



Decomposition and decoupling analysis of carbon emissions from agricultural economic growth in China's Yangtze River economic belt

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Abstract In this study, carbon emissions from agricultural energy consumption (CEAEC) are fully analyzed using data from the Yangtze River Economic Belt (YEB) between 2000 and 2017. First, generalized LMDI is adopted to decompose the drivers of CEAEC into five components. Then, the decoupling indicator and the decoupling effort indicator are constructed to quantify the decoupling degrees and examine the government's emission reduction efforts, respectively. The results show that (1) CEAEC in the YEB has shown a phased increase, reaching a peak at 1732.2510^4t in 2012. Except for some decreases found in Shanghai, Chongqing, and Guizhou, it is shown that all provinces' CEAEC have risen to varying degrees. In contrast, the intensity of CEAEC in the YEB has been declining since 2005. (2) The economic output effect acts as the major contributor to the growth of CEAEC, followed by the population effect. In contrast, both the energy intensity effect and

the energy structure effect are the primary reasons for reductions in CEAEC. The spatial difference in CEAEC in the YEB increased significantly from 2000 to 2017. (3) There was an alternating change from decoupling to coupling and then to negative decoupling from 2000 to 2017. Based on the conclusions mentioned above, it is proposed that the formulation of low-carbon agricultural development strategies should consider the structural adjustment of agricultural energy consumption and the advancements of agricultural technology.

Keywords The Yangtze River Economic Belt · Carbon emissions from agricultural energy consumption · LMDI · Decoupling index · Temporal and spatial characteristics

Introduction

According to the IPCC's Fifth Assessment Report, the global average temperature increased by approximately $0.85\text{ }^{\circ}\text{C}$ between 1880 and 2012 (IPCC, 2014). Agriculture is one significant source of anthropogenic greenhouse gas (GHG) emissions (Lynch, 2019). A report published on the United Nations website on December 30, 2019, titled "Agricultural sector plays a pivotal role in mitigating climate change," shows that 25% to 30% of global greenhouse gas emissions come

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from agriculture and land. Therefore, it is necessary to consider agricultural economic benefits and environmental friendliness and to ultimately achieve sustainable agricultural development. Reducing agricultural carbon emissions is an essential part of improving agriculture's ability to respond to global warming. Climate-smart agriculture should reshape conventional agricultural production systems to improve global food security (Lipper et al., 2014).

As one of the largest agricultural economies, China's greenhouse gas emissions from the agricultural sector represent approximately 17% of its total emissions, among which the CH₄ and NO₂ produced in agricultural production account for 50% and 92%, respectively (Rebolledo-Leiva et al., 2017). The energy consumed in the agricultural sector of China has been rising. One report from the Lawrence Berkeley National Laboratory's China Energy Group showed that China's agricultural energy consumption was 77.99 million Tce in 2010, and it is forecasted that China's total agricultural energy usage will increase to approximately 161.61 million Tce by 2025 (Fei & Lin, 2017). The primary element affecting agricultural energy usage is the increasing popularity of agricultural mechanization (Xu et al., 2020), and thus the continuous promotion of agricultural mechanization in China will unavoidably increase energy consumption in the agricultural sector (Jiang et al., 2020).

The Chinese government made a solemn commitment to decrease carbon emissions intensity by 40–45% by 2020 compared with its 2005 status, demonstrating the Chinese government's determination to deal with global climate change. It is vital to coordinate the connection between agricultural output and carbon emissions and thereby formulate reasonable emission reduction policies. As one of the three key growth engines to ensure China's future economic development, the Yangtze River Economic Belt covers 2.05 million square kilometers, including 11 provinces from west to east; it is a favorable location for agriculture, as it holds 36% of the country's water resources. In 2017, the YEB had a gross value of agricultural production of 4570.2 billion Yuan, which contributed approximately 42% of China's gross domestic product. Therefore, the YEB is chosen as a case study to calculate agricultural carbon emissions from energy consumption and identify its spatiotemporal characteristics.

The rest of this study is organized as follows. The second part presents a review of the related literature on factors affecting carbon emissions and the relationship between activity output and carbon emissions from energy consumption in the agricultural sector. The third part describes the data sources and presents the theoretical models. The fourth part reports and discusses the study results on agricultural carbon emissions and their driving elements. The fifth section makes some concluding remarks and proposes specific policy implications.

Literature review

Calculating carbon emissions from agricultural energy consumption and identifying the impacting elements is a critical task under the scenario of carbon neutrality. Currently, an increasing number of studies are concerned with the factors affecting the emissions of carbon dioxide (Sun et al., 2021). The focus of existing research has gradually changed from unilateral to multidimensional analyses of agricultural ecosystems. (Li et al., 2016) measured the carbon emissions from agricultural production in the European Union, adopted the Shapley/Sun index to decompose their driving effects into the carbon emission factor and energy intensity and found that energy intensity was the key driver behind dropping agricultural carbon emissions. (Nwaka et al., 2020) identified the linkage between agricultural carbon emissions and economic growth among 15 ECOWAS countries in West Africa by adopting quintile decomposition techniques and showed that heterogeneity existed in the conditional drivers with respect to environmental quality. (Wang et al., 2014) adopted the LMDI model to investigate the primary drivers dominating energy usage in China between 1991 and 2011 and recognized that the energy intensity effect had the primary impact on reducing energy consumption. Similarly, (Xiong et al., 2016) identified that the labor factor, labor productivity, and carbon intensity were the key drivers producing agricultural carbon emissions. (Asumadu-Sarkodie & Owusu, 2017) used the partial least-squares regression model to investigate the elements affecting environmental pollution from 1971 to 2011 and found that there was a linear correlation between agricultural growth and carbon emissions. (Han et al., 2018) found that the economic

effect played a leading role in raising the usage of energy resources, while the energy intensity effect had a key impact on dropping energy consumption.

There are also some studies investigating the linkage between carbon emissions and economic growth using different methods (Sun et al., 2020). Wang and Su, (2020) studied the decoupling status between economic growth and carbon emissions with panel data of 192 countries between 2000 and 2014. Wang et al. (2016) adopted the Tapio decoupling model to examine the decoupling mechanisms of carbon emissions from economic growth in China's industries and found two decoupling statuses: "weak decoupling" and "expansive decoupling." Bennetzen et al. (2016) adopted the novel Kaya–Porter identity framework and found that agricultural production had been steadily decoupled from carbon emissions globally. Chen et al. (2018) analyzed the changes in China's agricultural carbon emissions between 2005 and 2013 and decomposed them into eight factors using a two-chain LMDI model. Han et al. (2018) investigated the coupling and decoupling status of carbon emissions from economic growth and the influencing factors. Some scholars further analyzed the decoupling of agricultural production from carbon emissions in the temporal and spatial dimensions. Zhang et al. (2019) examined the nexus of the environment-energy-economy and validated the EKC hypothesis with agricultural panel data from China's thirteen provinces. Chen et al. (2020b) quantified the decoupling degrees between energy usage and economic development in the agricultural sector using data from 89 countries from 2000 to 2016. Tian et al. (2014) calculated the spatial-temporal difference in agricultural carbon emissions in China between 1995 and 2010. Castesana et al. (2020) studied the temporal-spatial variability in N₂O emissions from Argentina's agricultural sector at the national, provincial, and district levels from 2000 to 2012.

The above review of the literature found that most of the existing research on agricultural carbon emissions accounts for emissions from agricultural land use, agricultural chemical fertilizer, livestock and poultry breeding, and farmland N₂O, but it lacks carbon emissions from agricultural energy consumption (Qian et al., 2020). In addition, the existing research mainly focuses on judging the level of decoupling or the reasons for decoupling. However,

the effectiveness of decoupling efforts in various regions to alleviate environmental pressure has not been deeply studied. Furthermore, YEB covers approximately 2.05 million km² and makes up approximately 21% of China's total area, including 11 provinces. The total GDP of the YEB accounted for over 44% of China's GDP in 2017, while the agricultural output value represented approximately 40% of China's total. Rapid economic growth has been accompanied by rising carbon emissions, and the YEB accounts for approximately 44.6% of China's total emissions (Ding et al., 2019; He et al., 2020). Nevertheless, only a few studies have focused on carbon emissions from agricultural energy consumption in the YEB. Therefore, there is a significant research gap in studying the drivers resulting in carbon emissions and their decoupling from economic growth in the YEB's agricultural sector.

