



The green paradox puzzle: fiscal decentralisation, environmental regulation, and agricultural carbon intensity in China

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Abstract

China has the highest carbon dioxide emissions worldwide. Exploring the mechanism of fiscal decentralisation on agricultural carbon intensity can help China reach its carbon peak and become carbon neutral. This study used panel data for 30 provinces in Mainland China from 2000 to 2019 and constructed a spatial Durbin model to investigate the spatial–temporal patterns and internal relationships among fiscal decentralisation, environmental regulation, and agricultural carbon intensity. The results indicated that (1) from 2000 to 2019, the agricultural carbon intensity showed a downward trend and showed a spatial pattern of ‘high in the north and low in the south’. The degree of fiscal decentralisation has gradually increased, and the spatial pattern of ‘high in the north and low in the south’ has also emerged. The intensity of environmental regulation continues to increase, and the intensity of environmental regulation in inland areas is higher than that in coastal areas. (2) From 2000 to 2019, the global Moran index of agricultural carbon intensity showed a development trend of first rising and then falling, and the spatial correlation changed from strong to weak. Agricultural carbon intensity tends to develop from polarisation to balanced development. (3) Both fiscal decentralisation and environmental regulation can reduce agricultural carbon intensity, and environmental regulation has a negative spatial spillover effect. (4) Under the influence of fiscal decentralisation, environmental regulation is not conducive to reducing agricultural carbon intensity due to the characteristics of ‘race to the bottom’, causing the ‘green paradox’ effect. (5) Environmental regulation and fiscal decentralisation in main grain producing areas have less impact on agricultural carbon intensity than in non-main grain producing areas. Therefore, the central government should focus on optimising the fiscal decentralisation system, formulating a differentiated agricultural carbon emission control system, regulating competition among local governments, and optimising a political performance evaluation system.

Keywords Fiscal decentralisation · Environmental regulation · Agricultural carbon intensity

Introduction

The greenhouse effect has become an environmental problem of global pollution. To reduce carbon dioxide emissions, countries globally are vigorously advocating energy conservation and emission reduction, and China is no exception. China is already the world’s largest carbon

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emitter and energy consumer (Liu and Song 2020; Wang et al. 2017; Zheng et al. 2019). Moreover, China is still in the middle of industrialisation (Huang 2018), and the growth of population and the acceleration of urbanisation means that China’s economy cannot completely get rid of the dependence on traditional fossil energy. As such, when implementing the international initiative of carbon reduction and emission control under the Paris Agreement, the Chinese government did not commit to ‘zero emissions’ like other countries but set the vision target of peaking carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060. The ‘double carbon’ goal is a major commitment made by the Chinese government in light of its national conditions.

Agriculture is both a climate change influencer and one of the industries most affected by climate change (Gul

et al. 2021; Rehman et al. 2021a, 2020). At the same time, agriculture is also the second-largest source of carbon after industry, which means, it must play its part in achieving the ‘double carbon’ goal. China has been working hard to feed 21% of the world’s population with 7% of the world’s arable land, and ensuring adequate food supplies has always been the most important challenge facing China (He et al. 2019; Ye et al. 2020). Fortunately, China has successfully solved the food problem of 1.4 billion people. The total grain output rose from 113.18 million tons in 1949 to 669.49 million tons in 2020 (see Fig. 1). However, behind the high food yield is the excessive use of pesticides and fertilisers and the dependence on traditional fossil energy. *The Bulletin of the State of the Ecological Environment in China (2018)* shows that the utilisation rate of fertilisers and pesticides for the three major food crops in China is

Fig. 1 China’s grain output from 1949 to 2020 (data from *China Statistical Yearbook* and *60 Years of New China Statistical Data Compilation*)

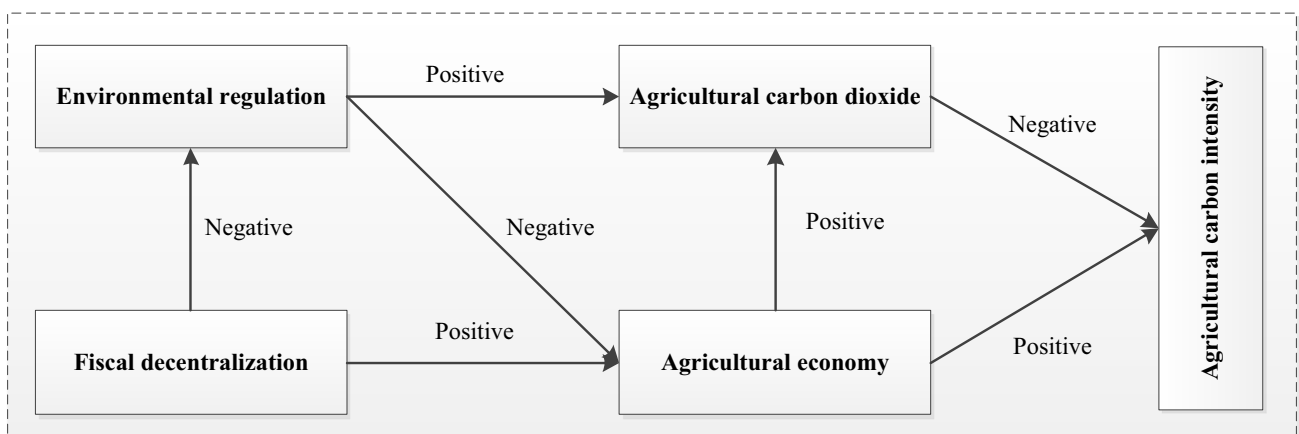
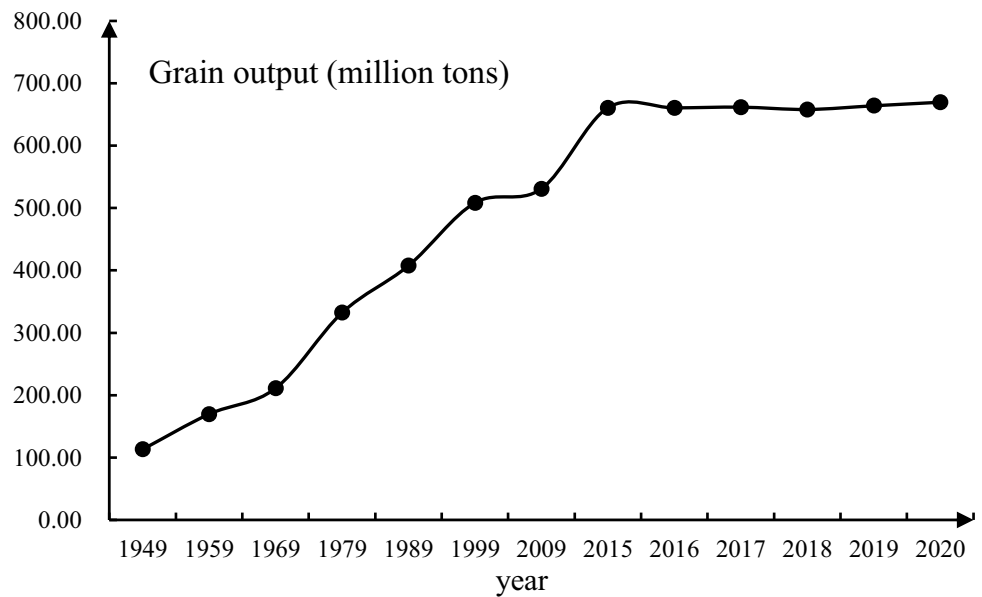


Fig. 2 Mechanism path diagram of fiscal decentralisation and environmental regulation influencing agricultural carbon intensity

only approximately 38% (Shuqin and Xiaoxu 2018) and the efficiency of agricultural energy use is also low (Fei and Lin 2016; Yang et al. 2018). These are one of the main sources of agricultural carbon emissions. Therefore, under the ‘double carbon’ target, China’s agricultural production has a huge space for carbon emission reduction and the prospect of developing low-carbon agriculture.

Agricultural carbon emission reduction is inseparable from the discussion of government systems, particularly in countries with distinctive institutional arrangements like China. In 1994, China began to implement the tax-sharing reform, which marked the gradual improvement of the reform of fiscal decentralisation system and constituted an important part of ‘Chinese-style decentralization’. The reform of the fiscal decentralisation system is considered an important institutional factor under political centralisation (Shen et al. 2012). The reform of the fiscal decentralisation system is regarded as an important institutional incentive for Chinese local governments to participate in economic activities with high enthusiasm (He and Sun 2018; Martinez Vazquez et al. 2015). Under such a system, the local government not only plays an important role in local economic development but also plays an irreplaceable role in ecological environment protection. Moreover, with the continuous development of the economy and society, resource and environmental problems are becoming increasingly serious. The Chinese government’s financial expenditure on technological innovation is also increasing. In this context, it is necessary to investigate the impact mechanism of fiscal decentralisation on agricultural carbon emissions.

