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Can income growth and environmental improvements go hand in hand? An empirical study of Chinese agriculture

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Abstract: Advancing agricultural carbon emission efficiency and farmers' income simultaneously is crucial for the sustainable progress of agriculture. Our study centered on 31 provinces and cities in China and investigated regional variances and the dynamic evolution aspects of coordinated development in farmers' income and agricultural carbon emission efficiency, utilising panel data from 2005 to 2021. The analysis revealed the following trends: Firstly, China's overall agricultural carbon emission efficiency was steadily increasing, mainly because of technological advancements. Secondly, the correlation between farmers' income and agricultural carbon emission efficiency in China had notably improved from 0.318 to 0.775. Throughout the observation period, disparities in the levels of coordinated development were observed in various provinces with a diminishing fluctuation, indicating regional disparities as the primary instigator. Thirdly, the level of coordinated development highlighted positive clustering attributes, demonstrating an 'east high, west low' pattern; the evolution of coordinated development levels exhibited stability in maintaining the current status. This study holds significant value for developing countries in enhancing farmers' income and agricultural carbon emission efficiency in a coordinated manner.

Keywords: agricultural carbon emission efficiency; farmers' income; coupling coordination degree; Super-Efficiency Slack-Based Measure Model

Climate change is a pressing global challenge in the 21st century. The increase in atmospheric greenhouse gas emissions has resulted in a 1.1 °C rise in global surface temperature during 2011–2020 compared to the period of 1850–1900 (IPCC 2023). These rising temperatures have caused serious problems that pose a threat to the human survival (Brown et al. 2007; Auffhammer 2018; Brown et al. 2023). Research revealed that carbon dioxide accounts for approximately 80% of the total emissions (Lashof and Ahuja 1990), and human activities are the primary cause of CO_2 emissions (Lamb et al. 2021). Particularly, global agricultural production and land use changes account for about 24% of total carbon emission. Therefore, agricultural carbon reduction (Norse 2012), reducing agricultural carbon emissions (ACE) and further increasing agricultural carbon emission efficiency (ACEE) are crucial for addressing climate change.

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China is a top emitting country in agricultural greenhouse gas (Huang et al. 2019). Limited *per capita* arable land and unstable land rights have encouraged people to invest in agricultural inputs to pursue agricultural income growth (Zhang et al. 2004; Hu et al. 2020), which further led to a significant amount of carbon emissions. In 2022, China's agriculture emitted 828 million tonnes of carbon dioxide equivalent. To reduce agricultural carbon emissions, China is supporting sustainable agricultural practices, including climate adaptive agriculture (Feng et al. 2023), facility agriculture (Liu and Xin 2023) and fertigation technology (Zheng et al. 2023). In theory, enhancing agricultural carbon emission efficiency entails decreasing conventional material inputs like fertilizers and promoting the adoption of innovative resources such as energy-efficient agricultural tools. While this could potentially result in reduced grain production and diminished farm incomes, the utilization of energy-saving materials signifies enhanced production efficiency, decreased labour input, and offers non-agricultural employment opportunities for farmers to augment their income. Therefore, studying the coordinated development of farmers' income (FI) and agricultural carbon emission efficiency in China can provide valuable insights into the intricate relationship between environmental quality and rural development, as well as offer guidance for other developing countries.

A multitude of studies on agricultural carbon emissions provided a solid basis for further investigation (Vleeshouwers and Verhagen 2010). Initially, research primarily focused on the the present state of agricultural carbon emissions and their influential factors. Various studies later opted for emission factor analysis, modeling simulations, and field measurements for evaluation. The prominent focus of emission factor analysis is the consideration of carbon sources and emission coefficients in agricultural production due to its extensive applicability and wide-ranging significance. As an illustration, Huang et al. (2019) examined agricultural carbon emissions in China spanning from 1997 to 2016. Exploiting this, some scholars utilize models such as the LMDI (logarithmic mean Divisia index) model, STIRPAT (stochastic impacts by regression on population, affluence, and technology) model, and the Kaya Identity to probe into the determinants of agricultural carbon emissions. For instance, Tian et al. (2014) deduced from the LMDI model that the impacts of efficiency, labour, and structure on agricultural carbon emissions were gradually waning, whereas the economic influence was mounting.