Therefore, in light of the above facts, this study calculates CEAEC in the YEB, including direct carbon emissions from fossil energy such as coal and oil in agricultural production and indirect carbon emissions from electricity consumption. Then, the LMDI model (Ang, 2004; Ang et al., 2015) is adopted to study the factors driving CEAEC, identify the temporal decomposition and spatial decomposition effects using panel data from 2000 to 2017. Next, the Tapio decoupling model developed by (Tapio, 2005) is adopted to test the relationship between carbon emissions and economic development. The decoupling effort indicator is constructed based on the decomposition results, quantifying the provincial governments' emission reduction efforts. The procedure mentioned above provides a valuable and meaningful reference that the government can use to formulate a win-win policy between agricultural growth and emission reduction. The innovations of this study are as follows:

- (1) A framework for assessing carbon emissions from agricultural energy consumption is developed based on the IPCC methodology, including direct and indirect energy sources, which can be a benchmarking tool at the province scale.
- (2) Temporal decomposition and spatial decomposition are combined here to reveal the influential factors of carbon emissions from four dimensions, making the results tell more information than a separate model.

- (3) By dividing 11 provinces into upstream, middle, and downstream, the decoupling analyses consider the spatial difference. In addition, a decoupling effort indicator is designed to estimate the efforts devoted by provincial governments, which is helpful to find the efforts gap between provinces and make differentiating policies.

Data and methodology

The theoretical framework of this study consists of three parts, namely, calculation, decomposition, and decoupling. These three parts are naturally linked together via carbon emissions step by step. The calculation of CEAEC is the basis of the whole study and is required for the analysis of decomposition and decoupling. Then, the decomposition process is developed based on the LMDI model to identify the causes influencing the changes in CEAEC. Here, five components are considered in the developed LMDI model in reference to the related literature: the emission factor, structure, intensity, activity, and population. Finally, decoupling analysis is carried out to quantify the linkage between carbon emissions and production output, and the efforts of the regional government to decouple them are also assessed. The data required by this study come from official institutions and is deemed quite reliable.

Calculation of CEAEC

At present, China's agricultural carbon emissions data cannot be obtained through the statistical bulletin. According to the IPCC Guidelines, the general carbon emission calculation is that the amount of emissions equals the product of the amount of energy usage and the carbon emission coefficients (Xu et al., 2014). Here, the carbon emissions resulting from the combustion of fuels such as coal and coke in agricultural production and the carbon emissions due to electricity usage are considered. As stated in the "China Energy Statistical Yearbook," agricultural energy is divided into seven types: coal, coke, gasoline, kerosene, fuel oil, diesel, and electricity. The calculation of carbon emissions is shown in Formula (1):

$$C = \sum_{i=1}^n C_i = \sum_{i=1}^n E_i \times \beta_i \quad (1)$$

In Formula (1), C is the amount of CEAEC; C_i is CEAEC from the i th energy source; E_i is the energy usage of the i th energy source, and it is the amount of the i th fuel consumed as found in the original data and converted into a standard quantity according to the conversion coefficient. β_i is the carbon emission coefficient of the i th energy source; i is the type of energy source. The coefficients are shown in Table 1.

LMDI method

Structural and index decomposition analysis (SDA/IDA) are models commonly adopted in the decomposition literature. The former is based on the IO framework and require extensive disaggregated data. IDA uses aggregated data and is more convenient for spatiotemporal research (Wang et al., 2017). Among IDA methods, the LMDI method is more popular because it can handle zeros and negative value problems. In this study, the LMDI method is adopted for its robustness and convenience. The LMDI structure is founded on the Kaya identity to incorporate multiple drivers by considering that there are seven types of fossil fuel. Here, the changes in emissions resulting from agricultural energy usage were analyzed by decomposing the contributions to five driving effects: emissions factor, structure, intensity, activity, and population.

The CEAEC is decomposed into five drivers, as shown in Formula (2):

$$\begin{aligned} C &= \sum_{i=1}^n C_i = \sum_{i=1}^n \frac{C_i}{E_i} \times \frac{E_i}{E} \times \frac{E}{G} \times \frac{G}{P} \times P \\ &= \sum_{i=1}^n f_i \times m_i \times e \times g \times P \end{aligned} \quad (2)$$

In Formula (2), C is the amount of carbon emissions from energy consumption in the agricultural sector. $E = \sum_i E_i$ is the quantity of consumed energy in YEB's agricultural sector; G is the agricultural output value; P is the local population; and f_i is the emission parameter of the i th fuel type, which is a fixed value during the research period, as shown in Table 1. m_i is the proportion of the i th fuel type to the total agricultural energy usage, which is known as the energy consumption structure in the fields of energy

Table 1 Fixed coefficients given by energy source

Energy source	Conversion factor (kg standard coal)	Carbon emission factor (ton carbon/ton standard coal)
Coal	0.7143	0.7570
Coke	0.9714	0.8553
Gasoline	1.4714	0.5516
Kerosene	1.4714	0.5682
Diesel	1.4571	0.5930
Fuel oil	1.4286	0.6114
Electricity	0.1229	1.7729

Data source: Conversion coefficients are sourced from the IPCC and China’s National Development and Reform Commission; emission parameters are sourced from China’s National Bureau of Statistics

economics; e is the energy usage per unit of agricultural output, that is, energy consumption intensity; g is G per capita, and measures economic scale. CEAEC is linked with energy type, economic output, and population change through the above formula.

Time difference decomposition model

The decomposition framework proposed and further developed by (Ang et al., 2015) was adopted to study the temporal-spatial characteristics of CEAEC in the YEB. Assuming time changes from 0 to T , year 0 is the base year, and year T is the target year. Here, C^0 and C^T represent carbon emissions in year 0 and year T , respectively. The total change in CEAEC from 0 to T equals the sum of changes in structure, intensity, economic output, and population in the case of the additive decomposition framework, as shown in Formula (3):

$$\Delta C^{T-0} = C^T - C^0 = \Delta m^{T-0} + \Delta e^{T-0} + \Delta g^{T-0} + \Delta p^{T-0} \tag{3}$$

Furthermore, the components of change Δm^{T-0} , Δe^{T-0} , Δg^{T-0} , and Δp^{T-0} are calculated as shown in Formulas (4)–(7):

$$\Delta m^{T-0} = \sum_{i=1}^n \overline{W}_i(t^*) \left(\ln \frac{m^T}{m^0} \right) \tag{4}$$

$$\Delta e^{T-0} = \sum_{i=1}^n \overline{W}_i(t^*) \left(\ln \frac{e^T}{e^0} \right) \tag{5}$$

$$\Delta g^{T-0} = \sum_{i=1}^n \overline{W}_i(t^*) \left(\ln \frac{g^T}{g^0} \right) \tag{6}$$

$$\Delta p^{T-0} = \sum_{i=1}^n \overline{W}_i(t^*) \left(\ln \frac{p^T}{p^0} \right) \tag{7}$$

In Formula (3), ΔC^{T-0} is the total change in CEAEC, which can be decomposed into $\Delta m^{T-0}, \Delta e^{T-0}, \Delta g^{T-0}, \Delta p^{T-0}$, where Δm^{T-0} is defined as the energy structure effect (ESE), reflecting the influence of energy structure changes on CEAEC. Δe^{T-0} is the energy intensity effect (EIE), which demonstrates the impact of changes in agricultural energy intensity on CEAEC. Δg^{T-0} is the economic output effect (EOE), which reflects the impact of economic growth on CEAEC. Δp^{T-0} is the population effect (PE), which demonstrates the impact of population changes on CEAEC.

