs in China. Although numerous studies have examined the decoupling relationship among the economy, energy use, and emissions, there have only been a few studies that used the decoupling method to investigate the agricultural sector (Luo et al. 2017). Of these studies, Zhen et al. (2017a) assessed the decoupling effect of carbon emissions from crop farming in the Guangdong province using a decoupling model. In addition, Luo et al. (2017) investigated the decoupling of agricultural carbon emissions from agricultural economic growth in China. These investigations highlighted the interactions between agricultural carbon emissions and agricultural economic growth, but the decoupling relationship between them was solely assessed from a single perspective. Consequently, these studies were limited by the lack of a discussion of the coupling relationship between emissions and growth.

In contrast with decoupling, coupling refers to the phenomenon by which two or more systems, or forms of motion, interact with each other to create a joint effect (He et al. 2017). The coupling method has been widely used to assess the relationship between agricultural emissions and growth (Yang et al. 2017; Wang et al. 2017c). By combining the coupling and decoupling methods, we can avoid one-sided conclusions, and the two methods become mutually complementary. Thus, a demonstration of the coupling and decoupling relationships between agricultural carbon emissions and agricultural economic growth could result in robust conclusions. Here, we explored the coupling and decoupling relationships between agricultural carbon emissions and agricultural economic growth in a unified framework. Moreover, we identified the driving factors of agricultural carbon emissions using the LMDI decomposition model. The results of this study provide a useful supplement to the current body of literature on this topic. Further, we expect that our study will assist in providing a more robust conclusion regarding the relationship between agricultural carbon emissions and agricultural economic growth. Our contributions are summarized as follows: (1) we investigated CO_2 emissions as a result of agricultural land use activities, as well as CH_4 gas emissions from rice production. We further considered differences among regions and rice varieties in determining the CH_4 emission coefficients from rice production. (2) This investigation explores the coupling and decoupling relationships between agricultural carbon emissions and agricultural economic growth in a unified framework. Thus, we avoid one-sided conclusions and draw more robust conclusions than have been previously supposed. (3) A LMDI decomposition model was employed at both the temporal and spatial scales to determine the driving factors of agricultural carbon emissions in China.

The second section of the current study introduces details of the model, methods, and sources of data. The third section of the manuscript presents and discusses the results, while conclusions are presented in the fourth section.

Methodology and data

Research methods

Measurement model of carbon emissions

Following Tian and Zhang (2013), the equation used to measure carbon emissions was

$$E = \sum(T_i \times \delta_i), \tag{1}$$

where E represents the amount of agricultural carbon emissions; i represents the source of agricultural carbon emissions; T represents the characterization data of agricultural carbon emission sources; and δ represents the carbon emission coefficient of agricultural carbon emission sources.

Many stages of the agricultural production process result in carbon emissions. Further, agricultural carbon emissions result from diverse and complex carbon sources. We focused on CO_2 emissions as a result of agricultural resource use and energy consumption from agricultural land use activities, as well as CH_4 gas emissions from rice production, according to the characteristics of agricultural production and previous studies (Tian et al. 2014b; Li et al. 2015). In addition, to render our results more convenient, we unified measurement units by converting CO_2 and CH_4 emissions to standard C equivalents (C; described below). According to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC 2007), the greenhouse effects produced by 1 ton of CO_2 and CH_4 are equivalent to those produced by 0.2727 and 6.8175 tons of C, respectively.

GHG emissions are generated during agricultural land use activities, the use of agricultural materials, and consumption of agricultural energy, in addition to other processes. According to Li et al. (2011) and Tian et al. (2012), the carbon emissions of agricultural land activities mainly result from (1) the production and use of fertilizers, pesticides, agricultural plastic sheets, and agricultural diesel oil; (2) destruction of the soil organic carbon pool by agricultural plowing; and (3) consumption of fossil fuel for electricity in agricultural irrigation (i.e., indirect carbon emissions). A comprehensive list of emission coefficients for various carbon sources and their associated references is shown in Table 1.

Rice fields are a major source of CH_4 emissions, and China is both a major producer and consumer of rice. The CH_4 emissions from rice fields have a considerable effect on the global atmosphere, and thus, a scientific measurement of CH_4 emissions from rice fields is essential. The CH_4 emissions resulting from different rice varieties or different rice fields vary. Therefore, the determination of CH_4 emission coefficients should consider differences in regions and rice varieties. Min and Hu (2012) measured the CH_4 emission coefficients of different rice varieties from different regions.

Table 1 Carbon emission sources, coefficients, and associated references

Carbon sources	Carbon emission coefficient	Reference
Fertilizers	0.8956 kg C kg^{-1}	West and Marland (2002)
Pesticides	4.9341 kg C kg^{-1}	Zhi and Gao (2009)
Agricultural plastic sheets	5.18 kg C kg^{-1}	Tian et al. (2014a)
Diesel oil	0.5927 kg C kg^{-1}	IPCC (2007)
Tillage	312.6 kg C hm^{-2}	Wu et al. (2007)
Irrigation	20.476 kg C hm^{-2}	Dubey and Lal (2009)

Considering the above, we converted CH_4 emission coefficients to C emission coefficients and present the C emission coefficients of early season rice, late season rice, and in-season rice from different Chinese provinces (Table 2).

Coupling development degree model

We explored the coupling effect between agricultural carbon emissions and agricultural economic growth using a coupling development degree model. To analyze the coupling relationship between agricultural carbon emissions and agricultural economic growth, we constructed an evaluation model based on previous studies (Tang 2015; Wang et al. 2017c) that assesses the coupling relationship between the two properties:

$$CP = \left(\frac{G' \times E'}{\left(\frac{G'+E'}{2} \right)^2} \right)^k \qquad (2)$$

Here, CP is the degree of coupling and is a description and measurement of the coupling relationship between agricultural carbon emissions and agricultural economic growth; G' is the standardized output value of farming and indicates agricultural economic growth; E' represents standardized agricultural carbon emissions; and k is the adjustment coefficient that is mainly used to increase the degree of discrimination of coupling ($k \geq 2$) (Li et al. 2012). According to He et al. (2017) and Yang et al. (2017), we used a $k = 2$, because the degree of coupling can be discriminated well when $k = 2$.