Under the fiscal decentralisation system, the local government’s environmental behaviour is the key to environmental governance. Environmental regulation has been effective in reducing carbon emissions, improving energy efficiency, and solving environmental pollution externalities (Pan et al. 2019; Zhang et al. 2020; Zhao et al. 2020). However, there is an obvious urban–rural dualistic structure in China’s environmental governance. Considering China’s environmental governance system, it is mainly aimed at the prevention and control of urban and industrial pollution. This environmental governance system is not suitable for agricultural pollution with uncertain location, route and quantity, large randomness, wide release range, and difficulty in prevention and control (Merrington et al. 2002). Therefore, the impact of environmental regulation on agricultural carbon emissions is more easily affected by the behaviour of local governments. For example, the interaction of environmental regulations between local governments may also lead to a ‘race to the bottom’, weaken the intensity of environmental regulations, and hinder agricultural carbon emission reduction (Li et al. 2021b; Madsen 2009; Yijing and Jue 2019). As such, what is the relationship between fiscal

decentralisation, environmental regulation, and agricultural carbon emissions? Does environmental regulation have the feature of ‘race to the bottom’ and will it weaken the impact of fiscal decentralisation on agricultural carbon emissions? We believe that the feature of ‘race to the bottom’ of environmental regulation may be an important factor restricting fiscal decentralisation to play its role. Therefore, it is necessary to put fiscal decentralisation and environmental regulation into the same analytical framework to study. Simultaneously, the essence of agricultural carbon emission reduction is to coordinate the relationship between agricultural carbon emission and agricultural economic development. Therefore, this study chooses an index that can comprehensively reflect agricultural economic growth and agricultural carbon emissions, namely agricultural carbon intensity. Based on the spatial spillover effect, this paper discusses the influence mechanism of fiscal decentralisation and environmental regulation on agricultural carbon intensity, hoping to provide reference policy suggestions for optimising fiscal decentralisation system and coordinating the development of agricultural economy and agricultural carbon emission reduction.

At present, the literature on the impact of fiscal decentralisation on agricultural carbon intensity in the Chinese context is very limited, and its mechanism of action has not been investigated in depth. The issue of how fiscal decentralisation affects environmental regulation is still controversial and needs to be confirmed by further discussion. To this end, this study proposes a theoretical hypothesis on the effect of fiscal decentralisation on agricultural carbon intensity in the context of China, based on previous studies on fiscal decentralisation. This study has three major contributions to the literature. The first contribution is that fiscal decentralisation, environmental regulation, and agricultural carbon intensity are all included in the same analytical framework. Therefore, the conclusion of this study is helpful to better clarify the internal mechanism of fiscal decentralisation, environmental regulation, and agricultural carbon intensity. So far, no literature has studied their relationship in China in this context. The second contribution is that most scholars have studied fiscal decentralisation, or investigated its impact on agricultural economic growth, or discussed its relationship with agricultural carbon emissions. Few scholars have discussed both agricultural economy and agricultural carbon emissions. The third contribution is that this study uses the spatial Durbin model (SDM) to study the relationship between fiscal decentralisation, environmental regulation, and agricultural carbon intensity, which ensures the accuracy of the estimation results. Another characteristic is that this study takes 2000 as the base year and spans 20 years, which can better understand the spatio-temporal evolution characteristics of fiscal decentralisation, environmental regulation, and agricultural carbon intensity in China.

The rest of the article is set as follows. ‘[Literature review](#)’ section briefly introduces literature synthesis. ‘[Research hypothesis](#)’ section is the research hypothesis of this paper. The fourth section calculates the agricultural carbon intensity of China and briefly explains the estimation methods and data used in this study. ‘[Results and discussion](#)’ section presents empirical results and discussion. ‘[Conclusions, policy implications, and research prospects](#)’ section provides conclusions and relevant policy recommendations and proposes the paper’s inadequacies and future research directions.

Literature review

Currently, there is no systematic study on the relationship between Chinese fiscal decentralisation and agricultural carbon intensity. However, from the analysis of its mechanism, the influence path of fiscal decentralisation on agricultural carbon intensity is mainly that it affects agricultural economic development first, followed by agricultural carbon emissions and agricultural carbon intensity. In the study of fiscal decentralisation and agricultural economic development, most scholars believe that fiscal decentralisation can promote agricultural economic growth (Chau and Zhang 2011; Han 2009). On the one hand, fiscal decentralisation can provide local governments with more financial control and authority, which gives local governments more independent decision-making power and greatly improves the efficiency of resource allocation and thus promotes economic growth (Lin and Liu 2000). On the other hand, as economic growth is linked to promotion incentives of local officials, local governments tend to establish a good business environment and promote economic growth to enhance the attraction and competitiveness of the local capital market (Guo 2009; Xun 2012). In rural China, most public goods are provided by the government. Fiscal decentralisation enables local governments to better provide public goods and services to promote the development of agriculture (Da-yi 2009). In addition, fiscal decentralisation has a positive impact on agricultural production, financial support for agriculture, and rural compulsory education (Ba 2011; Rishipal and Sheoran 2013; Salqaura et al. 2019).

Studies on agricultural economic development and agricultural carbon emissions have been very mature, and most of them believe that agricultural economic growth must be accompanied by an increase in agricultural carbon emissions. Xiong et al. (2020) found that agricultural mechanisation level, agricultural structure, and agricultural economic development capacity are important factors to improve agricultural carbon emissions by referring to the Kaya formula and combining with the actual situation of

agricultural carbon emissions. Chen and Li (2020) and Cui et al. (2018) found that agricultural added value, proportion of agricultural labour force, and per capita arable land have a positive impact on agricultural carbon emissions. In addition, agricultural energy use, fertiliser application, sown area, and available water are positively correlated with agricultural carbon emissions (Chen et al. 2018; Li and Zhang 2021; Rehman et al. 2021b; Rehman et al. 2019). It can be observed that agricultural economic growth will indeed increase agricultural carbon emissions correspondingly, and relevant literature has been abundant.

From the analysis of the mechanism of environmental regulation and agricultural carbon intensity, the impact of environmental regulation on agricultural carbon emissions is mainly realised through the agricultural economy and agricultural carbon emissions. There are three viewpoints on the relationship between environmental regulation and the agricultural economy. The first view supports the ‘Porter hypothesis’. It believes that reasonable environmental regulation can promote enterprises to carry out more innovative activities, thus both improving output and protecting the environment (Cohen and Tubb 2018; Weimin et al. 2021). The second view is that the ‘Porter hypothesis’ is not necessarily valid and believes that environmental regulation will inhibit the growth of the agricultural economy (Inkábová et al. 2021; Managi 2004). The third view holds that the impact of environmental regulation on the agricultural economy is uncertain due to regional differences, industrial types, and environmental regulation quality (Feix et al. 2008; Kriechele and Ziesemer 2009; Song et al. 2021; Tovey 2017). This study believes that the overall impact of environmental regulation on China’s agricultural economy may be relatively consistent with the second view. This is owing to the low level of agricultural technological innovation in China at this stage, and the intensity of agricultural research and development (R&D) investment is much lower than that of the USA and other high-income Asian countries (Chai et al. 2019; Chen 2017; Li and Zheng 2018). Moreover, agriculture itself has the characteristics of a long production cycle, slow return, high capital pressure, and weak anti-risk ability, which makes the impact of environmental regulations on the agricultural sector inhibit the growth of the agricultural economy. In the research on environmental regulations and agricultural carbon emissions, most scholars believe that environmental regulations can reduce agricultural carbon emissions. This is mainly manifested in that environmental regulations can effectively alleviate agricultural pollutant emissions, thereby achieving the goal of reducing agricultural carbon emissions. Hansen et al. (2019) pointed out that environmental regulations have significantly improved the environmental conditions of groundwater in Denmark. Li et al. (2021a) found that environmental regulations have a significant direct positive effect on plastic film recycling.

Essentially, the literature supporting environmental regulation can reduce agricultural carbon emissions is far from this (Hai-rong 2010; Li et al. 2019; Yoder 2019).

By reviewing the literature, it can be found that although scholars have paid attention to the impact of fiscal decentralisation on agricultural carbon intensity, as well as the relationship between environmental regulation and agricultural carbon intensity. However, there is no systematic study on how fiscal decentralisation affects the carbon intensity of agriculture by affecting environmental regulation.

Research hypothesis

Fiscal decentralisation and agricultural carbon intensity

Agricultural carbon intensity is an important index used to balance agricultural economic growth and agricultural carbon emissions. According to the formula of agricultural carbon intensity, the higher the agricultural economic level, the lower the agricultural carbon intensity, the more agricultural carbon emissions, the higher the agricultural carbon intensity. Then, is the impact of the Chinese-style fiscal decentralisation on agricultural carbon intensity ‘inhibiting’ or ‘promoting’? This study considers that the impact of fiscal decentralisation in China on agricultural carbon intensity is ‘inhibiting’. Based on the decoupling theory of carbon emissions and the perspective of agricultural technological progress, the relationship between agricultural economic growth and agricultural carbon emissions will gradually weaken or even disappear, and the driving effect of agricultural economic growth on agricultural carbon emissions will gradually weaken (Fang and Liu 2019; Liu et al. 2021; Zhou and Hu 2020). Accordingly, the following hypothesis is proposed in this study:

H1. The enhancement of fiscal decentralisation will reduce agricultural carbon intensity.