According to (De Boer & Rodrigues, 2020), the logarithmic mean function of the two endpoints of the variable is used as the decomposition weight, which is defined as shown in Formula (8):

$$L(a, b) = \begin{cases} (a - b) / (\ln a - \ln b), & a \neq b \\ a, & a = b \neq 0 \\ 0, & a = b = 0 \end{cases} \tag{8}$$

Then, based on the definition of the logarithmic mean function, the calculation of the weight function value can be obtained as shown in Formula (9):

$$\overline{W}_i(t^*) = \frac{C_i^T - C_i^0}{\ln C_i^T - \ln C_i^0} \tag{9}$$

Spatial difference decomposition model

A multiregional spatial decomposition model can be constructed to describe the influencing elements that lead to carbon emissions variations among various regions. This model developed by (Ang, 2015) has been commonly applied in studies on carbon and energy, such as (Román-Collado & Morales-Carrión, 2018; Wang et al., 2020; Zhang et al., 2021). In fact, this model has some significant strengths and is more elaborate than the bilateral–regional and radial–regional models compared and summarized by (Ang, 2015). In this study, the spatial difference of the CEAEC in the YEB agricultural sector is represented by the difference in average carbon emissions among the 11 provinces. The spatial decomposition analysis can be further expressed in Formula (10):

$$\begin{aligned} \Delta C^{R_j-R_\mu} &= C^{R_j} - C^{R_\mu} \\ &= \Delta m^{R_j-R_\mu} + \Delta e^{R_j-R_\mu} + \Delta g^{R_j-R_\mu} + \Delta p^{R_j-R_\mu} \end{aligned} \tag{10}$$

In Formula (10), $\Delta C^{R_j-R_\mu}$ is the total change in CEAEC, which is then decomposed into $\Delta m^{R_j-R_\mu}, \Delta e^{R_j-R_\mu}, \Delta g^{R_j-R_\mu}$, and $\Delta p^{R_j-R_\mu}$. C^{R_j} and C^{R_μ} respectively represent carbon emissions generated by region j and the group average of carbon emissions in the YEB. $\Delta m^{R_j-R_\mu}, \Delta e^{R_j-R_\mu}, \Delta g^{R_j-R_\mu}$, and $\Delta p^{R_j-R_\mu}$ are calculated as shown in Formulas (11)–(14):

$$\Delta m^{R_j-R_\mu} = \sum_{i=1}^n \bar{W}_i(r^*) \left(\ln \frac{m^{R_j}}{m^{R_\mu}} \right) \tag{11}$$

$$\Delta e^{R_j-R_\mu} = \sum_{i=1}^n \bar{W}_i(r^*) \left(\ln \frac{e^{R_j}}{e^{R_\mu}} \right) \tag{12}$$

$$\Delta g^{R_j-R_\mu} = \sum_{i=1}^n \bar{W}_i(r^*) \left(\ln \frac{g^{R_j}}{g^{R_\mu}} \right) \tag{13}$$

$$\Delta p^{R_j-R_\mu} = \sum_{i=1}^n \bar{W}_i(r^*) \left(\ln \frac{p^{R_j}}{p^{R_\mu}} \right) \tag{14}$$

In Formula (10), $\Delta m^{R_j-R_\mu}$ is the energy structure effect, which stands for the impact of the variation in the energy structure effect between region j and the regional average in the spatial variations in CEAEC. $\Delta e^{R_j-R_\mu}$ is the energy intensity effect, which represents the impact of the difference in energy intensity between region j and the regional average level on the spatial difference of CEAEC. $\Delta g^{R_j-R_\mu}$ is the economic output effect and reflects the impact of the difference in economic output between region j and the regional average economic growth on the spatial difference in CEAEC. $\Delta p^{R_j-R_\mu}$ is the population effect, which reflects the impact of the change in population between region j and the regional average on the spatial difference in CEAEC.

Decoupling model

The decoupling indicator developed by Tapio is used in this study, referring to Wang et al. (2020), which is obtained by the variations in CEAEC divided by the change in economic output. Its formula is as shown in Formula (15):

$$\beta = \frac{\Delta C/C}{\Delta G/G} \tag{15}$$

In Formula (15), β is the decoupling indicator between CEAEC and gross agricultural output value. ΔC is the gap in CEAEC between year 0 and year T .

Table 2 Criteria for the classification of decoupling indicators

States	β	$\Delta C/C$	$\Delta GDP/GDP$	Grades	No
Decoupling	$\beta < 0$	< 0	> 0	Strong decoupling	I
	$0 \leq \beta \leq 0.8$	> 0	> 0	Weak decoupling	II
	$\beta > 1.2$	< 0	< 0	Recessive decoupling	III
Negative decoupling	$\beta < 0$	> 0	< 0	Strong negative decoupling	IV
	$0 \leq \beta \leq 0.8$	< 0	< 0	Weak negative decoupling	V
	$\beta > 1.2$	> 0	> 0	Expansive negative decoupling	VI
Coupling	$0.8 \leq \beta \leq 1.2$	> 0	> 0	Expansive coupling	VII
	$0.8 \leq \beta \leq 1.2$	< 0	< 0	Recessive coupling	VIII

ΔG is the variation in gross agricultural output value between year 0 and year T .

According to the literature, the decoupling statuses can be divided into three types according to the value of β , referring to (Song & Zhang, 2017): decoupling, negative decoupling, and coupling. The detailed classification and criteria corresponding to these types are displayed in Table 2.

To test the effectiveness of the government’s decoupling efforts in agricultural carbon emissions, only if the government makes sufficient efforts to reduce carbon emissions can it offset the expansion of carbon emissions due to agricultural economic development. The decoupling efforts were defined by Diakoulaki (Diakoulaki & Mandaraka, 2007), and the indicators of decoupling efforts are as shown in Formulas (16)–(17):

$$\Delta L = \Delta C - \Delta G = \Delta M + \Delta E + \Delta P \tag{16}$$

$$D = -\frac{\Delta L}{\Delta G} = -\frac{\Delta M + \Delta E + \Delta P}{\Delta G} = -\frac{\Delta M}{\Delta G} - \frac{\Delta E}{\Delta G} - \frac{\Delta P}{\Delta G} = Dm + De + Dp \tag{17}$$

In Formula (17), ΔL is the variation in emissions excluding EOE, and D is the decoupling effort indicator. Dm , De and Dp respectively represent the degree of decoupling effort due to the variations with respect to energy structure, energy intensity, and population size.

There exist three types of decoupling efforts:

- (1) $D \geq 1$, defined as “strong decoupling effort,” indicates that the hindering effect of Dm, De , and Dp on CEAEC is greater than the driving effect of economic development, namely, that total CO2 emissions drop while the economy increases;
- (2) $0 < D < 1$, defined as “weak decoupling effort,” indicates that the hindering effect of Dm, De , and Dp has been significantly offset by economic growth; in other words, CEAEC increases to some extent followed by economic growth;
- (3) $D \leq 0$, defined as “no decoupling effort,” signifies that CEAEC is rising to a larger extent than economic output.

Data sources

By considering statistical consistency and data availability, this study covers the period of 2000–2017. The total agricultural output value and regional population data are collected from China’s National Bureau of Statistics. The data on energy consumption come from the China Energy Statistics Yearbook. Furthermore, there are some adjustments and additional details listed as follows:

- (1) The agricultural economic output value (G). G was adjusted according to the constant 2000 price in all provinces in the YEB. That is, all data were converted into the constant price of 2000 based on the relevant index of the output of agriculture (last year = 100).
- (2) The population index. The population data use the year-end population in the YEB. (Unit: ten thousand people)
- (3) The agricultural energy consumption index. This includes seven kinds of energy sources, which are converted into tons of standard coal equivalent.