Although CP can reveal the degree of interaction between agricultural carbon emissions and agricultural economic growth to a certain extent, it cannot reflect their overall level of interaction. Thus, we revised the coupling evaluation model as follows:

$$\begin{cases} T = \alpha G' + \beta E' \\ CP' = \sqrt{T \times CP} \end{cases} \qquad (3)$$

Here, T is the index of comprehensive development of agricultural carbon emissions and agricultural economic growth and reflects the overall level of agricultural carbon emissions

and agricultural economic growth; α and β are the parameters to be determined and reflect the relative importance of agricultural carbon emissions and agricultural economic growth, and we used the following assumption: $\alpha = \beta = 0.5$[1]; CP$'$ is the degree of coupling development and comprehensively reflects the degree of interaction between agricultural carbon emissions and agricultural economic growth, in addition to the overall developmental level of both. The other variables represent the same metrics as in Eq. (2).

The coupling development degree, CP$' \in [0, 1]$, where greater values indicate higher degrees of coupling between agricultural carbon emissions and agricultural economic growth. Conversely, lower values indicate lower degrees of coupling. To comprehensively analyze the coupling relationship between agricultural carbon emissions and agricultural economic growth, this paper follows previous studies (Liu et al. 2015). Using the median segmentation method, 0.3, 0.5, and 0.8 were used as classification thresholds. The degree of coupling development between agricultural carbon emissions and agricultural economic growth is divided into four levels: minimal ($0 \leq CP' < 0.3$), low ($0.3 \leq CP' < 0.5$), moderate ($0.5 \leq CP' < 0.8$), and high ($0.8 \leq CP' \leq 1$) coupling.

The Tapio decoupling assessment model

We used the Tapio decoupling assessment model to assess the decoupling relationships between agricultural carbon emissions and agricultural economic growth in selected provinces (Tapio 2005):

$$t = \frac{\%\Delta E}{\%\Delta G} = \frac{(E_{end} - E_{start})/E_{start}}{(G_{end} - G_{start})/G_{start}}, \qquad (4)$$

where t represents the Tapio decoupling index between agricultural carbon emissions and agricultural economic growth; $\%\Delta G$ and $\%\Delta E$ represent the rates of change for agricultural output values and the amount of agricultural carbon emissions, respectively; E_{start} and E_{end} represent the agricultural carbon emissions in the initial and final year of a research period, respectively; and G_{start} and G_{end} represent the agricultural output values of the initial and final year of a research period, respectively.

The Tapio decoupling index is a flexible value, as indicated in Eq. (4). Specifically, the index represents the percent change in agricultural carbon emissions when the agricultural production changes by 1 %. To more accurately reflect the decoupling relationship between agricultural carbon emissions and agricultural economic growth, we partitioned the decoupling relationship into three decoupling types and eight decoupling states, as shown in Table 3 (Tapio 2005; Zhang and Yang 2014; Luo et al. 2017). "Strong decoupling"

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[1] This paper argues that agricultural carbon emissions and agricultural economic growth play equally important roles.

indicates that the agricultural economy rapidly grows and agricultural carbon emissions rapidly decrease ($t < 0$). This represents an ideal state to achieve low-carbon agricultural economic development. In contrast, "strong negative decoupling" indicates that the agricultural economy rapidly decreases and agricultural carbon emissions rapidly increase ($t < 0$). This represents the most unfavorable state of agricultural economic growth. The other states exist between these two extremes. In particular, "weak decoupling" indicates that the agricultural economy rapidly increases and agricultural carbon emissions slowly increase ($0 < t < 0.8$). "Recessive decoupling" indicates that the agricultural economy slowly decreases and agricultural carbon emissions rapidly decrease ($t > 1.2$). "Expansive negative decoupling" indicates that the agricultural economy slowly increases and agricultural carbon emissions rapidly increase ($t > 1.2$). "Weak negative decoupling" indicates that the agricultural economy rapidly decreases and agricultural carbon emissions slowly decrease ($0 < t < 0.8$). "Expansive coupling" indicates that both the agricultural economy and agricultural carbon emissions rapidly increase ($0 < t < 0.8$). Lastly, "recessive coupling" indicates that both the agricultural economy and agricultural carbon emissions rapidly decrease ($0 < t < 0.8$).

LMDI decomposition model

To investigate the driving factors of agricultural carbon emissions, we used the LMDI method based on the Kaya identity to decompose agricultural carbon emissions. The Kaya identity was proposed by the Japanese scholar Yoichi Kaya (1989) and is as follows:

$$E_w = \frac{E_w}{PE_w} \times \frac{PE_w}{G_w} \times \frac{G_w}{P_w} \times P_w, \qquad (5)$$

where E_w represents the amount of carbon dioxide emissions; PE_w represents the amount of energy consumption; G_w indicates gross domestic product; and P_w indicates the total population. The Kaya identity establishes a link between carbon emissions and energy with economic and demographic factors that can be used to estimate the impact of the aforementioned factors on carbon emissions. However, the Kaya identity cannot factorize carbon emissions from non-energy use activities such as land use, fertilizer and pesticide use, and rice cultivation (Yuan and Pan 2013). To remedy this shortcoming, Raupach et al. (2007) modified the Kaya identity so that it does not have to consider the energy factors, as follows:

$$E_w = \frac{E_w}{G_w} \times \frac{G_w}{P_w} \times P_w, \qquad (6)$$

The agricultural carbon emissions analyzed here are mainly derived from non-energy use activities. Consequently, we borrowed the construction ideas of formula (6) to decompose the factors affecting agricultural carbon emissions as follows:

Table 2 C emission coefficients of different rice varieties in different provinces (kg hm^{-2})

Province	Early season	Late season	In-season
Beijing	0	0	901.955
Tianjin	0	0	773.105
Hebei	0	0	1045.120
Shanxi	0	0	451.319
Inner Mongolia	0	0	608.803
Liaoning	0	0	629.937
Jilin	0	0	379.735
Heilongjiang	0	0	566.534
Shanghai	846.052	1874.813	3672.590
Jiangsu	1095.570	1881.630	3650.770
Zhejiang	979.675	2352.038	3951.420
Anhui	1141.930	1881.630	3493.290
Fujian	527.675	3586.005	2963.570
Jiangxi	1054.670	3122.415	4460.010
Shandong	0	0	1431.680
Henan	0	0	1216.920
Hubei	1193.740	2658.825	3965.740
Hunan	1002.850	2324.768	3836.890
Guangdong	1026.030	3517.830	3887.340
Guangxi	846.052	3347.393	3257.400
Hainan	915.590	3367.845	3564.870
Chongqing	446.546	1261.238	1754.140
Sichuan	446.546	1261.238	1754.140
Guizhou	347.693	1431.675	1503.260
Yunnan	162.257	518.130	494.269
Shaanxi	0	0	852.869
Gansu	0	0	465.635
Qinghai	0	0	0
Ningxia	0	0	501.086
Xinjiang	0	0	715.838

Source: Min and Hu (2012)

$$E = \frac{E}{G} \times \frac{G}{G'} \times \frac{G'}{P} \times P = EG \times GG' \times G'P \times P, \qquad (7)$$

where E represents the amount of agricultural carbon emissions; G represents the agricultural output value; G' represents the gross output value of agriculture, forestry, animal husbandry, and fishery; and P represents the agricultural labor amount[2]; $EG = \frac{E}{G}$ represents the intensity of agricultural carbon emissions, i.e., the amount of carbon emissions per unit of agricultural production, and thus represents the technical progress of agricultural factors; $GG' = \frac{G}{G'}$ is a ratio representing agricultural output value relative to the gross output value

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[2] The amount of agricultural labor is represented by the number of primary industry employees.

Table 3 Classification and criteria of decoupling relationships between agricultural carbon emissions and agricultural economic growth

Decoupling type	Decoupling state	$\%\Delta E$	$\%\Delta G$	t	Interpretation
Decoupling	Strong decoupling	<0	>0	$t < 0$	Agricultural economy ↑; agricultural carbon emissions ↓
	Weak decoupling	>0	>0	$0 < t < 0.8$	Agricultural economy ↑; agricultural carbon emissions ↗
	Recessive decoupling	<0	<0	$t > 1.2$	Agricultural economy ↘; agricultural carbon emissions ↓
Negative decoupling	Expansive negative decoupling	>0	>0	$t > 1.2$	Agricultural economy ↗; agricultural carbon emissions ↑
	Strong negative decoupling	>0	<0	$t < 0$	Agricultural economy ↓; agricultural carbon emissions ↑
	Weak negative decoupling	<0	<0	$0 < t < 0.8$	agricultural economy ↓; agricultural carbon emissions ↘
Coupling	Expansive coupling	>0	>0	$0.8 < t < 1.2$	Agricultural economy ↑; agricultural carbon emissions ↑
	Recessive coupling	<0	<0	$0.8 < t < 1.2$	Agricultural economy ↓; agricultural carbon emissions ↓

Sources: Tapio (2005), Zhang and Yang (2014), and Luo et al. (2017)

Notes: "↑" rapid growth, "↓" rapid decrease, "↗" slow growth; "↘" slow decrease

of agriculture, forestry, animal husbandry, and fishery, and it represents the agricultural industrial structure factor; $G'P = \frac{G'}{P}$ is the production per unit of agricultural labor, and it represents the agricultural economic development scaling factor. Lastly, P represents the agricultural population scaling factor.

The additive decomposition is superior to the multiplicative decomposition in the LMDI method based on the decomposition of driving factors of agricultural carbon emissions (Chen and Shang 2014). Thus, we decomposed the driving factors of emissions using the summed decomposition based on Eq. (5). The changes in agricultural carbon emissions from the base year (year 0) to the reporting period (year T) can be expressed as follows (Zhang et al. 2016):

$$\Delta E = E^T - E^0 = \Delta E_{EG} + \Delta E_{GG'} + \Delta E_{G'P} + \Delta E_P, \quad (8)$$

where ΔE represents the total effect, i.e., the sum of the effects from all driving factors of agricultural carbon emissions; ΔE_{EG} represents the agricultural technical progress effect and reflects the effect of factors associated with progress in agricultural technology on agricultural carbon emissions; $\Delta E_{GG'}$ represents the agricultural industrial structure effect and reflects the effect of agricultural industrial structural factors on agricultural carbon emissions; $\Delta E_{G'P}$ represents the effect of agricultural economic development scale and reflects the effects of the agricultural economic development scaling factors on agricultural carbon emissions; ΔE_P represents the effect of agricultural population scale and reflects the effect of the agricultural population scaling factor on agricultural carbon emissions.