Further research on agricultural carbon emission efficiency based on agricultural carbon emissions is needed. The concept of carbon emission efficiency stems from ecological efficiency (Schaltegger and Sturm 1990). When applied in the agricultural sector, it integrates economic and ecological aspects into agricultural production, aiming to maximise expected outputs while minimising unexpected outputs. Current assessments of agricultural carbon emission efficiency mainly rely on Stochastic Frontier Analysis and Data Envelopment Analysis (DEA). Among these methods, the non-radial and non-angular DEA-SBM (Slacks-Based Measure) model, an extension of DEA, addresses biases from traditional models by including slack variables, which leads to more accurate and scientifically sound measurements (Tone 2001). Scholars have also conducted assessments of agricultural carbon emission efficiency across different countries and regions (Wu et al. 2021; Zhang et al. 2022). Alongside evaluating agricultural carbon emission efficiency, some researchers have examined the spatiotemporal distribution of this efficiency. For instance, a study by Liu and Yang (2021) indicated a 1.5% increase in China's agricultural carbon emission efficiency from 2009 to 2019. Although China's agricultural carbon emission efficiency displays spatial agglomeration effects, this effect appears to be diminishing.

Numerous scholars delve into the relationship between agricultural carbon emissions and agricultural economic growth. Some researchers substantiate the Environmental Kuznets hypothesis (Zhang et al. 2019; Liu et al. 2021). Certain scholars explored the decoupling dynamics between agricultural carbon emissions and agricultural economic growth (Han et al. 2018). Some researchers correlate agricultural carbon emissions with agricultural modernization, technology, and emphasize that efforts to curtail agricultural carbon emissions will directly or indirectly influence agricultural productivity and rural livelihoods. For instance, Zhou et al. (2023) identified that Internet utilisation boosted rural household income and fostered the adoption of carbon-efficient farming practices and low-carbon fertilization technologies to enhance crop carbon emission efficiency. Xia et al. (2022) scrutinised the coordinated coupling of agricultural carbon emissions and agricultural modernization in China from 2010 to 2020, revealing a consistent enhancement in coordination between

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agricultural carbon emissions and agricultural modernisation over the years.

The interaction between ACEE and agricultural economic growth are highlighted in the previous analysis. It is imperative to clarify the coupling coordination mechanism between these systems to drive the synergistic progress of agricultural carbon emission efficiency and agricultural economic growth. Subsequently, we utilised panel data from 31 provinces and cities in China spanning 2005 to 2021. The Super-Efficiency SBM model with unexpected outputs was applied to calculate agricultural carbon emission efficiency. Through a coupling coordination model, an assessment was conducted on the synchronized development level between farmers' income and agricultural carbon emission efficiency. The examination involved a comprehensive utilisation of the Dagum Gini coefficient, Moran's index and the Markov chain model to explore regional discrepancies and dynamic evolution characteristics of the coordinated development between farmers' income and agricultural carbon emission efficiency. This study enhances existing research by supplementing the analysis of efficiency loss factors related to agricultural carbon emission efficiency. Furthermore, it encompasses a thorough assessment of the coupling coordination between farmers' income and agricultural carbon emission efficiency in China using the coupling coordination model. This aids in comprehending the association between agricultural economy and environmental coordinated development, enriching the relevant body of research. Spatial variances and origins of coordinated development levels between farmers' income and agricultural carbon emission efficiency in China were examined through the Dagum Gini coefficient and decomposition analysis. Additionally, kernel density estimation and Markov chain analysis were utilised to investigate the dynamic evolution characteristics of coordinated development levels between farmers' income and agricultural carbon emission efficiency in China, aiming to provide insights into regional coordinated development and sustainable agricultural practices.

MATERIAL AND METHODS

Methodology

Undesirable slacks-based measurement. Considering the unexpected outputs in the production process, the Super-Efficiency SBM model with unexpected outputs is more representative of real scenarios and is commonly utilised in studies focusing on carbon emission efficiency (Zhou et al. 2019), ecological efficiency (Du et al. 2021), and energy efficiency (Cong et al. 2021). In many efficiency assessment studies, it is common for multiple decision units to exhibit a 100% 'efficiency status', highlighting the importance of discerning these efficient decision units for efficacy ranking. To ensure a more accurate efficiency assessment, this research, in alignment with the work of Tone (2002), adopted the Super-Efficiency SBM model with unexpected outputs to compute agricultural carbon emission efficiency.