Results and discussion

Spatiotemporal differentiation characteristics of CEAEC in the YEB

Temporal change in CEAEC in the YEB

In 2000, the total CEAEC in the YEB was $1039.037 \times 10^4 t$; it increased to $1627.843 \times 10^4 t$ in 2017 and reached its peak value in 2012 at $1732.25 \times 10^4 t$. Figure 1 was drawn to visually observe the temporal changes in CEAEC in the YEB from 2000 to 2017 and clearly identify the changing trends. The CEAEC showed a phased upward trend, with an overall increase of 57% from 2000 to 2017. Only in 2000–2001, 2007–2008, 2012–2013, and 2015–2016 was there a slight decline, of which the largest drop was in 2012–2013. The main reason for the downward trend in 2012 was that provinces actively responded to the national “12th Five-Year Plan for Energy Conservation and Emission Reduction” and focused on their agricultural carbon

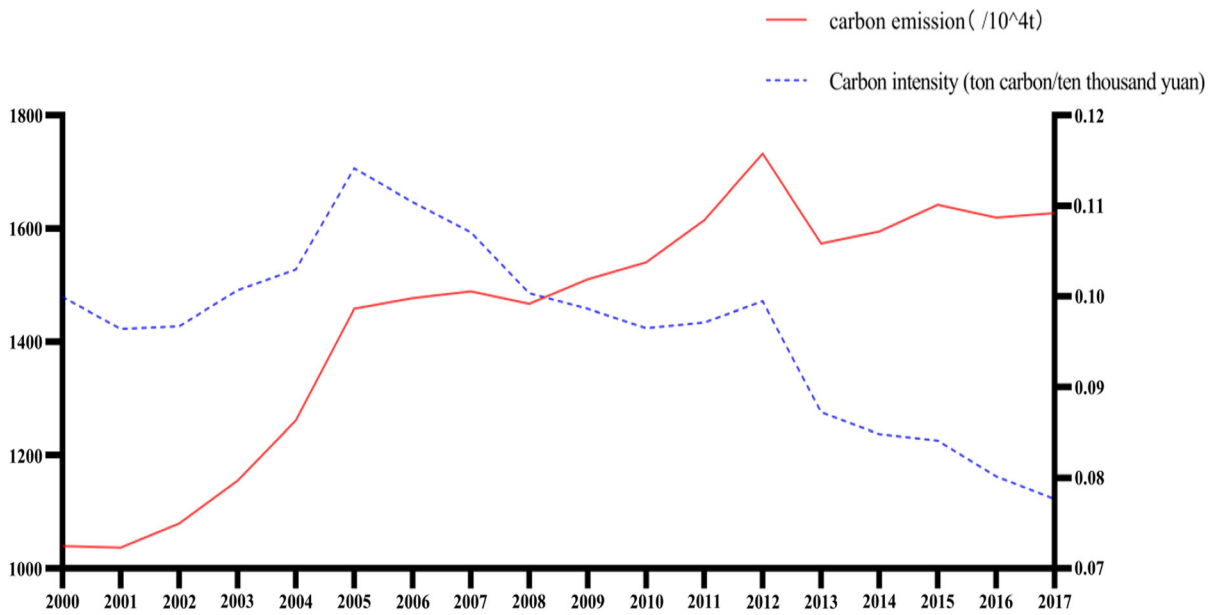


Fig. 1 Changes in CEAEC and carbon intensity in the YEB between 2000 and 2017

emissions. The implementation of the “Action Plan for Energy Conservation, Emission Reduction, and Low-carbon Development for 2014–2015” promoted the transformation of energy conservation technologies and thus, to a certain extent, the development of low-carbon agriculture.

Carbon emission intensity generally displayed a decreasing trend, as shown in Fig. 1. This is in

accordance with the statistical results from FAOSTAT by the Food and Agriculture Organization of the United Nations. Huang et al. (2019) also found that carbon emission intensity exhibits significant spatial variations resulting from crop portfolios and mixed patterns of land and energy use (Zhao et al., 2018). After 2005, the agricultural carbon emission intensity displayed an apparent decreasing trend from $0.11t/10^4$

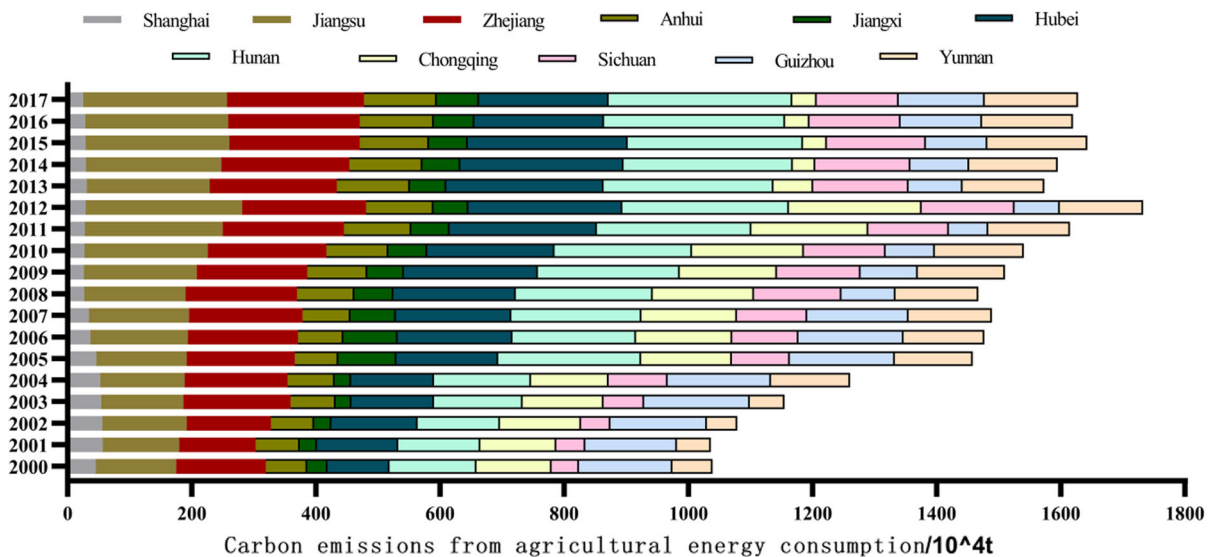


Fig. 2 Total CEAEC in provinces in the YEB from 2000 to 2017

RMB to $0.08t/10^4$ RMB between 2005 and 2017. However, overall, the decline has been relatively mild, indicating that there is still some space to enhance energy usage efficiency in the agriculture sector, and more efforts should be dedicated to agricultural emissions reduction.

Spatial change in CEAEC in the YEB

There was a spatial difference in CEAEC in the YEB from 2000 to 2017 (see Fig. 2). Hunan, Hubei, Zhejiang, and Jiangsu have a large amount of CEAEC, accounting for 15.23%, 13.37%, 12.62%, and 12.53%, respectively, and altogether representing 53.76% of the total, and they have had a significant impact on the control of CEAEC. Due to developed agricultural production and high grain output, they are the main contributors to high CEAEC. Shanghai’s CEAEC accounts for 5.6%, which is the smallest value among the 11 provinces. To explain the spatial variations, food categories and farming systems may be essential causes of carbon emissions (Pieper et al., 2020). In fact, each province may have its particularities resulting from different driving factors, in which case, “one-size-fits-all” solutions should be avoided to coordinate carbon emissions (Wang & Feng, 2021).

Temporal–spatial changes in CEAEC in the YEB

From the perspective of temporal-spatial changes (see Fig. 3), CEAEC shows an increasing trend, except for in Shanghai, Chongqing, and Guizhou. CEAEC in

Hunan, Hubei, Jiangsu, and Sichuan shows an apparent rising trend, while CEAEC in Chongqing shows an evident downward trend after 2012. However, it is worth noting that the CEAEC in Shanghai is continuously declining, while that in Chongqing and Guizhou is volatile.

Agricultural energy consumption structure in the YEB

From the perspective of the carbon emission structure from 2000 to 2017 (see Fig. 4), the carbon emissions from coal and diesel were the primary source of CEAEC. Among them, the main source of CEAEC in the upstream region is diesel, while in the downstream region, it is coal. In addition, the long-term structure of energy consumption in the agricultural sector in the YEB remained unimproved. Coal and diesel consistently comprised a relatively large percentage of the total consumption in the provinces, and the agricultural energy usage mixture in each province did not vary significantly. This shows that carbon emissions reduction efforts have not changed the traditional energy consumption structure, and high-carbon energy sources still dominate the agricultural sector. This finding is supported by the findings of other related studies on China’s energy consumption in agriculture (Long & Tang, 2021; Yu et al., 2020). Studies have also found that high-carbon energy sources, for example, coal and diesel, continue to be the primary contributors to agricultural carbon emissions. Therefore, there is indeed an urgent need to optimize crop portfolios and change the agricultural