The calculations for the right-hand side terms in Eq. (6) follow that of Ang (2004) and Zhen et al. (2017b) and are as follows.

$$\Delta E_{EG} = \frac{E^T - E^0}{\ln(E^T) - \ln(E^0)} \times \ln\frac{EG^T}{EG^0} \quad (9)$$

$$\Delta E_{GG'} = \frac{E^T - E^0}{\ln(E^T) - \ln(E^0)} \times \ln\frac{GG'^T}{GG'^0} \quad (10)$$

$$\Delta E_{G'P} = \frac{E^T - E^0}{\ln(E^T) - \ln(E^0)} \times \ln\frac{G'P^T}{G'P^0} \quad (11)$$

$$\Delta E_P = \frac{E^T - E^0}{\ln(E^T) - \ln(E^0)} \times \ln\frac{P^T}{P^0} \quad (12)$$

Data sources

Considering the accessibility and quality of data, we investigated panel data for 30 provinces (including province-level municipalities) in mainland China from 1997 to 2015. Tibet was not included due to missing data. Raw data were primarily obtained from the China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Statistical Report, and the China Agriculture Yearbook. The agricultural output values, as well as the gross output values of agriculture, forestry, animal husbandry, and fishery, are calculated at constant prices relative to 1997.

Results and discussion

Agricultural carbon emission calculations

We calculated the amount of agricultural carbon emissions from 30 Chinese provinces in the period between 1997 and 2015 according to Eq. (1). For brevity, we only analyzed the average annual agricultural carbon emissions and the average annual growth rates for each province (Fig. 2).

The five provinces with the highest average annual agricultural carbon emissions were Jiangsu (14,944,610 tons), Hunan (14,248,350 tons), Anhui (13,112,860 tons), Hubei (12,832,680 tons), and Henan (11,719,200 tons), whereas the five provinces with the lowest emissions were Qinghai (294,800 tons), Beijing (365,620 tons), Tianjin (541,510 tons),

Fig. 2 Average annual agricultural carbon emissions and their average annual growth rate for various provinces
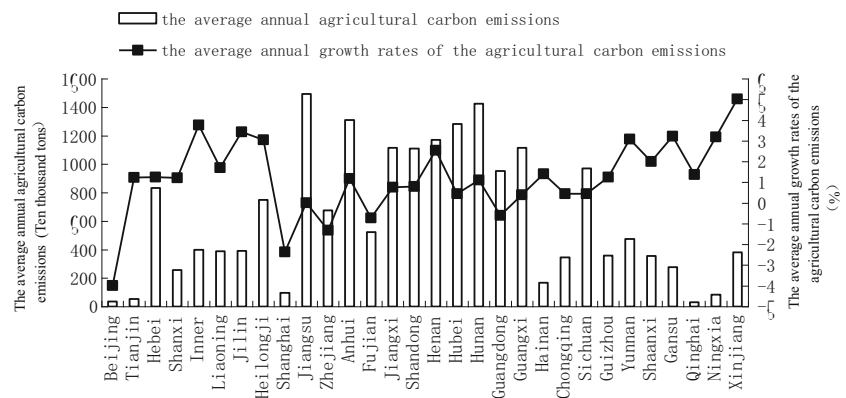
Ningxia (841,290 tons), and Shanghai (957,590 tons; Fig. 2). Thus, traditional agricultural provinces had higher average annual agricultural carbon emissions. The average annual growth rates of agricultural carbon emissions were all below 6%. The provinces with five highest average annual growth rates were Xinjiang (5.016%), Inner Mongolia (3.772%), Jilin (3.435%), Gansu (3.217%), and Ningxia (3.185%), whereas the five provinces with the lowest annual growth rates were Beijing (− 3.987%), Shanghai (− 2.362%), Zhejiang (− 1.320%), Fujian (− 0.720%), and Guangdong (− 0.604%), which were all negative. Taken together, the results indicated that progress was made towards agricultural carbon emission reduction in these provinces.

Coupling effects of agricultural carbon emissions

Based on the coupling development degree model, we calculated the degree of coupling development between agricultural carbon emissions and agricultural economic growth for all provinces from 1997 to 2015. We analyzed the coupling effects of all provinces in two time periods (1997 and 2015) and visualized the coupling effects in the ArcGIS software package (Fig. 3).

Several observations could be drawn from the analyses presented in Fig. 3. First, the degree of coupling development between agricultural carbon emissions and agricultural economic growth were generally higher in the central region and lower in the western region in both 1997 and 2015. The average coupling development degrees in 1997 for the eastern, central, and western regions were 0.551, 0.679, and 0.453, respectively.[3] The average coupling development degrees in 2015 for the eastern, central, and western regions were 0.530,

0.683, and 0.502, respectively. Thus, the degrees of coupling development were the highest in the central region in 1997 and 2015 and lowest in the western region. The coupling effects in all provinces exhibited four levels (minimal, low, moderate, and high coupling) in either 1997 or 2015. Second, the provinces exhibiting a minimal coupling state in 1997 included Beijing, Tianjin, Shanghai, Hainan, Qinghai, and Ningxia, while provinces exhibiting a minimal coupling state in 2015 were Beijing, Tianjin, Shanghai, Qinghai, and Ningxia. The coupling effect of Hainan Province evolved from a minimal coupling in 1997 to a low coupling effect in 2015. Third, provinces exhibiting a low coupling state in 1997 included Shanxi, Inner Mongolia, Liaoning, Jilin, Chongqing, Guizhou, Shaanxi, Gansu, and Xinjiang. Four provinces, Shanxi, Chongqing, Guizhou, and Gansu, still exhibited a low coupling state in 2015. However, five provinces, Inner Mongolia, Liaoning, Jilin, Shaanxi, and Xinjiang, evolved from low coupling in 1997 to moderate coupling in 2015. Fourth, provinces exhibiting a moderate coupling state in 1997 included Hebei, Heilongjiang, Zhejiang, Fujian, Jiangxi, Guangxi, and Yunnan. All seven of these provinces still exhibited a moderate coupling state in 2015. Fifth, provinces exhibiting a high coupling state in 1997 included Jiangsu, Anhui, Shandong, Henan, Hubei, Hunan, Guangdong, and Sichuan. Three of these provinces, Jiangsu, Shandong and Henan, still exhibited a high coupling state in 2015, whereas five provinces, Anhui, Hubei, Hunan, Guangdong, and Sichuan, evolved into a moderate coupling state in 2015.