Environmental regulation and agricultural carbon intensity

This study believes that the impact of environmental regulation on China’s agricultural carbon emissions may have the phenomenon of ‘free-riding’ and ‘mutual imitation’. Although environmental regulation is an important means to solve market failures, China’s pollution control system is mainly aimed at industrial and urban pollution (Zhang et al. 2004), and the effect of environmental regulation on agricultural carbon emission control is difficult to achieve. In particular, when the political assessment mechanism emphasises economic indicators and ignores agricultural carbon emissions, local governments will cover up agricultural carbon emissions for economic indicators,

causing adverse selection behaviour that is not conducive to agricultural carbon emissions reduction (Yuan and Zhu 2015). Simultaneously, because agricultural carbon emissions are composed of scattered, unclear, and non-single sources, and the effects of environmental regulations are typically non-exclusive, the phenomenon of ‘free-riding’ may become the norm. In the context of the political competition system and the pursuit of rapid economic development, ‘I emit, you govern’ has become the first choice of local governments, which makes environmental regulations ‘race to the bottom’ in agricultural carbon emission reduction. It can be observed that environmental regulations have a restraining effect on the growth of China’s agricultural economy and the degree of restraint on agricultural carbon emissions may be weakened due to the phenomenon of ‘race to the bottom’ and ‘free-riding’. Accordingly, this study puts forward the following hypothesis:

H2. Although environmental regulation will reduce agricultural carbon intensity, it does have a negative spatial spillover effect.

Fiscal decentralisation, environmental regulation, and agricultural carbon intensity

Incorporating fiscal decentralisation and environmental regulation into a unified framework to discuss their mechanism of agricultural carbon intensity is the focus of this research. The specific path is shown in Fig. 2.

Incorporating fiscal decentralisation and environmental regulation into a unified framework to discuss its research on the agricultural economy and agricultural carbon emissions is still relatively small. Most of the existing literature studies the effects of Chinese-style fiscal decentralisation on the agricultural economy or agricultural carbon emissions and consider environmental regulations as one of the influencing factors. Due to the different preference structures of local governments and the central government, local governments are out of self-interested considerations, making local governments ‘race to the bottom’ and undertake ‘mutual imitation’ in the process of formulating and implementing environmental policies (Woods 2020), which weakens fiscal distribution. The impact of rights on agricultural carbon intensity triggers the ‘green paradox’ effect (Sinn 2008). Accordingly, this study puts forward the following hypothesis:

H3. Under the influence of fiscal decentralisation, environmental regulation is not conducive to reducing the agricultural carbon intensity due to the characteristics of ‘race to the bottom’, causing the ‘green paradox’ effect.

Research methods and data

Measurement of agricultural carbon emissions and carbon intensity

Measurement of agricultural carbon emissions

This research considers general agriculture (agriculture, forestry, animal husbandry, and fishery) as the study object. Simultaneously, as China does not have statistical data on agricultural carbon emissions, this study estimates China's agricultural carbon emissions. There are many and complex sources of agricultural carbon emissions, but according to previous literature, the sources of agricultural carbon emissions mainly include the following four types. The first is agricultural input, which mainly includes raw coal, gasoline, diesel, electricity, pesticides, fertilisers, and agricultural film. The second type is methane emissions caused by rice planting. The third type is methane and nitrous oxide emissions caused by livestock production, mainly including methane emissions from animal intestinal fermentation and methane and nitrous oxide emissions from animal manure. The fourth type is nitrous oxide released from the soil during crop planting. According to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), the greenhouse effect caused by one ton of methane is equivalent to 6.8182 tons of C, and the greenhouse effect caused by one ton of nitrous oxide is equivalent to 81.2727 tons of C (Pachauri et al. 2014). At the same time, this study draws on the following agricultural carbon emission equations proposed by Tian et al. (2014), Huang et al. (2019), and Zhang et al. (2019b):

$$CO_2 = \sum_{i=1}^n CO_{2,i} = \sum_{i=1}^n C \times \beta_i \times \frac{44}{12} \quad (1)$$

where CO_2 is the agricultural carbon dioxide emissions, $CO_{2,i}$ is the carbon dioxide emissions of the i -th type of carbon source, C is the agricultural carbon emissions, and β_i is the emission coefficient of the i -th type of carbon source. This study refers to the carbon emission coefficients of previous studies (Duan et al. 2011; Eggleston et al. 2006; Luo et al. 2017; Ma et al. 2019; Zhen-qin 2015).

Measurement of agricultural carbon intensity

An effective method to achieve low-carbon development in China's agriculture is by reducing agricultural carbon intensity. Therefore, this study draws on the practice of Zhou et al. (2019) and Zhang et al. (2019a) to define agricultural carbon intensity as:

$$ACI = CO_2 / AV \quad (2)$$

where ACI represents agricultural carbon intensity, which is also the dependent variable of this study, CO_2 is the agricultural carbon dioxide emissions calculated according to formula (1), and AV represents the added value of the primary industry.

Variables and data

Independent variable: fiscal decentralisation (FD)

There are many ways to measure fiscal decentralisation, but this study mainly focuses on the impact of local government fiscal autonomy on agricultural carbon emissions. Therefore, this study draws on the research of Jin et al. (2005) and Chen and Chang (2020) and uses the ratio of provincial per capita fiscal expenditure to that of the central government to measure the degree of fiscal decentralisation. In addition, through literature analysis, it can be observed that fiscal decentralisation will affect the agricultural development in the region by affecting the structure of fiscal expenditure (Gudeta et al. 2021; Hong and Viet 2016). This is also the main reason why this study chooses the ratio of the provincial per capita fiscal expenditure to the central level per capita fiscal expenditure to measure the degree of fiscal decentralisation.

Independent variable: environmental regulation (ER)

Environmental regulation is divided into cooperative, persuasive, regulatory, and economical categories (Böcher 2012). As economical regulation can more effectively achieve the internalisation of external costs, this study chooses economical regulation as the category of environmental regulation. In addition, the purpose of this research is to reflect the environmental protection awareness and efforts of local governments at the level of environmental regulation. Therefore, based on the availability of data and referring to the practice of Wang et al. (2010) and Zhang et al. (2019c), economic environmental regulation is further focused on investment in environmental pollution control, and the ratio of investment in environmental pollution control to gross domestic product (GDP) is used to represent environmental regulation.

Control variable

To find suitable control variables, this study refers to the IPAT and STIRPAT models. These two models are proposed to study the effects of various factors on driving carbon dioxide emissions (Liu and Song 2020; Wen and Li 2019; Zheng et al. 2020). The IPAT model is a well-known model used to evaluate environmental pressure. It considers population, affluence, and technology as three factors that affect environmental quality. The STIRPAT model is an

extension of the IPAT model, which allows population, wealth, and technology to be decomposed, and allows the introduction of other factors that may affect the environment. Therefore, according to the IPAT and STIRPAT models, the control variables are divided into the population, affluence, technology, and other factors. Population variables are represented by urbanisation rate and rural population density. As rural population density increases, intensive farming gradually replaces extensive production, which may reduce agricultural carbon emissions (Rehman et al. 2021a; Xiong et al. 2020). The acceleration of urbanisation will cause rural labour to transfer to cities, and the large loss of rural labour may cause the replacement of labour by fossil energy and increase agricultural carbon emissions (Zhang et al. 2017). Select industrial structure and per capita GDP to represent economic indicators. Large agricultural provinces and economically developed provinces may have a large amount of agricultural technology research and development capital and may have higher production efficiency and lower agricultural carbon intensity (Yang et al. 2022). The technical indicators are measured by the proportion of R&D investment in regional GDP. The improvement of technology level will bring higher production efficiency and reduce agricultural carbon emissions (Ismael et al. 2018). In addition, Lin and Chen (2020) found that transportation infrastructure has an important impact on energy and environmental efficiency, which in turn affects carbon dioxide emissions. Therefore, road traffic infrastructure is selected as one of the control variables of this study. The specific meanings, symbols, and measured values of these variables are shown in Table 1.