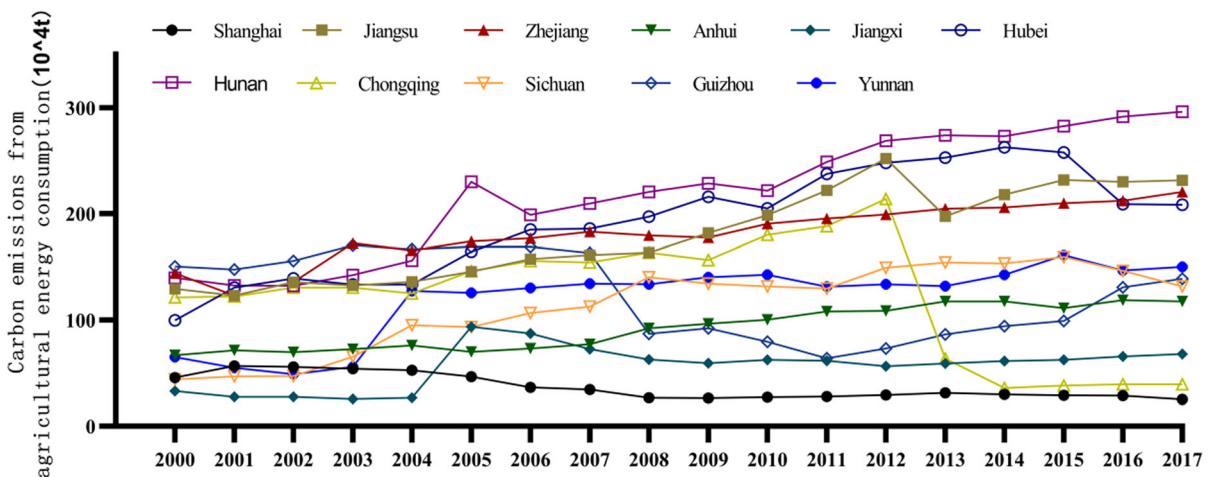


Fig. 3 The trend in CEAEC in provinces in the YEB from 2000 to 2017

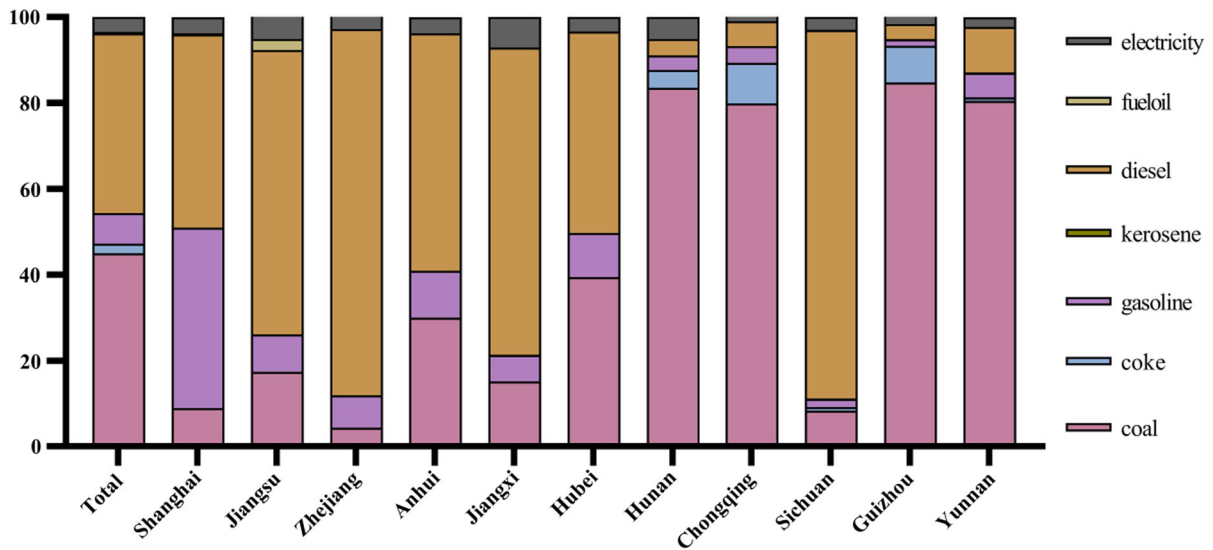


Fig. 4 The share of energy consumption by energy source

energy consumption mix to achieve a carbon emissions peak by approximately 2030.

In summary, CEAEC in the YEB shows a rising trend, while agricultural carbon emission intensity shows a declining trend. Moreover, the decrease in magnitude is relatively flat, indicating a rich gap for an upswing in energy efficiency and the promotion of low-carbon practices. In addition, the quantity of CEAEC varies significantly among provinces. In terms of energy structure, it did not change significantly from 2000 to 2017, and diesel and coal remained the two most important energy sources. This indicates that agriculture in the YEB is facing a transformation of its energy consumption structure,

which is crucial to achieving agricultural carbon emission reduction.

Decomposition analysis

Temporal differentiation

Based on the national economic and social policy, the research period was divided into four stages, namely, the 10th Five-Year Plan (FYP) (2001–2005), the 11th FYP (2006–2010), the 12th FYP (2011–2015), and the 13th FYP (2016–2017). As displayed in Fig. 5, CEAEC would greatly increase because the total effect was at a high level between 2000 and 2005.

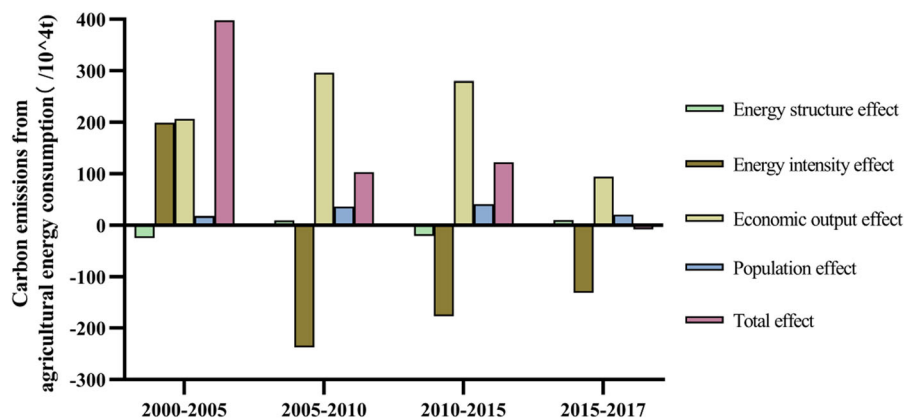


Fig. 5 The factors driving CEAEC in each subperiod of the YEB from 2000 to 2017

Table 3 Decomposition results for changes and the contribution values of CEAEC in the YEB

Year	Total effect	ESE		EIE		EOE		PE	
		Share	Contribution (%)	Share	Contribution (%)	Share	Contribution (%)	Share	Contribution (%)
2000–2001	- 2.66	10.56	- 397.19%	- 45.63	1715.96	26.63	- 1001.32	5.78	- 217.45
2001–2002	42.49	- 2.62	- 6.17%	11.23	26.44	27.67	65.12	6.21	14.61
2002–2003	76.22	- 16.56	- 21.72%	52.82	69.29	31.63	41.50	8.34	10.94
2003–2004	105.65	2.68	2.54%	40.28	38.13	54.13	51.24	8.55	8.10
2004–2005	176.40	- 19.02	- 10.78%	140.50	79.65	66.30	37.59	- 11.38	- 6.45
2005–2006	19.04	- 3.73	- 19.61%	- 35.06	- 184.17	52.46	275.59	5.37	28.19
2006–2007	7.18	- 7.20	- 100.37%	- 48.35	- 673.78	57.30	798.49	5.43	75.66
2007–2008	3.37	12.04	357.06%	- 86.70	- 2571.63	70.92	2103.59	7.11	210.97
2008–2009	42.98	4.58	10.65%	- 30.69	- 71.39	62.13	144.54	6.96	16.19
2009–2010	30.50	3.83	12.56%	- 37.07	- 121.51	53.00	173.75	10.74	35.20
2010–2011	74.68	- 2.34	- 3.14%	13.10	17.55	56.51	75.67	7.41	9.92
2011–2012	117.50	- 3.13	- 2.67%	45.31	38.56	67.34	57.31	7.99	6.80
2012–2013	- 158.81	- 21.08	13.28%	- 194.42	122.42	48.22	- 30.36	8.47	- 5.34
2013–2014	50.07	15.57	31.09%	- 30.45	- 60.80	58.15	116.13	6.80	13.58
2014–2015	38.70	- 9.94	- 25.70%	- 10.70	- 27.64	49.89	128.89	9.46	24.44
2015–2016	- 23.05	7.13	- 30.94%	- 85.25	369.84	44.92	- 194.89	10.14	- 44.01
2016–2017	15.17	2.86	18.88%	- 46.66	- 307.55	48.88	322.23	10.08	66.44
Total	615.45	- 26.38	- 4.29%	- 347.72	- 56.50	876.09	142.35	113.46	18.44

However, the total effect was reduced by approximately three-quarters from the 10th FYP to the 11th FYP period. Although there was a slight rise in the total effect during the 12th FYP, it became a negative value during the 13th FYP, which would be due to

China’s emphasis on developing low-carbon agriculture and implementing a sustainable agricultural development strategy.