Decoupling effects of agricultural carbon emissions

The degree of coupling development that was analyzed in the previous section represents a static index. The metric reflects only the coupling relationship between agricultural carbon emissions and agricultural economic growth in different time periods and cannot reflect the overall characteristics of the coupling relationship within a certain period. Consequently, we used a dynamic index, the Tapio decoupling index, to

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[3] Chinese provinces were divided into eastern, central, and western regions. The eastern region included Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region included Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region included Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.
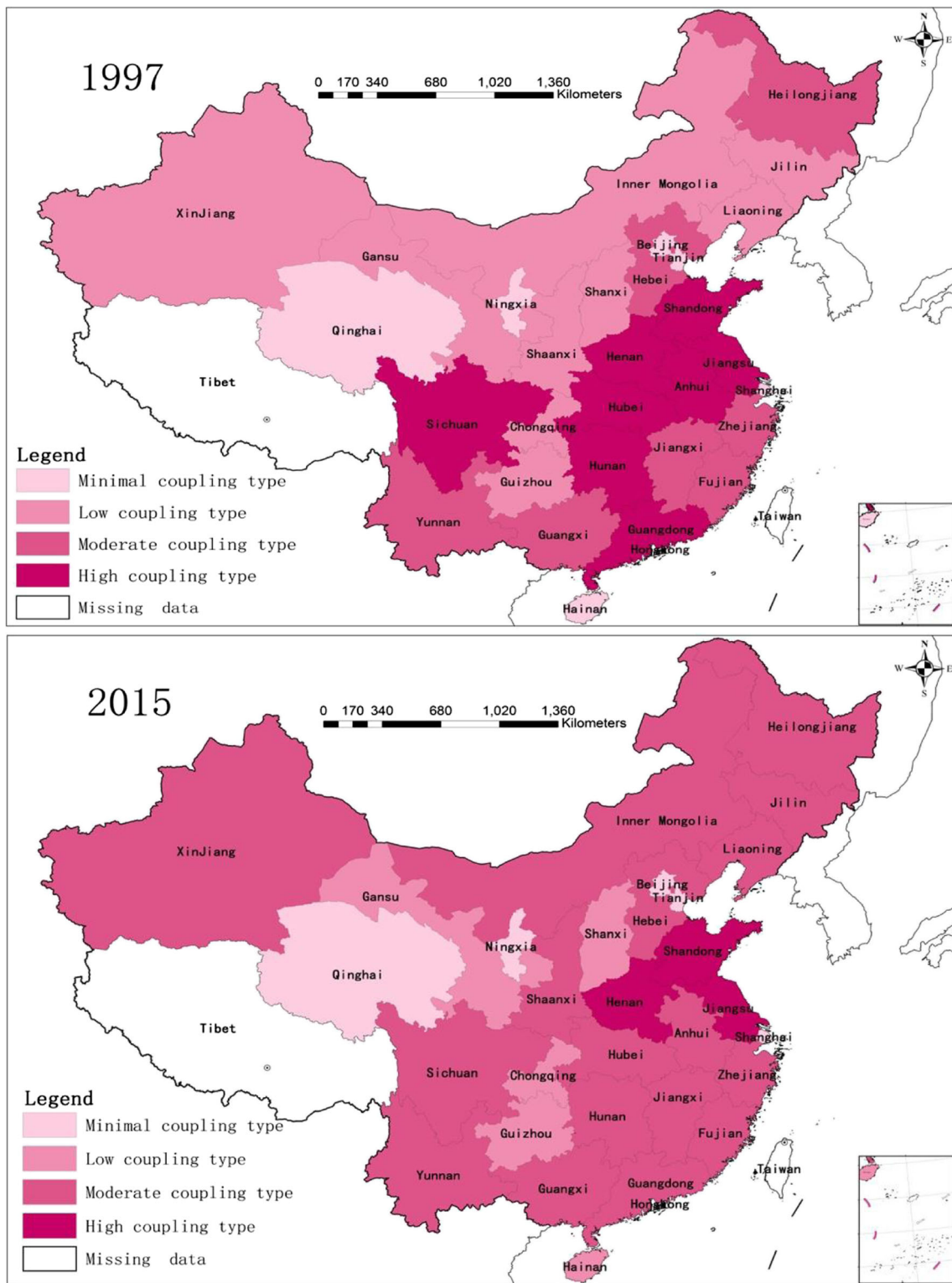
explore the characteristics of decoupling relationships over the entire study period from multiple perspectives (Table 4).

The decoupling effects of agricultural carbon emissions in all provinces from 1997 to 2015 comprised four types (Table 4): strong, expansive, recessive, and weak decoupling.

First, agricultural carbon emissions in four provinces, Beijing, Zhejiang, Fujian, and Guangdong, continuously declined with agricultural economy growth. The decoupling effects exhibited in these provinces indicated that they were in a strong decoupling state. These results thus showed that a sustainable

Table 4 The decoupling effects of agricultural carbon emissions for various provinces from 1997 to 2015