Samples and data sources

In this study, 30 provinces in Mainland China (excluding Tibet, Hong Kong, Macau, and Taiwan) from 2000

to 2019 were selected as the survey samples. The data for this study is from the ‘China Statistical Yearbook’, ‘China Environmental Statistics Yearbook’, ‘China Energy Statistics Yearbook’, ‘China Rural Statistics Yearbook’, ‘Provincial Statistical Yearbooks’, and ‘China Science and Technology Statistical Yearbooks’. To avoid heteroscedasticity, the index has been processed logarithmically. Due to inflation, the indicators related to the price index were adjusted to constant prices in 2000. The descriptive statistics of the variables involved in this study are shown in (Tables 2, 3, 4, 5, 6, 7, 8, and 9)

Measurement of spatial autocorrelation of agricultural carbon intensity

Spatial autocorrelation refers to the potential interdependence between observation data of some variables in the same distribution area and is a measure of the degree of aggregation of spatial unit attribute values. Global spatial autocorrelation is mainly the overall distribution characteristic of the same

Table 2 Descriptive statistics for the variables

Variables	N	Minimum	Maximum	Mean	Std. deviation
<i>ACI</i>	600	0.751	29.94	3.951	3.131
<i>FD</i>	600	1.087	14.830	5.058	3.023
<i>ER</i>	600	0.300	4.240	1.287	0.672
<i>UR</i>	600	23.300	89.600	51.197	15.184
<i>IS</i>	600	0.300	37.911	12.063	6.586
<i>TI</i>	600	0.012	2.299	0.199	0.368
<i>RTI</i>	600	0.106	9.966	1.442	1.677
<i>RPD</i>	600	0.926	34.833	6.403	3.963
<i>PGDP</i>	600	2661.557	164,222.000	34,730.800	27,477.050

Table 1 Definition of all relevant variables used in the study

Symbol	Variables	Definition	Unit of measurement
Explained variable			
<i>ACI</i>	Agricultural carbon intensity	Agricultural CO ₂ emissions/value-added of primary industry	Ton/10 thousand Yuan
Explanatory variable			
<i>FD</i>	Fiscal decentralisation	Provincial per capita fiscal expenditure/central level per capita fiscal expenditure	-
<i>ER</i>	Environmental regulation	Environmental pollution control investment/GDP	%
Control variable			
<i>UR</i>	Urbanisation rate	Proportion of provincial urban population in the total population	%
<i>IS</i>	Industrial structure	Value-added of primary industry/GDP	%
<i>TI</i>	Technique level	Technology R&D investment/GDP	%
<i>RTI</i>	Road traffic infrastructure	Road mileage per unit area in each province	Kilometre/square kilometre
<i>RPD</i>	Rural population density	Rural permanent population/cultivated area	Person/hectare
<i>PGDP</i>	Per capita GDP	GDP/total population	Yuan

Table 3 Global Moran's index of agricultural carbon intensity in China from 2000 to 2019

Year	Moran's index	Z-statistics	p-value	Year	Moran's index	Z-statistics	p-value
2000	0.096	2.303	0.011	2010	0.093	1.819	0.034
2001	0.097	2.179	0.015	2011	0.109	2.025	0.021
2002	0.102	2.300	0.011	2012	0.095	1.766	0.039
2003	0.098	2.361	0.009	2013	0.082	1.490	0.068
2004	0.104	2.232	0.013	2014	0.100	1.685	0.046
2005	0.101	2.029	0.021	2015	0.070	1.311	0.095
2006	0.125	2.344	0.010	2016	0.074	1.348	0.089
2007	0.109	2.126	0.017	2017	0.070	1.214	0.112
2008	0.107	2.027	0.021	2018	0.037	0.813	0.208
2009	0.118	2.345	0.010	2019	0.034	0.754	0.225

Table 4 LM test, Wald test, Hausman test, and LR test results

Test		
LM-LAG	510.03	***
Robust LM-LAG	23.59	***
LM-ERR	808.84	***
Robust LM-ERR	322.40	***
Wald-SAR	67.60	***
Wald-SEM	66.00	***
LR-SAR	64.01	***
LR-SEM	63.67	***
Hausman	375.70	***
LR-IND	47.86	**
LR-TIME	652.59	***

*** indicates that the estimated coefficients passed the Z-test at the 1% levels of significance

attribute spatial correlation degree, while local spatial autocorrelation is the individual distribution characteristic of the same attribute spatial correlation degree.

Setting of the spatial weight matrix

Choosing an appropriate weight matrix to reflect the strength of the observed geographic relationship is crucial to the spatial analysis of this research (Feng et al. 2019). Current research generally selects from spatial weight matrices, such as adjacency matrix, economic distance matrix, and geographic distance matrix. In addition to choosing the adjacency matrix ($W3$) and the geographical distance weight matrix ($W2$), this paper also draws on the practice of Earnest et al. (2007) and Liu and Dong (2019) to construct a spatial weight matrix ($W1$) based on the gravity model. This type of spatial weight distance matrix takes into account the basic economic conditions of both parties themselves, and better reflects the law that the role of economic and geographic factors in variables decreases continuously with spatial distance. The formula is as follows:

$$W_{ij} = \begin{cases} \frac{\bar{Q}_i \times \bar{Q}_j}{d_{ij}^2} & i \neq j \\ 0 & i = j \end{cases} \quad (3)$$

where W_{ij} is a spatial weight matrix constructed based on the gravity model; \bar{Q}_i and \bar{Q}_j represent the average per capita GDP of province i and province j from 2000 to 2019, respectively; and d_{ij} is the distance between province i and province j . The geographic spherical distance is calculated according to the latitude and longitude coordinates of the capital cities of the two provinces.

Global spatial autocorrelation

Agricultural carbon intensity may be spatially dependent on the carbon intensity of the surrounding area. The value range of the global Moran index is $[-1, 1]$. When the range is between 0 and 1, it indicates that similar attributes converge together. When the Moran index is closer to 1, it means that the positive correlation of space is becoming increasingly stronger. A range of -1 to 0 indicates that different attributes

Table 5 SDM estimation and test results

Variable	SDM-W ₁			SDM-W ₂			SDM-W ₃		
	<i>FD</i>	-1.148	(-12.93)	***	-1.190	(-13.23)	***	-1.252	(-14.80)
<i>ER</i>	-1.281	(-6.16)	***	-1.339	(-6.49)	***	-1.448	(-6.91)	***
<i>FD*ER</i>	0.153	(5.29)	***	0.161	(5.60)	***	0.194	(6.79)	***
<i>UR</i>	-0.125	(-4.89)	***	-0.118	(-4.63)	***	-0.170	(-7.16)	***
<i>IS</i>	-0.204	(-6.48)	***	-0.213	(-6.85)	***	-0.159	(-5.45)	***
<i>TI</i>	-1.565	(-2.09)	**	-1.608	(-2.15)	**	-1.617	(-2.25)	**
<i>RTI</i>	-0.200	(-2.84)	**	-0.233	(-3.28)	***	-0.292	(-4.32)	***
<i>RPD</i>	-0.045	(-1.82)	*	-0.036	(-1.42)		-0.049	(-1.98)	**
<i>lnPGDP</i>	-0.461	(-0.85)		-0.392	(-0.72)		0.428	(0.82)	
<i>W*FD</i>	0.300	(0.87)		-0.015	(-0.05)		-0.303	(-1.45)	
<i>W*ER</i>	3.000	(4.44)	***	1.882	(2.63)	***	0.476	(1.64)	*
<i>W*FD*ER</i>	-0.301	(-3.26)	***	-0.161	(-1.69)	*	-0.048	(-1.03)	
<i>W*UR</i>	0.113	(1.55)		0.201	(2.80)	***	0.237	(4.73)	***
<i>W*IS</i>	0.218	(3.01)	***	0.229	(3.30)	***	0.329	(5.35)	***
<i>W*TI</i>	0.064	(0.05)		-1.278	(-0.85)		-2.435	(-1.57)	
<i>W*RTI</i>	0.627	(2.91)	***	0.335	(2.05)	**	0.458	(3.22)	***
<i>W*RPD</i>	0.494	(4.62)	***	0.403	(4.93)	***	0.222	(4.09)	***
<i>W*lnPGDP</i>	-0.813	(-0.65)		-0.734	(-0.62)		-2.209	(-2.26)	**
ρ	-0.085	(-1.04)		-0.055	(-0.82)		-0.172	(-2.74)	***
R^2	0.7839			0.7936			0.7962		
<i>Log-likelihood</i>	-853.5854			-853.4154			-827.6772		
<i>Observations</i>	600			600			600		

*, **, and *** indicate that the estimated coefficients passed the Z-test at the 10%, 5%, and 1% levels of significance, respectively

Table 6 Direct effect, indirect effect, and total effect of factors affecting agricultural carbon emissions

Variable	Direct effect			Indirect effect			Total effect		
	<i>FD</i>	-1.246	(-14.45)	***	-0.072	(-0.41)		-1.318	(-6.55)
<i>ER</i>	-1.479	(-7.34)	***	0.648	(2.67)	***	-0.832	(-2.56)	**
<i>FD*ER</i>	0.199	(7.06)	***	-0.072	(-1.76)	*	0.127	(2.45)	**
<i>UR</i>	-0.180	(-7.64)	***	0.238	(5.48)	***	0.058	(1.36)	
<i>IS</i>	-0.171	(-6.17)	***	0.317	(6.14)	***	0.146	(2.32)	**
<i>TI</i>	-1.536	(-2.20)	**	-1.916	(-1.37)		-3.452	(-2.29)	**
<i>RTI</i>	-0.313	(-4.47)	***	0.453	(3.50)	***	0.140	(0.94)	
<i>RPD</i>	-0.059	(-2.60)	***	0.212	(4.30)	***	0.153	(2.67)	***
<i>LnPGDP</i>	0.551	(1.09)		-2.090	(-2.38)	**	-1.538	(-1.71)	*

*, **, and *** indicate that the estimated coefficients passed the Z-test at the 10%, 5%, and 1% levels of significance, respectively

come together and when the Moran index is closer to -1, the stronger the negative correlation becomes. The closer the Moran index is to 0, the weaker the spatial correlation is. The formula of the global Moran index is as follows:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \times \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (aci_i - \bar{aci})(aci_j - \bar{aci})}{\sum_{i=1}^n (aci_i - \bar{aci})^2} \tag{4}$$

where *I* is the global Moran index, *n* is the number of observations, *w_{ij}* is the spatial weight matrix of positions *i* and *j*, *aci_i* and *aci_j* are the observations of *i* and *j* respectively, and *aci* is the observation of *aci* average value.