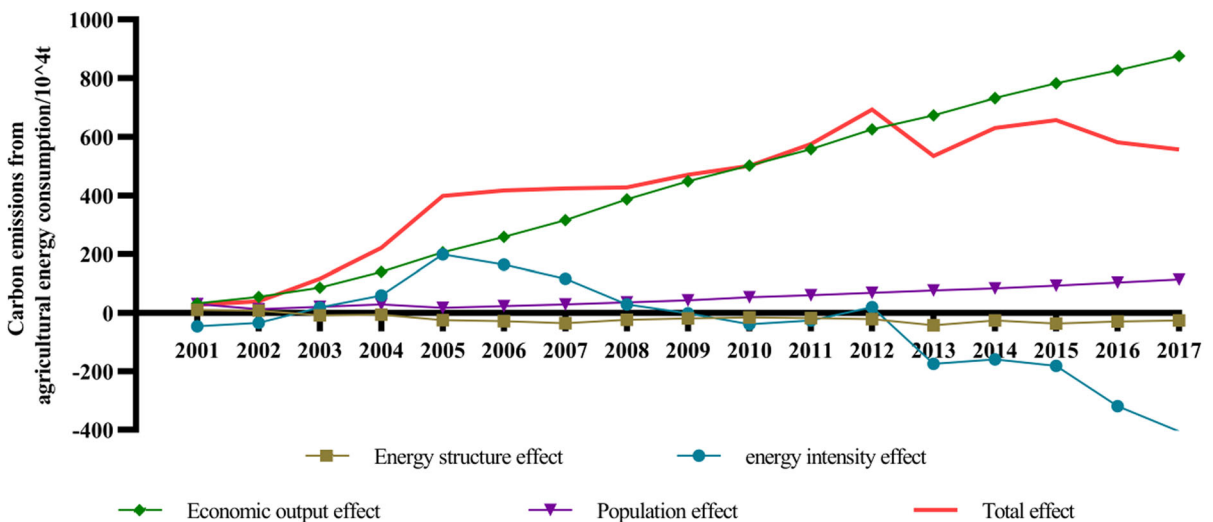


Fig. 6 Contribution trend in driving factors of CEAEC in the YEB from 2000 to 2017

Using the LMDI method, the changes in the contribution of the ESE, EIE, EOE, and PE to CEAEC over time are shown in Table 3 and Fig. 6.

The change in the total effect is 615.45×10^4t , with a yearly average rate of increase of 5.56%. Specifically, EOE was the most significant contributor to CEAEC, with PE being the second largest contributor during the investigation. This result is consistent with (Li et al., 2014), in which EOE and PE are the top two contributors to carbon emissions. Chen et al. (2018) found that the population effect was one of the causes of energy-related carbon emissions even though it was obviously weak in China's agriculture sector.

However, the energy intensity effect negatively contributed a cumulative quantity of 347.72×10^4t , with a contribution rate of -56.50% to CEAEC. It increased CEAEC in the 10th FYP period and then decreased it in the 11th, 12th, and 13th FYPs. The energy structure effect also offset the increase in CEAEC by -4.29% , causing a cumulative reduction of 26.38×10^4t during the whole period. This result is slightly different from that of Yu et al. (2020), in which the energy structure effect promoted agricultural carbon emissions. Some studies do support our findings, such as Chen et al. (2020a) and Xiong et al. (2020), who found that the energy structure effect inhibited carbon emissions to some extent.

As shown in Fig. 5, the energy intensity effect was larger than zero only during the 10th FYP period and became negative in the subsequent FYP periods. Correspondingly, the energy intensity effect increased CEAEC significantly in the 10th FYP period to approximately the same level as the economic output effect. In contrast, the energy intensity effect decreased CEAEC in the 11th, 12th, and 13th FYP periods. The economic output effect was the largest source of the growth in CEAEC from 2000 to 2017, with an increase of 48.9685×10^4t , accounting for a contribution rate of 142.35%. In addition, the economic output effect has been increasing annually since 2000. Since the 11th FYP period (except for 2011 and 2012), the increment in CEAEC resulting from the economic output effect completely offset the inhibiting effects of other factors and independently was already much higher than the actual measured value. Therefore, under the premise of rapid economic development, reasonable and flexible emission reduction measures should be adopted to curb the increase.

The population effect was an essential driving factor increasing CEAEC in the YEB and accounted for 18.44%. After 2000, China's population growth clearly slowed, but the growth rate remained positive. Coupled with the constant adjustment of the fertility policy, the population in the YEB continued to expand, with a yearly mean rate of 0.43%. The increase in rural population naturally drove the demand for agricultural products, which would result in greater energy consumption and increase CEAEC.

The energy intensity effect was the foremost restraint on the growth of CEAEC in the YEB, and the contribution rate was 17% in 2001, while it rose to -307.55% by 2017. Since the 12th five-year plan, low-carbon technologies have been vigorously developed and applied, improving energy efficiency and effectively curbing agricultural carbon emissions without affecting economic development. With the issuance of the "Outline of Yangtze River Economic Belt Development Plan" in the 13th FYP period and the realization of the proposal to "step up conservation of the Yangtze River and stop its overdevelopment", the energy intensity effect has increasingly and significantly been hindering CEAEC, which reflects remarkable achievements in emission reduction.

Based on the above decomposition analysis, the energy structure effect has a few influences on CEAEC. From 2000 to 2017, the agricultural development of the YEB maintained an energy structure dominated by high-carbon energy sources such as coal and diesel, and the energy usage structure was not effectively improved. Therefore, similar conclusions regarding the benefits of optimizing agricultural energy usage mixtures and improving energy efficiency are supported by existing studies (Colinet Carmona & Román Collado, 2016; Ren et al., 2021).

Spatial differentiation

The multiregion model introduced in "Spatial difference decomposition model" section was applied to study the spatial variations in CEAEC. Each region's energy consumption is compared with a benchmark reference given by the average of the 11 provinces, and the difference is decomposed, as shown in Table 4.

In terms of the energy structure effect, Guizhou showed the largest deviation from the average level, with only 18.3×10^4t in 2000, whereas Hunan saw the

Table 4 Decomposition results for factors driving CEAEC in provinces in 2000 and 2017

Region	ESE		EIE		EOE		PE		Total effect	
	2000	2017	2000	2017	2000	2017	2000	2017	2000	2017
Shanghai	- 10.22	- 26.77	52.62	47.96	- 20.27	- 96.20	- 68.75	- 45.38	- 46.61	120.39
Jiangsu	0.08	- 2.43	- 36.00	- 18.46	32.65	37.16	40.51	69.67	37.24	85.94
Zhejiang	- 5.18	- 4.50	44.67	106.22	19.72	- 32.97	- 7.40	7.16	51.81	75.90
Anhui	1.22	- 2.20	- 46.75	- 50.94	4.87	7.30	15.21	18.76	- 25.45	- 27.08
Jiangxi	- 1.58	- 5.90	- 45.82	- 55.89	- 1.47	0.72	- 10.53	- 15.52	- 59.40	- 76.59
Hubei	- 0.12	8.31	- 9.19	12.07	5.49	28.39	11.15	15.17	7.33	63.93
Hunan	12.48	41.30	6.97	54.08	- 1.19	8.21	29.32	44.58	47.59	148.18
Chongqing	12.69	- 0.97	98.03	- 45.28	- 25.79	- 13.92	- 55.80	- 44.91	29.13	- 105.08
Sichuan	- 11.40	- 10.01	- 59.42	- 58.67	- 5.80	3.53	28.34	52.23	- 48.28	- 12.91
Guizhou	18.30	12.51	125.18	76.91	- 56.84	- 39.12	- 30.71	- 56.11	55.93	- 5.81
Yunnan	0.99	13.90	- 5.66	- 8.93	- 12.03	15.17	- 12.79	- 16.79	- 29.49	3.35