Province	%ΔG	%ΔE	t
Beijing	0.240	− 0.519	− 2.165
Tianjin	0.374	0.245	0.656
Hebei	1.247	0.251	0.201
Shanxi	0.864	0.241	0.279
Inner Mongolia	1.170	0.947	0.809
Liaoning	1.437	0.354	0.246
Jilin	1.591	0.837	0.526
Heilongjiang	1.360	0.716	0.526
Shanghai	− 0.035	− 0.350	9.907
Jiangsu	0.894	0.002	0.003
Zhejiang	0.491	− 0.213	− 0.433
Anhui	0.733	0.236	0.321
Fujian	0.988	− 0.122	− 0.123
Jiangxi	0.867	0.146	0.168
Shandong	1.076	0.153	0.142
Henan	1.402	0.574	0.409
Hubei	0.830	0.083	0.100
Hunan	0.951	0.220	0.231
Guangdong	1.006	− 0.103	− 0.103
Guangxi	1.455	0.074	0.051
Hainan	2.568	0.285	0.111
Chongqing	1.048	0.085	0.081
Sichuan	0.714	0.082	0.115
Guizhou	0.957	0.250	0.261
Yunnan	1.475	0.727	0.493
Shaanxi	1.793	0.430	0.240
Gansu	1.846	0.768	0.416
Qinghai	0.889	0.279	0.314
Ningxia	1.876	0.758	0.404
Xinjiang	2.025	1.413	0.698

development pattern was basically achieved in these provinces with coordination between agricultural economic growth and reduced environmental perturbation. The decoupling degree was highest in Beijing and reached −

2.165. This result indicated that a resource-saving and environmentally friendly agricultural development pattern was initiated in Beijing and was likely due to concentrated scientific and technical resources in this province. Second, the decoupling effect within Inner Mongolia was in an expansive coupling state. This result indicated that local agricultural carbon emissions increased with the growth of the agricultural economy, and they exhibited similar growth rates. Third, the decoupling effect within Shanghai was in a recessive decoupling state. This indicates that both agricultural carbon emissions and the agricultural economy were in a negative growth state, and the declining rate of agricultural carbon emissions was higher than that of the agricultural economy. Lastly, agricultural carbon emissions and the agricultural economy increased in the same direction in the remaining 24 provinces. In addition, the growth rate of agricultural carbon emissions was clearly lower than that of the agricultural economy. The relationship between the two measurements indicated a weak decoupling state. Thus, in the period comprising 1997 to 2015, 80% of the 30 provinces effectively controlled excessive increases of agricultural carbon emissions while maintaining rapid growth of the agricultural economy. This result was achieved while agricultural carbon emissions continuously increased. Thus, a "win–win" situation for agricultural carbon emissions and agricultural economic growth was not fully achieved in these areas.

To compare regional differences in the decoupling effects of agricultural carbon emissions, we calculated the Tapio decoupling index between agricultural carbon emissions and agricultural economic growth across different regions of China (Table 5).

During the periods encompassing 1997 to 2000, 2000 to 2003, 2006 to 2009, and 2012 to 2015, agricultural carbon emissions continuously declined as the agricultural economy in the eastern region grew (Table 5). Thus, the eastern region was in a strong decoupling state over most of the time period considered here. During all time periods, the central and western regions were in weak decoupling states, as both agricultural carbon emissions and agricultural economies increased. However, the growth rates of agricultural carbon emissions

Table 5 Regional differences in decoupling effects of agricultural carbon emissions

Year	Eastern region			Central region			Western region		
	%ΔG	%ΔE	t	%ΔG	%ΔE	t	%ΔG	%ΔE	t
1997–2000	0.133	− 0.011	− 0.083	0.081	0.019	0.231	0.107	0.032	0.294
2000–2003	0.095	− 0.041	− 0.435	0.043	0.002	0.037	0.100	0.015	0.147
2003–2006	0.161	0.080	0.497	0.257	0.120	0.467	0.166	0.073	0.439
2006–2009	0.105	− 0.013	− 0.119	0.119	0.065	0.541	0.175	0.065	0.372
2009–2012	0.123	0.008	0.064	0.150	0.047	0.315	0.184	0.085	0.461
2012–2015	0.125	− 0.005	− 0.041	0.144	0.020	0.139	0.170	0.060	0.352

Fig. 4 Temporal characteristics of the factors driving agricultural carbon emissions in China (unit: 10,000 tons of carbon equivalent standard)
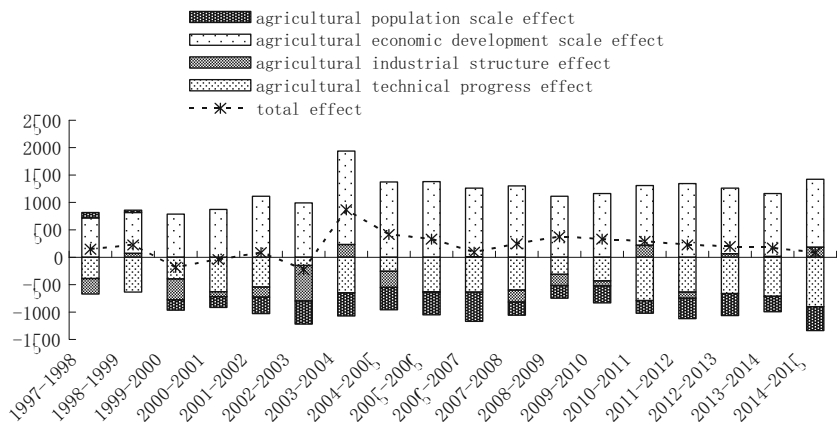
were clearly lower than those of agricultural economies. In contrast with the western region, the eastern region not only exhibited sustained growth in the agricultural economy but also focused on agro-environmental protection and effective control of carbon emissions from agricultural production, which likely occurred due to its advantages in resources, climate, and agricultural science and technology.