Local spatial autocorrelation

To further analyse the spatial heterogeneity of agricultural carbon intensity in various provinces of China, this study

Table 7 Empirical results at the level of region

Main grain producing areas								
Variable	Direct effect			Indirect effect			Total effect	
	<i>FD</i>	-0.104	(-1.19)		-0.138	(-1.16)		-0.242
<i>ER</i>	-0.713	(-5.27)	***	-0.018	(-0.10)		-0.731	(-3.98) ***
<i>FD*ER</i>	0.075	(3.43)	***	0.057	(1.85)	*	0.132	(4.14) ***
Control variable	Yes			Yes			Yes	
Non-main grain producing areas								
<i>FD</i>	-0.787	(-9.20)	***	-0.607	(-4.38)	***	-1.394	(-9.53) ***
<i>ER</i>	-0.947	(-4.73)	***	-0.401	(-1.19)		-1.348	(-3.34) ***
<i>FD*ER</i>	0.116	(4.31)	***	0.059	(1.46)		0.175	(3.51) ***
Control variable	Yes			Yes			Yes	

* and *** indicate that the estimated coefficients passed the Z-test at the 10% and 1% levels of significance, respectively

Table 8 Robustness test for substitution moderating variables

Variable	Direct effect			Indirect effect			Total effect	
<i>FD</i>	-0.767	(-12.35)	***	-0.331	(-3.00)	***	-1.098	(-9.80) ***
<i>ER(I)</i>	-1.213	(-3.66)	***	3.560	(5.60)	***	2.347	(3.48) ***
<i>FD*ER(I)</i>	0.404	(6.85)	***	-0.527	(-4.19)	***	-0.123	(-0.92)
Control variable	Yes			Yes			Yes	

*** indicates that the estimated coefficients passed the Z-test at the 1% levels of significance, respectively

uses local spatial autocorrelation to reflect the correlation between agricultural carbon intensity and the agricultural carbon intensity of the neighbouring provinces. The formula for the local Moran index is as follows:

$$I_i = \frac{n(ac_i - \overline{aci})}{\sum_{i=1}^n (ac_i - \overline{aci})^2} \sum_{j=1, j \neq i}^n W_{ij}(ac_j - \overline{aci}) \quad (5)$$

where I_i is the local Moran index and the remaining symbols are the same as formula (3). If I_i is greater than 0, then province i and the surrounding provinces enjoy spatial clustering and have similar agricultural carbon intensity. If I_i is less than 0, there is a significant difference in the agricultural carbon intensity of province i and surrounding provinces. The Moran scatter plot can show the local spatial autocorrelation between the provinces.

Spatial econometric model

Based on the IPAT and STIRPAT models and the variables identified in ‘Measurement of agricultural carbon emissions and carbon intensity’ and ‘Variables and data’ sections, the basic econometric model constructed is as follows:

$$ACI = \alpha_0 + \alpha_1 FD + \alpha_2 ER + \alpha_3 FD \times ER + \alpha_4 UR + \alpha_5 IS + \alpha_6 TI + \alpha_7 RTI + \alpha_8 RPD + \alpha_9 \ln PGDP + \varepsilon \quad (6)$$

where α_0 is the intercept, $\alpha_i (i=1, 2, \dots, 8, 9)$ is the coefficient of the variable, and ε is the random error term.

The spatial econometric model is a theoretical model that studies the influence of spatial geographic distribution on economic activities and is the development and extension of econometrics. In terms of research and analysis, as variables have different relationships or structures due to different geographic locations, the use of traditional panel regression models often fails to obtain scientific results. Therefore, it is necessary to introduce spatial econometric models to be more in line with the actual situation (Anselin 1988). Currently, the common spatial measurement models mainly include the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). SLM takes the spatial lag of the dependent variable as the independent variable, while SEM introduces the spatial lag of the error term as the independent variable. SDM introduces the spatial lag term of the dependent variable and the spatial lag term of the error as independent variables at the same time. The SDM formula of this study is as follows:

Table 9 2SLS estimation of instrumental variable

Variable	OLS	Instrumental variable method	
<i>FD</i>	-0.875 (-9.59) ***	-0.796 (-3.19) ***	-12.89 (-12.89) ***
<i>ER</i>	-1.091 (-4.85) ***	-3.261 (-4.53) ***	-5.79 (-5.79) ***
<i>FD*ER</i>	0.125 (3.90) ***	0.502 (4.47) ***	5.04 (5.04) ***
<i>Control variable</i>	Yes	Yes	Yes
<i>Fixed province</i>	Yes	Yes	Yes
<i>Fixed time</i>	No	Yes	Yes
<i>Kleibergen-Paap rk LM statistic</i>		34.265 ***	
<i>Kleibergen-Paap rk Wald F statistic</i>		52.385 [16.38]	

*** indicates that the estimated coefficients passed the Z-test at the 1% levels of significance, respectively; the values in curly bracket are the critical value at the 10% level of the Stock-Yogo weak identification test

$$\begin{aligned}
 ACI_{it} = & \alpha_0 + \alpha_1 FD_{it} + \alpha_2 ER_{it} + \alpha_3 FD_{it} \times ER_{it} \\
 & + \alpha_4 UR_{it} + \alpha_5 IS_{it} + \alpha_6 TI_{it} \\
 & + \alpha_7 RTI_{it} \\
 & + \alpha_8 RPD_{it} + \alpha_9 \ln PGDP_{it} \\
 & + \rho WACI_{it} + \beta_1 WFD_{it} + \beta_2 WER_{it} + \beta_3 WFD_{it} \times ER_{it} \\
 & + \beta_4 WUR_{it} + \beta_5 WIS_{it} \\
 & + \beta_6 WTI_{it} + \beta_7 WRTI_{it} + \beta_8 WRPD_{it} + \alpha_9 W \ln PGDP_{it} \\
 & + \varepsilon_{it}; \varepsilon_{it} = \rho w_{it} \varepsilon_i + \gamma_{it}
 \end{aligned}
 \tag{7}$$

where *i* is the *i*-th province, with *i* = 1, 2, ..., 30; *t* is the year (from 2000 to 2019); *W* is the spatial weight matrix; ρ and α are the coefficients of the spatial lag term of the dependent variable and the independent variable, respectively; γ_{it} is the random error term; and the remaining variables and symbols are consistent with the previous one.

Results and discussion

Evolution of the temporal and spatial patterns of China’s agricultural carbon intensity, fiscal decentralisation, and environmental regulation

To visually analyse the temporal and spatial evolution of China’s agricultural carbon intensity, fiscal decentralisation, and environmental regulation, this study uses ArcGIS 10.2 to present the agricultural carbon intensity and fiscal distribution of 30 provinces in 2000, 2007, 2012, and 2019 (see Fig. 3). Table 10 provides the names of Chinese provinces and their corresponding abbreviations. To facilitate the comparison between different years, this study adopted a unified standard for the classification of agricultural carbon intensity, fiscal decentralisation, and environmental regulation based on the practice of Feng et al. (2019) and divided them into four grades. The darker the colour, the higher the grade, the higher the degree of agricultural carbon intensity, fiscal decentralisation, and environmental regulation.

According to the spatial distribution of agricultural carbon intensity in 4 years, the following conclusions can be drawn. First, from 2000 to 2019, China’s agricultural carbon intensity showed a downward trend. The agricultural carbon intensity in the north and northwest regions was relatively high, and the agricultural carbon intensity in the southern region was relatively low. Second, in 2000, except for some provinces in the east, the agricultural carbon intensity values of the remaining provinces were all greater than 6. This may be because the eastern region has advanced agricultural production technology and a developed economy, which ensures the growth of the agricultural economy while reducing carbon emissions. Third, in 2007, the agricultural carbon emissions