Assuming there are n decision-making units, each unit having m inputs, $s1$ types of expected outputs and $s2$ types of unexpected outputs. The slack variables for inputs, expected outputs, and unexpected outputs are respectively represented by S_i^x, S_k^y, S_l^z. The weight vector is denoted by w_j, and the objective function is represented by ρ. x_{io}, y_{ko}, z_{lo} are indicative of the inputs, expected outputs, and unexpected outputs of decision unit o, where o ranges from 1 to n. This study selected input indicators based on the four fundamental elements of agricultural production: capital, labour, land, and technology. Capital input aided agricultural producers in adopting eco-friendly technologies and equipment to curb carbon emissions and enhance production efficiency, measured through the total agricultural fixed asset investment. Agricultural labour represented human capital input, with agricultural employees serving as the metric. Land, as a fundamental component for agricultural progress, was quantified by crop sowing areas, drawing from previous studies (Song et al. 2021). Technological input was evaluated by total power of agricultural machinery, reflecting the level of agricultural modernization in the region. Given the significant role of agricultural resources in production and the principle of prioritizing critical areas, fertilisers, pesticides, and agricultural films were specifically examined. This study balanced economic and ecological outcomes, hence utilising agricultural total output value and agricultural carbon sink as measures of expected outputs. Agricultural carbon emission efficiency acted as a comprehensive yardstick incorporating economic growth, resource utilisation, ecological outputs, and greenhouse gas emissions. Furthermore, along with economic and ecological output variables, consideration was given to unexpected outputs, primarily focusing on agricultural carbon emissions in this research. Based on the above analysis, the model was constructed as follows:

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$$min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{io}}}{1 - \frac{1}{s_1 + s_2}\left(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{ko}} + \sum_{l=1}^{s_2}\frac{s_l^z}{z_{lo}}\right)} \quad (1)$$

$$s.t.\begin{cases} x_{io} \geq \sum_{j=1, j\neq o}^{n} w_j x_j - s_i^x, \forall i \\ y_{ko} \leq \sum_{j=1, j\neq o}^{n} w_j y_j + s_k^y, \forall k \\ z_{lo} \geq \sum_{j=1, j\neq o}^{n} w_j z_j - s_l^z, \forall l \\ 1 - \frac{1}{s_1 + s_2}(\sum_{k=1}^{s_1}\frac{s_k^y}{y_{ko}} + \sum_{l=1}^{s_2}\frac{s_l^z}{z_{lo}}) > 0 \\ s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, w_j \geq 0, \forall i, j, k, l \end{cases} \quad (2)$$

The utilization of efficiency values derived from the inefficient SBM model, accounting for unexpected outputs, provided a static description. To comprehensively assess the changes in the dynamic efficiency of agricultural carbon emissions between two consecutive years, a dynamic analysis was necessary. Referring to Paster's study (Paster and Lovell 2005), we computed and decomposed the Malmquist index of the Global Malmquist-Luenberger (GML) global frontier.

$$GML_C^G = MEC_C \times MBPC_C \quad (3)$$

$$MEC_C = \frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{D_C^t\left(x^t, y^t, z^t\right)} \quad (4)$$

$$MBPC_C = \frac{\frac{D_C^G\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}{D_C^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)}}{\frac{D_C^G\left(x^t, y^t, z^t\right)}{D_C^t\left(x^t, y^t, z^t\right)}} \quad (5)$$

where: *GLM* – Globe Malmquist Luenberger index; *MEC* – Efficiency Change Index; MBPC – Best Practice Change Index.

Within the framework of efficiency measurement on a common frontier, *D* represents the derived efficiency values based on the dataset. Specifically, x^t, y^t, z^t and x^{t+1}, y^{t+1}, z^{t+1} respectively indicated the input, expected output and unexpected output values of decision units during the time periods t and $t + 1$. Furthermore, GML_C^G signified the variation in agricultural carbon emission efficiency, where $GML_C^G > 1$ indicates an improvement in this efficiency, whereas $GML_C^G < 1$ implies a decline. Additionally, MEC_C captures the change in technical efficiency, revealing the impact of fixed inputs on output, while $MBPC_C$ represents the alteration in technical progress, where the output effect of decision units is shaped by technological advancements.

Coupling coordination degree (CCD) model. The CCD model serves as a model utilized for measuring the interdependent development relationship and degree of coordination development of two or more subsystems. In this study, the aim was to scientifically measure the level of coordination between agricultural carbon emission efficiency (U_1) and farmers' income (U_2) throughout the developmental process. To accomplish this, a coupling coordination model was constructed. The fundamental formula is presented as follows:

$$C = 2\frac{\sqrt{U_1 \times U_2}}{U_1 + U_2} \quad (6)$$

$$T = \alpha U_1 + \beta U_2 \quad (7)$$

$$D = \sqrt{C \times T} \quad (8)$$

where: C – the degree of coupling; T – overall coordination degree; α, β – undetermined coefficients, which are set to 0.5.