Table 5 Decoupling state of CEAEC in the YEB from 2000 to 2017

Time (Year)	β	Grades	$\Delta C/C$	$\Delta GDP/GDP$
2000–2001	- 0.074537	I	- 0.002503	0.033577
2001–2002	1.084254	VII	0.040995	0.037809
2002–2003	2.445881	VI	0.070593	0.028862
2003–2004	1.364313	VI	0.091466	0.067042
2004 – 2005	3.590660	VI	0.156569	0.043604
2005–2006	0.275901	II	0.012866	0.046632
2006–2007	0.207379	II	0.008204	0.039561
2007–2008	- 0.282653	I	- 0.014643	0.051804
2008–2009	0.624808	II	0.029291	0.046880
2009–2010	0.466689	II	0.019811	0.042450
2010–2011	1.161772	VII	0.048483	0.041732
2011–2012	1.536130	VI	0.072752	0.047361
2012–2013	- 2.528578	I	- 0.091679	0.036257
2013–2014	0.319931	II	0.013596	0.042498
2014–2015	0.784598	II	0.029957	0.038181
2015–2016	- 0.403946	I	- 0.014032	0.034739
2016–2017	0.135733	II	0.005115	0.037687

greatest effect at 41.3×10^4t in 2017. In both 2000 and 2017, the absolute value of CEAEC caused by each province’s energy structure effect was no more than 30×10^4t , and only that of Hunan was more than 20×10^4t , which indicates that the regional differences between the 11 provinces are not obvious. Agricultural development has consistently maintained

an energy structure dominated by high-carbon energy such as coal.

A positive EIE value in one province indicated that it was less efficient in energy consumption than the average level in the YEB. In 2000, Shanghai, Zhejiang, Hunan, Chongqing, and Guizhou had a positive EIE values that increased the CEAEC.

Table 6 Decoupling results of 11 provinces in the YEB

Region	Time Province	2000–2005		2005–2010		2010–2015		2015–2017	
		β	Grade	β	Grade	β	Grade	β	Grade
Downstream	Shanghai	- 0.29	IV	12.24	III	- 0.76	IV	0.99	VIII
	Jiangsu	0.52	II	1.56	VI	0.90	VII	- 0.03	I
	Zhejiang	1.33	VI	0.57	II	1.31	VI	1.04	VII
	Average	0.78	II	0.70	II	0.93	VII	0.44	II
Middle reaches	Anhui	0.40	II	1.47	VI	0.47	II	0.80	VII
	Jiangxi	6.87	VI	- 1.27	I	0.00	I	1.01	VII
	Hubei	3.00	VI	0.90	VII	0.87	VII	- 2.31	I
	Hunan	2.49	VI	- 0.13	I	1.39	VI	0.62	II
	Average	3.09	VI	0.20	II	0.87	VII	- 0.43	I
Upstream	Chongqing	0.75	II	0.86	II	- 3.07	I	0.42	II
	Sichuan	3.35	VI	2.00	II	0.96	VII	- 2.01	I
	Guizhou	0.66	II	- 1.94	I	0.74	II	3.03	VI
	Yunnan	2.93	VI	0.37	II	0.35	II	- 0.55	I
	Average	1.34	VI	0.00	I	- 0.51	I	0.05	II
YEB average		1.76	VI	0.23	II	0.30	II	0.44	II

Among them, Guizhou had the largest value of $125.18 \times 10^4 t$. The EIE of other provinces was negative, indicating that the other six provinces' energy utilization efficiency was higher than the average level. In 2017, Shanghai, Zhejiang, Hunan, Guizhou, and Hubei had positive values, which means that the spatial differences in the energy intensity effect have not yet been eliminated. The value of Chongqing's energy intensity effect changed from $98.03 \times 10^4 t$ in 2000 to $-45.28 \times 10^4 t$ in 2017, indicating that Chongqing's energy utilization efficiency improved significantly. Therefore, Shanghai, Zhejiang, Hunan, Guizhou, and Hubei can introduce Chongqing's approach to reduce their difference from the average level.

A positive value of the economic output effect signified that the agricultural economic output scale of the given province was above the YEB's average level. In 2000, there were four provinces with a positive value, namely, Jiangsu, Zhejiang, Anhui, and Hubei. The values for the other provinces' economic output effects were negative, indicating that the others' agricultural economic output scale was below the average level. In 2017, Shanghai's value was the smallest because the proportion of Shanghai's

agriculture in national GDP shrank, while Jiangsu's value remained the largest.

Table 7 Decomposition of decoupling effort indicators in the YEB from 2000 to 2017

Time	D	D_m	D_e	D_p
2000–2001	1.10	- 0.40	1.71	- 0.22
2001–2002	- 0.54	0.09	- 0.41	- 0.22
2002–2003	- 1.41	0.52	- 1.67	- 0.26
2003–2004	- 0.95	- 0.05	- 0.74	- 0.16
2004–2005	- 1.66	0.29	- 2.12	0.17
2005–2006	0.64	0.07	0.67	- 0.10
2006–2007	0.87	0.13	0.84	- 0.09
2007–2008	0.95	- 0.17	1.22	- 0.10
2008–2009	0.31	- 0.07	0.49	- 0.11
2009–2010	0.42	- 0.07	0.70	- 0.20
2010–2011	- 0.32	0.04	- 0.23	- 0.13
2011–2012	- 0.74	0.05	- 0.67	- 0.12
2012–2013	4.29	0.44	4.03	- 0.18
2013–2014	0.14	- 0.27	0.52	- 0.12
2014–2015	0.22	0.20	0.21	- 0.19
2015–2016	1.51	- 0.16	1.90	- 0.23
2016–2017	0.69	- 0.06	0.95	- 0.21

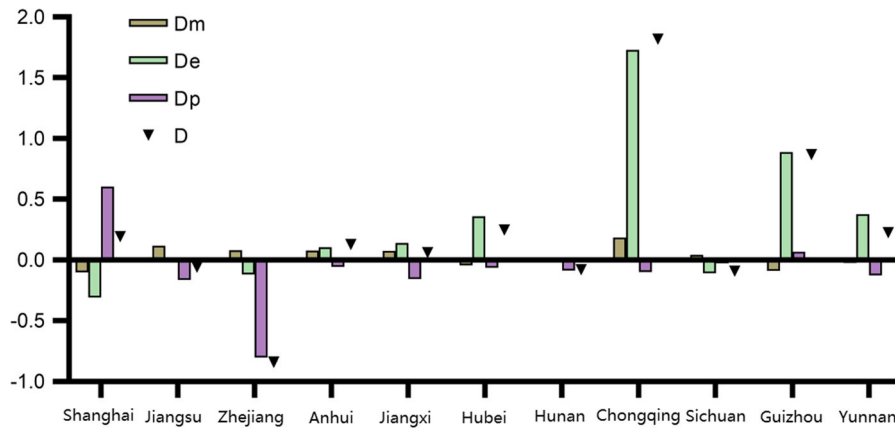


Fig. 7 Decomposition of decoupling effort indicators in the YEB

In 2000, Jiangsu, Anhui, Hubei, Hunan, and Sichuan had a positive value for the population effect, and the remaining provinces had a negative value. In 2017, Jiangsu, Anhui, Hubei, Hunan, Sichuan, and Zhejiang had positive values, and the values of the remaining five provinces were negative. This is because these six provinces have large populations, which promotes the increase in total CEAEC and is higher than the average level. Shanghai and Chongqing are municipalities and occupy a small area. Guizhou, Yunnan, and Jiangxi are sparsely populated, economically weak, and have a large net population outflow, resulting in carbon emissions from the population effect below the average level.

Decoupling analysis

Decoupling status of CEAEC and the economy in the temporal dimension

According to Formula (15), Table 5 displays the decoupling outcomes between CEAEC and GDP in the YEB from 2000 to 2017. There were four decoupling states between CEAEC and economic output. The decoupling states of the whole YEB alternated from decoupling to connecting and then to negative decoupling. Additionally, since 2012, the YEB has entered a relatively ideal state of strong or weak decoupling, which also indicates that green development practices helped to reduce carbon emissions.