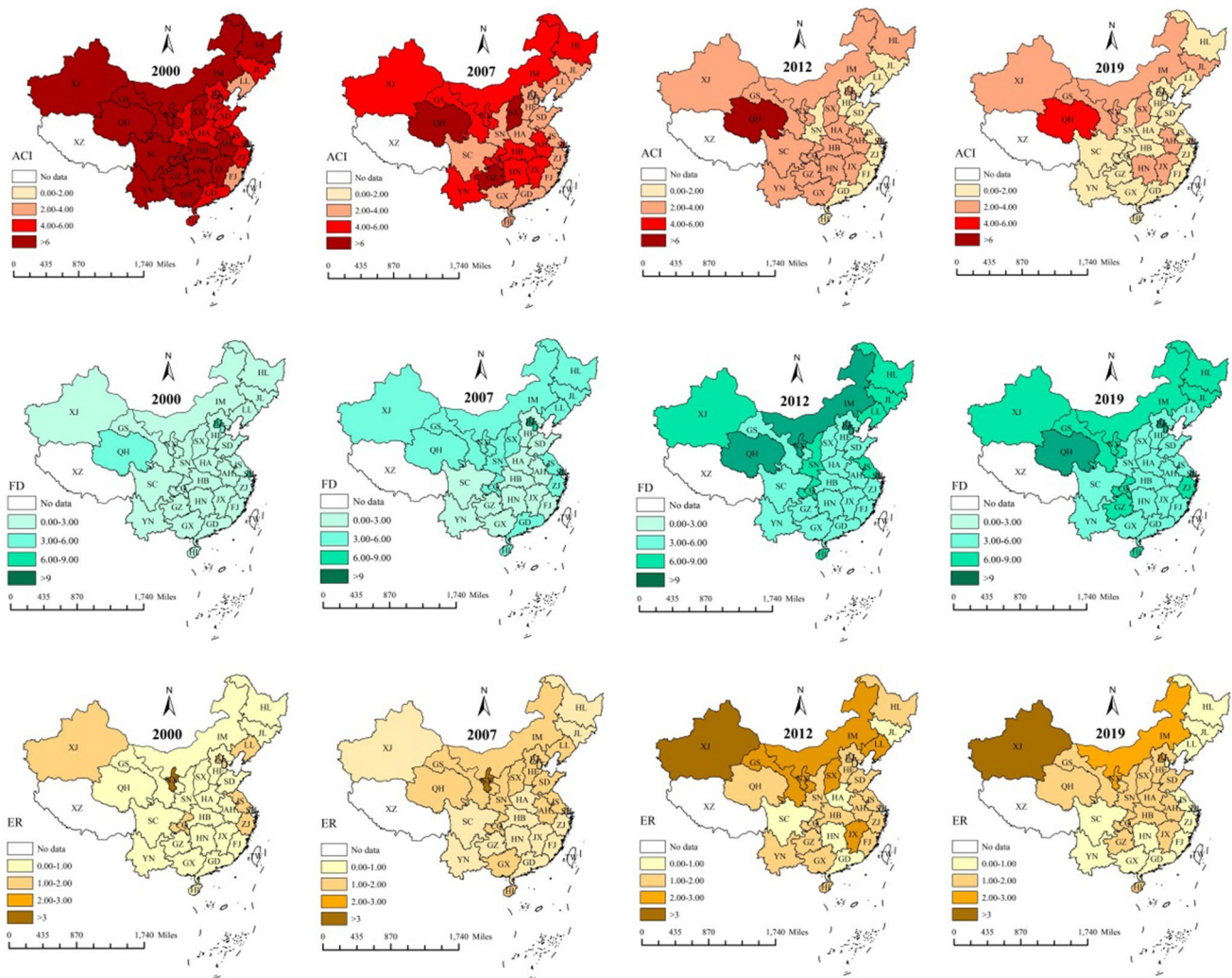


Fig. 3 Spatial distribution of agricultural carbon intensity, fiscal decentralisation, and environmental regulation in China

of Qinghai, Shanxi, and Guizhou provinces were greater than 6, and the provinces with the highest agricultural carbon emissions were mainly concentrated in the southwest and northwest regions. In 2012, only Qinghai Province had agricultural carbon emissions greater than 6, and the agricultural carbon emissions of the remaining provinces all fell below 4. Fourth, in 2019, the agricultural carbon emission value of Qinghai Province was the highest, between 4 and 6, and compared with 2012, the agricultural carbon emission value of the southwestern region dropped significantly.

According to the spatial distribution of fiscal decentralisation in 4 years, the following conclusions can be drawn. First, from 2000 to 2019, the degree of fiscal decentralisation in China gradually increased, and the degree of

fiscal decentralisation in the north and northwest regions is greater than that in the south. Second, high degrees of fiscal decentralisation in 2000 were in Beijing (China's political centre) and Shanghai (China's economic centre). Third, compared with 2000, the degree of fiscal decentralisation in 2007 and 2012 has significantly improved in the western region. This may be because China implemented the Western Development Strategy in 2000, which increased fiscal expenditures in the western region. Fourth, from 2012 to 2019, the degree of fiscal decentralisation in Inner Mongolia began to decline, and the degree of fiscal decentralisation in Qinghai, Beijing, Tianjin, and Shanghai was at a high level. The degree of decentralisation is greater in the south. This may be because the level of economic development in the north and northwest regions is still relatively low, and the infrastructure construction

and urbanisation process are still in a stage of rapid development, resulting in higher fiscal expenditures than in the south.

According to the spatial distribution of environmental regulation in 4 years, the following conclusions can be drawn. First, from 2000 to 2019, the intensity of China’s environmental regulation continued to increase, and some provinces such as Jiangsu, Zhejiang, and Fujian showed an upward and downward development trend. On the whole, the intensity of environmental regulation in inland areas was higher than that in coastal areas. Third, compared with 2000, the intensity of environmental regulation in 2007 and 2012 has greatly improved the intensity of environmental regulation in most provinces. This shows that China’s emphasis on environmental pollution is constantly increasing. Fourth, from 2012 to 2019, the intensity of environmental regulation in coastal areas first appeared at inflexion points. This may be because the technical level of coastal areas is higher than

that of inland areas, making the expected results brought by environmental regulation come early.

Spatial autocorrelation of China’s agricultural carbon intensity

During 2000–2019, based on the spatial weight matrix constructed by the gravity model, Stata16 software was used to calculate the global Moran index of agricultural carbon intensity. Table 3 shows that the global Moran index of China’s agricultural carbon intensity from 2000 to 2019 is positive and most of them are significant at the 10% level. Therefore, the distribution of China’s agricultural carbon intensity is positively autocorrelated in space and clustered in space rather than randomly being distributed. Therefore, when studying the factors influencing China’s agricultural carbon intensity, its spatial effects must be considered, which also shows that the

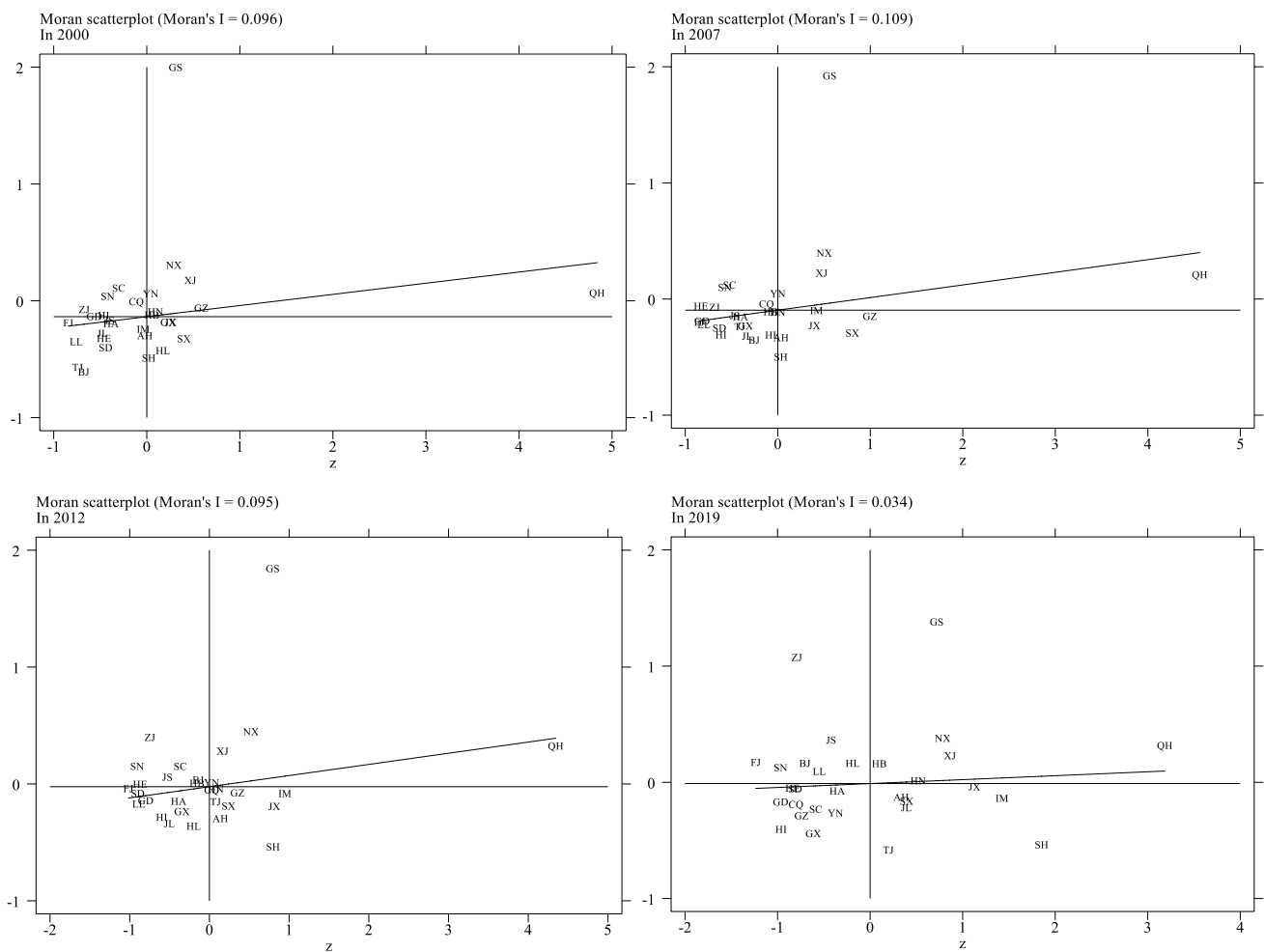


Fig. 4 Moran’s index scatter plots of agricultural carbon intensity in China for 2000, 2007, 2012, and 2019

choice of spatial econometric model in this study is correct. Simultaneously, the global Moran index of China's agricultural carbon intensity from 2000 to 2014 was in a stable state, between 0.082 and 0.125. For 2015–2019, the global Moran index of agricultural carbon intensity began to gradually decline and the spatial correlation began to weaken, indicating that China's agricultural carbon intensity tends to develop in a balanced manner.