Driving factors of agricultural carbon emissions

Based on the agricultural carbon emissions of 30 provinces from 1997 to 2015, we calculated the yearly quantitative values of driving factors in all provinces using Eqs. (6)–(10). The following two sub-sections discuss the driving factors of agricultural carbon emissions from temporal and spatial perspectives.
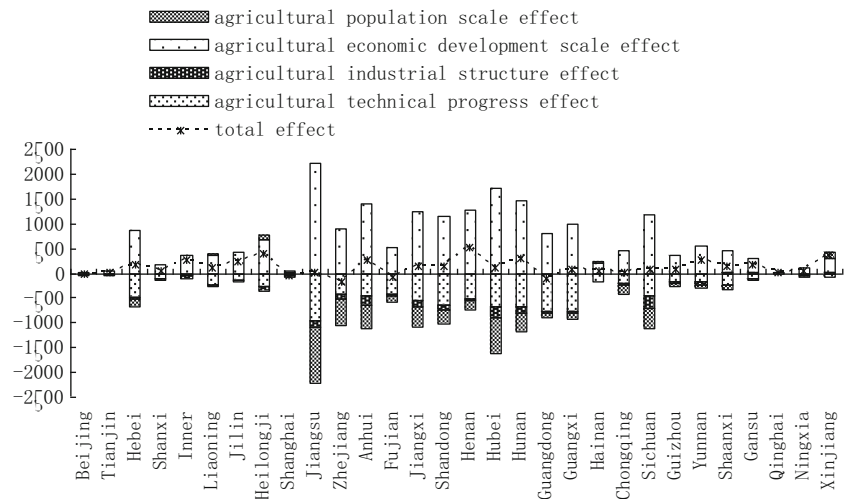
Temporal characteristics of driving factors of agricultural carbon emissions

We derived the effects of driving factors of agricultural carbon emissions at the national level from 1997 to 2015 by summing the annual quantitative values of driving factors for all provinces (Fig. 4).

Several observations can be drawn from the results shown in Fig. 4. First, the effect of agricultural development scale was the primary factor driving increases in agricultural carbon emissions. The contributions of the agricultural development scale to agricultural carbon emissions were positive from 1997 to 2015. The contributions exceeded 10,000,000 tons after 2003 and reached a peak annual value of 17,080,540 tons between 2003 and 2004. One explanation for this result is that the grain yield in China increased continuously over the previous 10-year period. Thus, the scale of agricultural production increased continuously, and considerable progress within the agricultural economy was achieved. However, the rapid growth of the agricultural economy was due to excessive use of chemical fertilizers and pesticides. Thus, the agricultural environment

concomitantly exhibited continuous deterioration over this time period. If agricultural development cannot evolve into an intensive pattern, the effect of agricultural development scale will continue to be the primary driving factor of agricultural carbon emissions in the future. Therefore, assessing how to achieve a 'win–win' situation for agricultural carbon emissions and agricultural economic growth is an important issue and challenge in the development of agriculture. Second, the effect from technical progress of agriculture is the primary driving factor reducing agricultural carbon emissions. The effect of agricultural technical progress on the reduction in agricultural carbon emissions was positive from 1997 to 2015. The cumulative contribution to agricultural carbon-reduction exceeded 90,000,000 tons, and the contribution reached a peak value of 9,025,990 tons between 2014 and 2015. The results indicated that improvement in agricultural mechanization and the widespread application of clean agricultural technologies greatly increased agricultural technical progress and facilitated agricultural energy conservation and emissions reduction. Third, the effect of agricultural industrial structure on agricultural carbon emissions was not stable, but its cumulative contribution was negative and reached − 17,465,720 tons. The contribution from agricultural industrial structure reached a peak value of 6,440,480 tons between 2002 and 2003. Lastly, the effects of agricultural population scale on the reduction of agricultural carbon emissions were positive in all but 2 years: from 1997 to 1998 and from 1998 to 1999. The cumulative contribution of agricultural population scale was 52,381,720 tons, which was less than that of the effect from agricultural technical progress. One explanation for this result is that as progress increases in industrialization and urbanization processes, a large number of farmers migrate from rural areas to cities (i.e., from agricultural to non-agricultural industries). The number of agricultural labors continuously decreases, but the quality and agricultural technological skills of agricultural labors continuously improve. Thus, the energy conservation of agricultural energy is greatly improved.

Fig. 5 Spatial characteristics of the factors driving agricultural carbon emissions in China (unit: 10,000 tons of carbon equivalent standard)

Spatial characteristics of the driving factors of agricultural carbon emissions

We derived the effects of the driving factors of agricultural carbon emissions for every province by summing the annual quantitative values of these driving factors over time (Fig. 5).

The effect from agricultural development scale is the primary driving factor related to increases in agricultural carbon emissions (Fig. 5), and the contributions of this effect were positive in all provinces. The highest contribution was observed in Jiangsu, while the lowest was observed in Qinghai. The cumulative effect of the agricultural development scale in Jiangsu was an increase of 22,092,520 tons of carbon, while that of Qinghai was an increase of 277,300 tons. The effect from agricultural technical progress was the primary driving factor related to reduction of agricultural carbon emissions. The contributions of the effect of agricultural technical progress were positive in all provinces. The three highest contributions occurred in the Jiangsu, Guangxi, and Guangdong provinces with cumulative contributions towards reduction of agricultural carbon emissions reaching 9,537,750, 7,788,640, and 7,701,960 tons, respectively. The effects of the agricultural industrial structure and agricultural population scale on agricultural carbon emissions differed among provinces. Adjustment of the agricultural industrial structure increased agricultural carbon emissions in Gansu, Shanghai, Shanxi, and Xinjiang but reduced emissions in the 26 other provinces. The highest reduction of agricultural carbon emissions occurred in the Sichuan province with a cumulative reduction of 2,458,940 tons. Changes in the agricultural population scales in Liaoning, Shanxi, Inner Mongolia, Hainan, Heilongjiang, and Xinjiang resulted in increases in agricultural carbon emissions, as opposed to reductions in the 24 other provinces.