In order to give the degree of coupling a reference value, we referred to Liu et al. (2020) and divided the coupling coordination into 10 levels, as shown in Table 1.

Table 1. Grading of coordination degree

Level	Coupling coordination degree
Extreme disorder	[0.0, 0.1)
Severe disorder	[0.1, 0.2)
Moderate disorder	[0.2, 0.3)
Mild disorder	[0.3, 0.4)
On the verge of disorder	[0.4, 0.5)
Barely coordinated	[0.5, 0.6)
Primary coordination	[0.6, 0.7)
Intermediate coordination	[0.7, 0.8)
Good coordination	[0.8, 0.9)
High quality coordination	[0.9, 1.0]

Source: Authors' own processing

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Table 2. Descriptive statistics results of the variables

Target level	Normative layer	Variable	Mean	SD	Min	Max
Farmers' income	farmers' income	farmers' income (EUR)	1 191.0181	743.5032	218.8872	4 492.2099
Agricultural carbon efficiency	input element	total agricultural fixed asset investment (billions)	544.0365	678.6618	1.6000	4 465.7160
	input element	agricultural employees (10 000 people)	830.7636	627.3105	25.0000	3 138.8300
	input element	crop sowing areas (1 000 ha)	5 246.6540	3 762.3480	88.6000	15 065.0300
	input element	total power of agricultural machinery (million kilowatts)	3 068.4340	2 822.8990	93.9700	13 353.0200
	input element	fertilizer (10 000 tons)	178.0357	142.6986	4.2000	716.1000
	input element	pesticide (10 000 tons)	5.2348	4.2335	0.0485	17.3461
	input element	agricultural film (10 000 tons)	7.3836	6.5612	0.0441	34.3524
	expected outputs	agricultural total output value (10^8 EUR)	196.2680	156.5157	5.6023	703.0904
	expected outputs	agricultural carbon sink (10 000 tons)	2 287.9170	1 956.8720	37.3315	8 174.0440
	unexpected outputs	agricultural carbon emissions (10 000 tons)	925.7670	639.8953	18.7524	2 455.5230

Source: Authors' own processing

Data

Data utilised in this study mainly originated from the China Statistical Yearbook (2005–2021), statistical yearbooks of various provinces and cities, statistical bulletins of various provinces and cities. Descriptive statistics for each variable are shown in Table 2.

RESULTS AND DISCUSSION

The overall level of ACEE

The Global Malmquist-Luenberger (GML) index exhibited features like comparability across different time periods and transitivity. Therefore, the annual GML index provided a dynamic reflection of the overall growth level of agricultural carbon emission efficiency up to that year. Since the first period was represented by 2005, Figure 1 commences reporting from 2006.

The fluctuations in the index depicted in Figure 1 highlight a varying trend in the agriculture carbon emission efficiency change rate. As shown in Figure 1, this paper divided the study period into 2006–2013 and 2014–2021, mainly because 2014 was an important turning point in China's agricultural development and was regarded as the first year of China's comprehensive deepening reform. The mean GML index for the period between 2006 and 2013 was approximately 1.013, while for 2014 to 2021, it measured around 1.048; both numbers surpass 1. Additionally, the comprehensive average GML index from 2014 to 2021 exceeded that of the earlier years, signalling an uplift in China's overall agricultural carbon emission efficiency and indicating a positive developmental state. In detail, the GML index exhibited an increasing pattern from 2006 to 2008, followed by a significant downturn in 2009, reaching a nadir. This decline could potentially be attributed to the elimination of agricultural taxes in 2006, thereby markedly stimulating agricultural output and enhancing agricultural carbon emission efficiency. Nonetheless, post the worldwide financial crisis in 2008, fluctuations in the global food market and the volatility in costs of fertilizers, pesticides, and other agricultural inputs impacted agricultural resource and energy investments by farmers, leading to a decline in agricultural carbon emission efficiency (Brown et al. 2014). To mitigate the effects of the grain market, the government implemented a series of measures to incentivise farmers to engage in cultivation, consequently boosting agricultural carbon emission efficiency in 2010. After