To further analyse the spatial heterogeneity of agricultural carbon intensity in various provinces, this study chose to present Moran scatter plots for 2000, 2007, 2012, and 2019 (Fig. 4). In Fig. 4, the horizontal axis represents the standardised agricultural carbon intensity and the vertical axis represents the spatial lag value. The first quadrant represents the cluster of high values, the second quadrant represents the cluster of low values, the third quadrant represents the cluster of low values, and the fourth quadrant represents the cluster of high values surrounded by low values. Among them, provinces in the first and third quadrants accounted for 66.67% in 2000, up from 53.33% in 2019. This shows that the degree of spatial clustering of China's agricultural carbon intensity is decreasing. The reason is that Liaoning, Fujian, Beijing, Jiangsu, Tianjin, Inner Mongolia, Anhui, Jilin, and Heilongjiang have shifted from the first and third quadrants to the second or fourth quadrant.

Results for spatial panel regression

Spatial model selection

Choosing a specific spatial measurement model requires a series of tests. According to the principles proposed by Elhorst (2003), this study uses Stata16 software to first perform Lagrange multiplier (LM) tests (LM-LAG and LM-ERR) and their robustness tests (Robust LM-LAG and Robust LM-ERR) to examine whether non-spatial panel data models ignore the spatial effects of the data. The statistical results show (Table 4) that the LM-LAG, LM-ERR, Robust LM-LAG, and Robust LM-ERR tests all passed the significance test at the 1% level, which indicates that the SDM model can be introduced. To further test that the SDM model will not degenerate into the SLM model and SEM model, this article uses the Wald test ($p < 0.01$) and likelihood ratio (LR) test ($p < 0.01$) to pass the significance test under the conditions of the SDM model, which shows that SDM model will not degenerate into SLM model and SEM model. Simultaneously, the Hausman test ($p < 0.01$) found that the fixed-effects model is better than the random-effects model. Finally, through LR-IND ($p < 0.01$) and LR-TIME ($p < 0.01$), it is found that this study is suitable for the spatio-temporal double fixed-effect SDM model.

Results of spatial Durbin estimation

To ensure robustness, this study selected the spatial weight matrix (W1), geographic distance weight matrix (W2), and adjacency matrix (W3) based on the gravity model for regression analysis (Table 5). Based on three different weight matrices, the estimated coefficients are largely consistent in sign, size, and significance, which shows that the regression results are robust. Table 5 shows that from 2000 to 2019, agricultural carbon intensity was negatively correlated with fiscal decentralisation, environmental regulation urbanisation rate, industrial structure, technical level, road transportation infrastructure, and rural population density. It is positively correlated with the interaction terms of fiscal decentralisation and environmental regulation. Simultaneously, environmental regulation, industrial structure, road transportation infrastructure, and rural population density in neighbouring areas have a significant promoting effect on agricultural carbon intensity. The interaction terms of fiscal decentralisation and environmental regulation have a significant role in reducing agricultural carbon intensity. Due to the spatial lag term, the estimated coefficient of SDM cannot represent the marginal effect of the independent variable. On the contrary, it is necessary to decompose the spatial spillover effect of the independent variable's influence on agricultural carbon intensity, namely direct effect, indirect effect, and total effect.

Direct effects and spillover effects of influencing factors

R^2 of SDM- W_3 is 0.7962, which is higher than SDM- W_1 ($R^2 = 0.7839$) and SDM- W_2 ($R^2 = 0.7936$). Therefore, this study chose to present the direct effects and spillover effects of SDM- W_3 (Table 6). The direct effect means the influence of the province's factors, the indirect effect means the influence of the surrounding provinces, and the total effect is the sum of the two.

In terms of direct effects, the coefficient of fiscal decentralisation on agricultural carbon intensity is -1.246 , which has passed the significance test at the 1% level and is consistent with the results of the previous analysis. As such, the hypothesis 1 has been verified. The coefficient of environmental regulation on agricultural carbon intensity is -1.479 , which has passed the significance test at the 1% level and is consistent with the results of the previous analysis. As such, the first half of hypothesis 2 has been verified. The coefficient of interaction terms of fiscal decentralisation and environmental regulation on agricultural carbon intensity is 0.199 ($p < 0.01$), which indicated that fiscal decentralisation would weaken the inhibitory effect of environmental

regulation on agricultural carbon intensity. As such, the hypothesis 3 has been verified. The reason may be that the increase in the degree of fiscal decentralisation makes the local government more capable and motivated to intervene in the economic development and environmental governance of the region, especially when the performance appraisal mechanism emphasises economic development and ignores the rigid demand of the agricultural environment, the local government will appear. The self-interested fiscal expenditure preference of ‘emphasizing economy and ignoring governance’ has weakened the negative effect of environmental regulation on agricultural carbon emissions.

Among the control variables, the coefficient of the urbanisation rate to agricultural carbon intensity is -0.180 ($p < 0.01$). Urbanisation can reduce the agricultural carbon intensity. The reason may be that the higher the level of urbanisation, the more developed the economy, and the higher the level of agricultural science and technology, which is conducive to reducing agricultural carbon intensity. The coefficient of industrial structure on agricultural carbon intensity is -0.171 ($p < 0.01$). The higher the ratio of the added value of the primary industry to GDP, the better the agricultural production environment provided by the local government, and the more willing to use more resources for agricultural technology and environmental protection. The coefficient of technological level on agricultural carbon intensity is -1.536 ($p < 0.05$), and the influence coefficient was greater than all explanatory variables. Agricultural green production technology brought about by scientific and technological research and development has greatly reduced agricultural carbon emissions and improved agricultural production efficiency, thereby effectively reducing agricultural carbon intensity. The coefficient of road transportation infrastructure on agricultural carbon intensity is -0.313 ($p < 0.01$). The improvement of road traffic infrastructure is conducive to strengthening the connection and communication between rural areas and the outside world and is conducive to raising farmers’ awareness of environmental protection. The coefficient of rural population density to agricultural carbon intensity is -0.059 ($p < 0.01$). The higher the rural population density, the more they cherish their land, reduce the use of pesticides, fertilisers, and mulch, thereby reducing agricultural carbon intensity.

In terms of spillover effects, the coefficient of environmental regulation on the agricultural carbon intensity of the surrounding areas is 0.648 ($p < 0.01$), which is consistent with the previous analysis results, and the second half of hypothesis 2 has been verified. The coefficient of the interaction term of fiscal decentralisation and environmental regulation on the agricultural carbon

intensity of the surrounding areas is -0.072 ($p < 0.1$), and coefficient of fiscal decentralisation on agricultural carbon intensity in surrounding areas is not significant. The coefficient of urbanisation rate on the agricultural carbon intensity of surrounding areas is significantly positive. The higher the urbanisation, the stronger the siphon effect, which will make the rural labour force in the surrounding areas gather locally, and the large loss of rural labour force may cause the replacement of labour by fossil energy and increase the carbon emission of agriculture. Similarly, large agricultural provinces have obvious advantages in agricultural technology and capital, which makes the coefficient of industrial structure on the agricultural carbon intensity of surrounding areas significantly positive. The coefficient of road transportation infrastructure on the agricultural carbon intensity of surrounding areas is significantly positive. The higher the level of road transportation infrastructure, the more perfect the agricultural transportation system will be, and the agricultural resources in the surrounding areas will be concentrated locally, which is not conducive to the low-carbon development of agriculture in the surrounding areas. The coefficient of per capita GDP on agricultural carbon intensity in surrounding areas is significantly negative. This shows that the capital, technology, talents, and other elements flow and transfer in the economically developed areas to the surrounding areas, that is, there is an economic radiation effect.

Empirical results at the regional level

Due to China’s vast territory, there is a big gap in each region’s resource endowment, natural environment, and agricultural economic development. To compare whether there are differences in the impacts of fiscal decentralisation and environmental regulation on agricultural carbon intensity among regions, the samples are divided into major grain-producing areas and non-main grain producing areas for empirical analysis. Table 10 lists the specific provinces by region.