At the regional level, the effect of agricultural development scale in the eastern, central, and western regions was the primary driving factor associated with increased agricultural carbon emissions. The highest contribution was observed in the central region, while the lowest was observed in the western region. The cumulative effect of the agricultural development scale in the central region was an increase of 83,399,277 tons of carbon, while that in the western region was an increase of 50,610,603 tons. The contributions of the effects from agricultural technical progress, agricultural industrial structure, and agricultural population scale, were positive in all regions and associated with reduced agricultural carbon emissions. Of these, the effect from agricultural technical progress was the primary driving factor in the reduction of agricultural carbon emissions. The contributions of the effect of agricultural technical progress in the reduction of agricultural carbon emissions in the eastern, central, and western regions were 42,215,269, 33,923,336, and 23,139,957 tons, respectively.

Conclusions and policy implications

Conclusions

This study measured agricultural carbon emissions of 30 Chinese provinces from 1997 to 2015 and explored the coupling and decoupling effects of agricultural carbon emissions as well as the driving factors underlying emissions. The conclusions of this study are as follows:

(1) The degree of coupling development between agricultural carbon emissions and agricultural economic growth exhibited high levels in the central region, but low levels in the western region in both 1997 and 2015. The coupling effects of agricultural carbon emissions in all

provinces in 1997 and 2015 comprised four levels: minimal, low, moderate, and high coupling.

(2) The decoupling effects within all provinces from 1997 to 2015 comprised four types: strong decoupling, expansive coupling, recessive decoupling, and weak decoupling. Specifically, the decoupling effects of agricultural carbon emissions in Beijing, Zhejiang, Fujian, and Guangdong indicated a strong decoupling state. The decoupling effect in Inner Mongolia was in an expansive coupling state, and that in Shanghai was in a recessive decoupling state. The decoupling effects in the 24 other provinces were all in weak decoupling states. The above results indicate that most provinces have effectively controlled excessive agricultural carbon emissions while maintaining the growth of agricultural economies. However, agricultural carbon emissions continue to increase. Consequently, a "win–win" situation for agricultural carbon emission reduction and agricultural economic growth has not yet been fully achieved.

(3) The temporal characteristics of the driving factors of agricultural carbon emissions indicated that the contributions of the effects from agricultural development scale to agricultural carbon emissions were positive between 1997 and 2015. The contribution reached a peak value of 17,080,540 tons in the year between 2003 and 2004. The contributions of the effect of agricultural technical progress to agricultural carbon reduction were positive between 1997 and 2015, and the cumulative contribution exceeded 90,000,000 tons. The contribution of the effect of agricultural technical progress reached a peak value of 9,025,990 tons in the year between 2014 and 2015. The contributions of the effect of agricultural industrial structure to agricultural carbon emissions were unstable, although the cumulative contribution was negative ($-$17,465,720 tons). The contributions of the effect of agricultural population scale to the reduction of agricultural carbon emissions were positive except in 2 years (1997 to 1998 and from 1998 to 1999), and the cumulative contribution was 52,381,720 tons.

(4) Analysis of the spatial characteristics of the driving factors of agricultural carbon emissions indicated that the effect of agricultural development scale was the primary driving factor associated with increases in agricultural carbon emissions. The contributions of the effect of agricultural development scale were positive in all provinces from 1997 to 2015, while the contribution was highest in Jiangsu and lowest in Qinghai. The contributions of the effect of agricultural technical progress towards reduction of agricultural carbon emissions were positive in all provinces from 1997 to 2015, while the highest contributions were observed in Jiangsu, Guangxi, and Guangdong. The contributions of the effects of agricultural industrial structure and agricultural population scale to agricultural carbon emissions varied among provinces.

Policy implications

(1) Our results indicate that the effect of agricultural development scale is the largest factor that drove the increase of agricultural carbon emissions. However, agricultural economic growth should not be sacrificed in order to reduce agricultural carbon emissions. China is a developing country, and as such, has always regarded development as its top priority. Therefore, it is critical to properly balance the relationship between agricultural growth, resource management, and environmental concerns. Owing to the resources and environmental constraints, agricultural growth patterns are required to be transformed and accelerated. The extensive growth which pursues output and relies on energy consumption should be replaced by sustainable intensive development, focusing on quantity, quality, and efficiency. The terminal aim is to build a resource-saving and eco-friendly agricultural production system.

(2) Our results indicate that the effect of agricultural technical progress is the main driver in the reduction of agricultural carbon emissions. Therefore, it is necessary to increase the investment in agricultural science and technology, and in particular to vigorously develop techniques for soil testing and fertilizer application, soil pollution control technologies, and precision in agricultural and ecological recycling technologies. Moreover, we must improve the transformation of scientific and technological achievements in agriculture and the promotion of agricultural technology. In particular, we must strengthen grassroots, public-sector agricultural technology extension services, promote household management to adopt advanced agricultural science and technology practices, and guide farmers to use advanced agricultural technologies and production methods. By guiding farmers to use chemical fertilizers and pesticides scientifically and rationally, we will increase the utilization of chemical fertilizers and pesticides and achieve the goal of zero growth in chemical fertilizer and pesticide use.

Limitations of this paper

Geist and Lambin (2002) divided driving factors of carbon emissions into proximate causes and underlying driving forces. Driving factors of carbon emissions based on the Kaya identity are generally proximate causes (Yuan and Pan 2013). The underlying driving forces are that the deep-seated mechanisms that affect carbon emissions generally have a

relatively rigorous and independent logical response mechanism. Conversely, proximate causes have good observability, are direct representations of human economic activities, and often involve multiple underlying driving forces. This study relied on the Kaya identity, along with four factors that represented agricultural carbon emissions, and these were all proximate causes: agricultural technological progress, agricultural industrial structure, agricultural economic development scaling, and agricultural population scaling. There may be interactions and mutual influences among these factors. In future studies, new methods should be used to mine and analyze the underlying driving forces that affect agricultural carbon emissions.

Compliance with ethical standards

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

Research involving human participants and/or animals Not applicable.

Informed consent Not applicable.

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