Decoupling the status of CEAEC and the economy in the spatial dimension

Table 6 displays the decoupling results according to Formula (15) from the spatial dimensions in the YEB from 2000 to 2017. Judging from the whole YEB, in the 10th FYP, the decoupling elasticity index showed an expansive negative decoupling state with a value of 1.76. The results showed that CEAEC increased faster than economic growth. Namely, agricultural economic development occurred at the cost of the ecological environment. After entering the 11th FYP, the decoupling elasticity index dropped significantly to 0.23, showing a weak decoupling status. Compared with the 10th FYP, the 11th FYP brought a higher proportion of agricultural added value while emitting carbon dioxide. In the 12th FYP, the decoupling elasticity index was 0.30, showing a weak decoupling status, and maintained a weak decoupling state from 2015 to 2017. This indicated that during these four periods, the agricultural emission reduction policy and the continuous improvement of agricultural machinery positively reduced CEAEC in the whole YEB.

Judging from the regional perspective, during the 10th FYP, the Yangtze River’s upstream and middle reaches presented an expansive negative decoupling state, while the downstream reaches presented weak decoupling. After entering the 11th FYP period, the three regions’ decoupling elasticity index decreased, all of them were decoupling, and the upstream region presented a strong decoupling state. However, after entering the 12th FYP, the decoupling elasticity

indices of the middle reaches and downstream showed expansive coupling. Since 2015, the three regions have decoupled, and the middle reaches have strongly decoupled. Decoupling was realized downstream first, and decoupling in the middle reaches and upstream followed gradually. The industrial adjustment in the lower and middle reaches and the occupation of agricultural arable land have resulted in slow growth in the value of agricultural output and the state of expanding connections during the 12th FYP.

Regarding provincial differences, the decoupling state shows notable fluctuations among the 11 provinces. During the 10th FYP, Shanghai showed a strong negative decoupling state, and Shanghai's agricultural output fell. This may mean that the agricultural development policies adopted by Shanghai were not effective during this period. Then, Shanghai entered a state of recessive decoupling, indicating a decline in CEAEC. However, in the 12th FYP, it again entered a strong negative decoupling state, which indicates that Shanghai sacrificed substantial economic benefits to reduce CEAEC. After 2015, Shanghai showed expansive decoupling, and the decoupling elasticity index improved. As a major agricultural province, Hubei's decoupling elasticity index decreased during the 10th FYP. In 2015, the decoupling index value showed the best performance among all provinces, dropping to -2.31, which has high significance for the potential of other provinces.

Analysis of the efforts to decouple CEAEC and the economy in the YEB

According to Formulas (16) and (17), Table 7 and Fig. 7 show the decoupling effort indicators at the temporal and spatial scales. The decoupling effort indicators are analyzed with the previous year's data as the base period. Varying decoupling efforts were identified in the remaining years, except for the periods of 2001–2004 and 2010–2011. Among them, the greatest decoupling effort was made in 2012, while the least was made in 2004. From various indicators of decoupling efforts, the effect of the energy structure was somewhat small, with an average value of less than 0.2, and in nearly half of the years it inhibited the realization of decoupling. The contribution of energy intensity was relatively large. To a considerable extent, the population has little effect on the

realization of total decoupling, with an average of approximately -0.14.

As shown in Fig. 7, from the spatial dimension perspective, there exists significant heterogeneity in the decoupling effort indicators among provinces. Decoupling efforts have been made in Shanghai, Anhui, Jiangxi, Hunan, Chongqing, Guizhou, and Yunnan, while strong decoupling efforts have been made in Chongqing. In Shanghai, the decoupling effort only came from the population scale, namely, population control played an important role. Among the 11 provinces, only the population size of Shanghai and Guizhou made decoupling contributions, which may be related to their population policies. In Chongqing, energy intensity played the most significant role in realizing decoupling, indicating that Chongqing had a high reference value for energy use efficiency. While Zhejiang made the lowest decoupling effort, both energy intensity and population size played a restraining role. Similar findings are discussed by Wang et al. (2019), in which different effort characteristics were identified for regions in different development phases. Karakaya et al. (2019) adopted the decoupling effort indicator to study the temporal distribution of decoupling status. To reduce the YEB's carbon emissions, changing the intraregional energy consumption structure and differentiated reduction policies have been proposed (Qi et al., 2021).

Discussion

In the past, some studies have been conducted in the context of China that focus on the assessment of carbon emissions, such as Li et al. (2014) and Xiong et al. (2016). While most of them dealt with regional (Ma et al., 2019) or sectoral (Peng & Wu, 2020) data, few consider carbon emissions from agricultural energy consumption. Long et al. (2018) investigated carbon emissions from the agricultural sector and its influencing factors in China, including three types of carbon sources, namely, agricultural production activities, farming, and livestock. Therefore, there is a research gap to be bridged, especially considering that the YEB is prioritized as a new national strategy. In this study, a process accounting for carbon emissions from agricultural energy consumption is developed based on the IPCC's methods.

Furthermore, this study makes up for the shortcomings of the traditional literature by expanding the

framework to simultaneously cover the analysis of influencing factors and decoupling analysis. In the developed framework, the LMDI decomposition method was adopted to identify the factors driving carbon emissions, and the Tapio decoupling model was used to explore the relationship between emissions and economic development and test the effectiveness of the government's decoupling efforts. The results are similar to the insights provided by previous literature. Our findings show that carbon intensity has a decreasing trend while total emissions are rising, and the economic output effect is the largest driving factor, which is consistent with the study of Ma et al. (2019). A strong or a weak decoupling status has appeared more commonly with strengthening environmental regulations (Luo et al., 2017), and the similar results were found in our study. The significant spatial variations among provinces in our findings are also supported by existing studies, such as Shi et al. (2019) and Wang et al. (2018). Therefore, the results from the study are reliable to support practical action and recommendations.

At the application level, the developed analytical framework helps to understand the carbon emissions from agricultural energy consumption, which is the basis for designing effective measures to reduce the negative impact of carbon emissions on the environment. Therefore, this study adds something new to the existing body of knowledge on carbon management and sustainability.

Conclusions

This study investigated the drivers of carbon emissions from agricultural energy consumption and examined the decoupling status between carbon emissions and economic growth with panel data between 2000 and 2017 in the Yangtze River Economic Belt. The major conclusions can be summarized as follows:

- (1) A significant spatiotemporal differentiation in changing trends in CEAEC and energy consumption structure was identified among the 11 provinces in the YEB. Coal and diesel were the two primary energy sources overall, even though the carbon emissions intensity appeared to decrease to some extent. The above

phenomenon told that there remained significant room for improvement on carbon management.

- (2) Two types of decomposition analysis based on LMDI were implemented to identify the factors influencing carbon emissions, including temporal decomposition analysis and spatial decomposition analysis. The results showed that the total CEAEC of the YEB was mainly increased by the economic output effect and decreased by the energy intensity effect. The four effects were identified to have different impacts on CEAEC in the 11 provinces.
- (3) In terms of decoupling in the YEB, there existed an alternating change from negative decoupling to decoupling from 2000 to 2017. The decoupling status for the 11 provinces was also examined to recognize the existing spatial variation and changing trend. Furthermore, the decoupling effort indicators were calculated to distinguish the decoupling efforts made by the 11 provincial governments. This could provide useful input to the policy development.

Our findings in this study have several potential implications for boosting the sustainable growth of the agricultural sector in the Yangtze River Economic Belt.

- (1) Emissions reduction policies should be designed according to the local conditions, considering the significant variations in geographical environment, economic status, and energy structure. Regional governments should devote more attention to the control of total carbon emissions and carbon intensity in the agriculture sector. Additionally, increasing policy support and establishing a long-term coordination mechanism are valuable tools to support low-carbon agriculture development in the YEB through effective national policy.
- (2) It is necessary to implement differentiated carbon policies according to the combined effect of driving factors at the provincial level. Notably, the YEB achieved the relatively ideal status of strong decoupling and weak decoupling, although high-carbon energy sources always dominated the agricultural energy structure. Optimizing the energy structure and improving energy efficiency are attractive tools for carbon management under the dual targets of

carbon neutrality and emission peaks. More targeted efforts should be made to promote strong decoupling between carbon emissions and agricultural output in all provinces.

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Author contribution DS and SC contributed to conceptualization. JG contributed to methodology, CZ to software, XY to validation, and ZC and HS to formal analysis. DS and SC carried out investigation, and SC performed data curation. JG and XY contributed to writing—original draft preparation. All authors have read and agreed to the published version of the manuscript.

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Data availability Data will be available if necessary.

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