By comparing the empirical results in Table 7, we can see that the negative relationship between environmental regulation and agricultural carbon intensity still holds true in both main grain producing areas and non-main grain producing areas. However, the impact of non-main grain producing areas on agricultural carbon intensity is greater than that of main grain producing areas. The reason for this may be that the main grain producing areas are tasked with the task of stable and high-yield grain production, which makes local governments may tolerate the excessive use of chemical pesticides and fertilisers in agricultural production, thereby weakening the carbon emission reduction impact of environmental regulations.

Fiscal decentralisation in main grain producing areas has little effect on agricultural carbon intensity, while fiscal decentralisation in non-main grain producing areas can better reduce agricultural carbon intensity. Compared with non-main grain producing areas, the stability of grain output in main grain producing areas has a pivotal impact on China's food security, thus making fiscal decentralisation less binding on agricultural carbon emissions. In general, environmental regulation and fiscal decentralisation in main grain producing areas have less impact on agricultural carbon intensity than in non-main grain producing areas.

Robustness testing and endogenous test

Robustness testing

In order to ensure the reliability of the research conclusions, this paper replaces the measurement indicators of the moderating variables to re-estimate the model. Drawing on the practice of Du and Li (2020) and Cheng et al. (2018), this paper calculates the comprehensive index of environmental regulation ($ER(1)$) through industrial wastewater discharge, industrial SO_2 discharge, and industrial smoke and dust discharge. The specific calculation process includes three steps:

First, standardise the industrial wastewater discharge, industrial SO_2 discharge, and industrial soot discharge in each province, as shown in Eq. (8):

$$PE_{ij}^s = [PE_{ij} - \min(PE_j)] / [\max(PE_j) - \min(PE_j)] \quad (8)$$

where PE is the emission of pollutant j in province i , and PE_{ij}^s is the standardised result of the index. $\min(PE_j)$ represents the minimum value of the emission of the j -th pollutant in all provinces, and $\max(PE_j)$ represents the maximum of the j -th pollutant emission in all provinces.

Second, calculate the weights of various pollutants, as shown in Eq. (9):

$$W_j = PE / \overline{PE_{ij}} \quad (9)$$

where $\overline{PE_{ij}}$ represents the average level of emission of the j th pollutant in 30 provinces in each year.

Finally, the comprehensive index of environmental regulation of province i is shown in Eq. (10).

$$ER(1) = \frac{1}{3} \sum_{j=1}^3 W_j PE_{ij}^s \quad (10)$$

According to the estimation results in Table 8, among the direct effects, the estimated coefficient of fiscal decentralisation and environmental regulation on agricultural carbon intensity is significantly negative, and the estimated coefficient of the interaction term of fiscal decentralisation and environmental regulation on agricultural carbon intensity is significantly positive. Among the indirect effects, the estimated coefficient of fiscal decentralisation on agricultural carbon intensity is significantly negative, the estimated coefficient of environmental regulation on agricultural carbon intensity is significantly positive, and the estimated coefficient of the interaction term of fiscal decentralisation and environmental regulation on agricultural carbon intensity is significantly negative. This is basically consistent with the estimated coefficients in Table 6, indicating that both environmental regulations can support the research hypothesis of this paper. It is worth noting that among the total effects, the estimated coefficient of environmental regulation on agricultural carbon intensity is significantly positive, which is opposite to the estimated coefficient in Table 6. But this does not affect the reliability of the research conclusions.

Endogenous test

Although the benchmark regression results in Table 9 are the same as the direct effects in Table 6, both confirm that fiscal decentralisation and environmental regulation can reduce agricultural carbon intensity, but there may be endogeneity problems in the research conclusions. To this end, this paper uses the sales of commercial housing in each province as an instrumental variable and uses the two stage least squares (2SLS) method to alleviate this endogeneity problem (data from *China Real Estate Statistical Yearbook*). The reason for choosing the sales of commercial housing as an instrumental variable is that the real estate industry is the pillar industry of China's national economic development (Wu et al. 2020) and one of the main sources of tax revenue for local governments. The more prosperous the real estate industry in an area, the stronger the degree of fiscal decentralisation that represents that area. At the same time, the development of the real estate industry has no obvious direct impact on agriculture. To sum up, the sales of commercial housing are highly correlated with fiscal decentralisation, but not directly correlated with agricultural carbon intensity, which satisfies the selection conditions of instrumental variable. In the 2SLS estimation results using commercial housing sales as an instrumental variable, the effects of

fiscal decentralisation and environmental regulation on agricultural carbon intensity are still valid. At the same time, the p -value of Kleibergen-Paap rk LM statistic is less than 1%, and the Kleibergen-Paap rk Wald F statistic is greater than the critical value of Stock-Yogo weak identification test at the 10% level, indicating the rationality of selecting commercial housing sales as an instrumental variable.

Conclusions, policy implications, and research prospects

Conclusions

This study incorporated fiscal decentralisation, environmental regulation, and agricultural carbon intensity into the same analytical framework, constructed an SDM, and empirically investigated the internal relationship between fiscal decentralisation, environmental regulation, and agricultural carbon intensity in 30 provinces in Mainland China from 2000 to 2019. The results of this study are as follows.

- (1) From 2000 to 2019, the agricultural carbon intensity showed a downward trend and showed a spatial pattern of ‘high in the north and low in the south’. The degree of fiscal decentralisation has gradually increased, and the spatial pattern of ‘high in the north and low in the south’ has also emerged. The intensity of environmental regulation continues to increase, and the intensity of environmental regulation in inland areas is higher than that in coastal areas.
- (2) From 2000 to 2019, the global Moran index of agricultural carbon intensity showed a development trend of first rising and then falling, and the spatial correlation changed from strong to weak. Agricultural carbon intensity tends to develop from polarisation to balanced development.
- (3) Both fiscal decentralisation and environmental regulation can reduce agricultural carbon intensity, and environmental regulation has a negative spatial spillover effect.
- (4) Under the influence of fiscal decentralisation, environmental regulation is not conducive to reducing agricultural carbon intensity due to the characteristics of ‘race to the bottom’, causing the ‘green paradox’ effect.

Policy implications

Based on the above findings, this research proposes the following policy recommendations:

- (1) The central government should focus on optimising the fiscal decentralisation system and guide local governments’ fiscal expenditures to tilt toward low-carbon agricultural projects to minimise agricultural carbon emissions and improve agricultural economic levels.
- (2) The central government should appropriately improve its power over environmental management, maintain a certain degree of centralisation in agricultural carbon emission reduction, and develop a differentiated agricultural carbon emission management system to replace the traditional environmental regulation mode according to the characteristics of agricultural development in each province.
- (3) The central government should regulate the competition between local governments and optimise the examination system so that change is given priority considering economic development, increase carbon emissions proportion in the performance evaluation indicators, evaluation system, and optimise the existing official promotion incentives to adjust the expenditure structure of local government, both economic and environmental coordinated development.

Research deficiencies and prospects

This study quantitatively studies the nonlinear effects of fiscal decentralisation and environmental regulation on China’s agricultural carbon intensity. However, some limitations can inspire further research. To ensure the reliability of agricultural carbon emission accounting, the coefficient mainly refers to the carbon emission reference coefficient published by the Chinese government and widely cited documents. However, the coefficients below the provincial level are still uncertain, which affects the reliability of the results. In addition, agriculture is not only an important source of carbon emission but can also sequester carbon. In the future, carbon emissions and carbon absorption can be calculated more comprehensively, and more accurate carbon emissions data can be obtained. Finally, due to the obvious gaps in the agricultural development of different regions in a province, when the data of the city or county is obtained, the relationship between fiscal decentralisation, environmental regulation, and agricultural carbon intensity can be more accurate and explanatory.

Appendix

Table 10

Table 10 Chinese provincial names and corresponding abbreviations

Province							
Main grain producing areas	Anhui (AH)	Hebei (HE)	Henan (HA)	Heilongjiang (HL)	Hunan (HN)	Hubei (HB)	Jilin (JL)
	Jiangsu (JS)	Jiangxi (JX)	Liaoning (LN)	Inner Mongolia (IM)	Shandong (SD)	Sichuan (SC)	
Non-main grain producing areas	Shanxi (SX)	Guangxi (GX)	Chongqing (CQ)	Guizhou (GZ)	Yunnan (YN)	Shaanxi (SN)	Gansu (GS)
	Qinghai (QH)	Ningxia (NX)	Xinjiang (XJ)	Tibet (XZ)	Beijing (BJ)	Hainan (HI)	Fujian (FJ)
	Shanghai (SH)	Tianjin (TJ)	Zhejiang (ZJ)	Hong Kong (HK)	Guangdong (GD)	Taiwan (TW)	Macao (MO)

() is the abbreviation of the province

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Author contribution QH: conceptualization and methodology. XD: software and writing — original draft. CL: writing — review and editing and visualisation. ZY: writing — original draft and writing — review and editing. FK: data curation. YQ: supervision.

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Declarations

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