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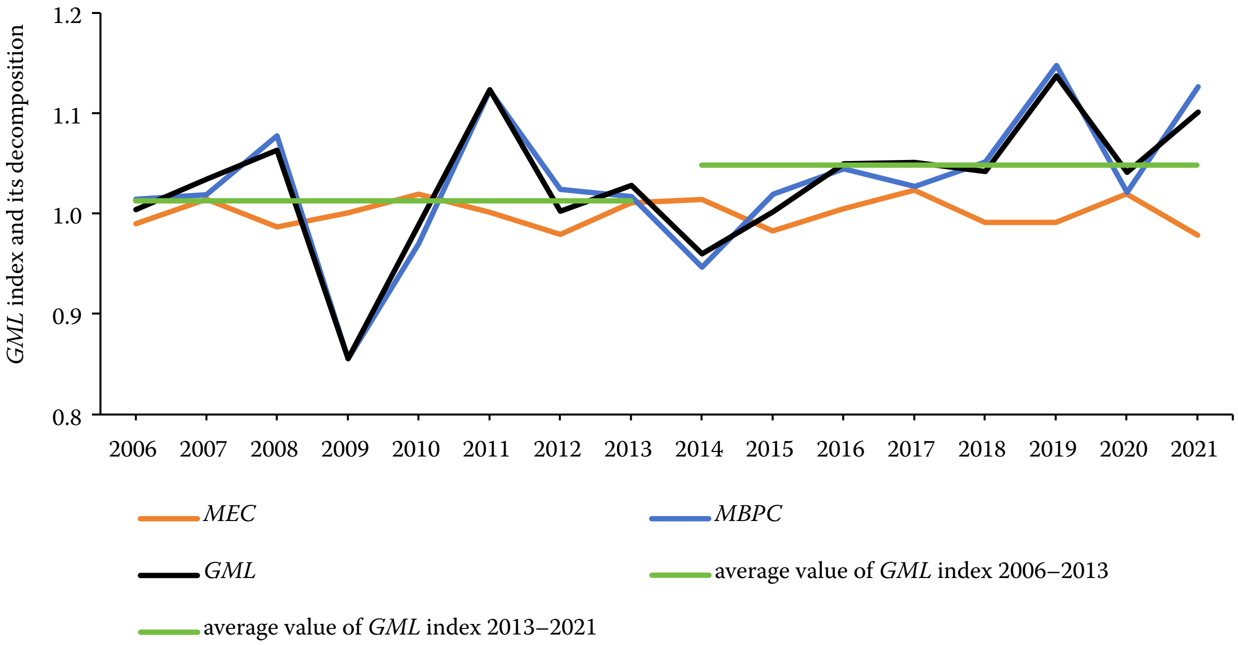

Figure 1. *GML* index and its decomposition components for China from 2006 to 2021

GML – Globe Malmquist Luenberger index; *MEC* – Efficiency Change Index; MBPC – Best Practice Change Index
Source: Authors' own processing

2010, with the exception of 2014, the GML index consistently exceeded 1, achieving its peak in 2019, showcasing a positive growth pattern. Through the prism of the decomposition index, fluctuations in the GML index aligned closely with those of *MBPC*, emphasising a strong link between technological progress and effectiveness in ACE. Since 2015, *MBPC* generally surpassed *MEC*, pointing to technological advancement as the primary driver behind the boost in agricultural carbon emission efficiency.

Input redundancy, unexpected output redundancy, and insufficient expected output reflected the gaps between the current status of related inputs and outputs and the expected optimal configuration. The size of relaxation variables can indicate redundancies and deficiencies in output for each decision-making unit, thus clarifying the areas that require improvement to enhance efficiency.

The relaxation variables were divided by the corresponding input and output values to calculate the redundancy rate and inadequacy rate (Figure 2). Upon examination of the national input redundancy and output inadequacy rates, it appears that there were relatively high rates of redundancy in film plastic and labour input. The heightened redundancy in film plastic may be a consequence of wasteful practices and environmental pollution resulting from excessive dependency on and improper utilisation of film plastic, consequently diminishing its overall yield and efficiency benefits. Conversely, the surplus in labour input may arise from the abundant rural labour force in China, impacting resulting labour inputs, thus factoring as the secondary factor in the decline of agricultural carbon emission efficiency. Sub-regionally, the reasons for the loss of agricultural carbon emission efficiency may be different in different regions. In order to deeply understand and compare the impacts of agricultural production methods, climatic conditions, resource utilisation and other factors on the efficiency of agricultural carbon emissions among different regions, this paper divided China into three major regions, namely, eastern, central and western, for the purpose of research. The specific regional divisions are shown in Figure 3. Major contributors to the decline in agricultural carbon emission efficiency in the eastern region included film, pesticide, and technical inputs. Being economically advanced, agricultural practices in the eastern region of China, heavily relied on contemporary technologies and chemical inputs. The primary factors fuelling the decreased efficiency in the western region were labour and film resources. Given the natural restrictions, agricultural operations significantly depend on manual

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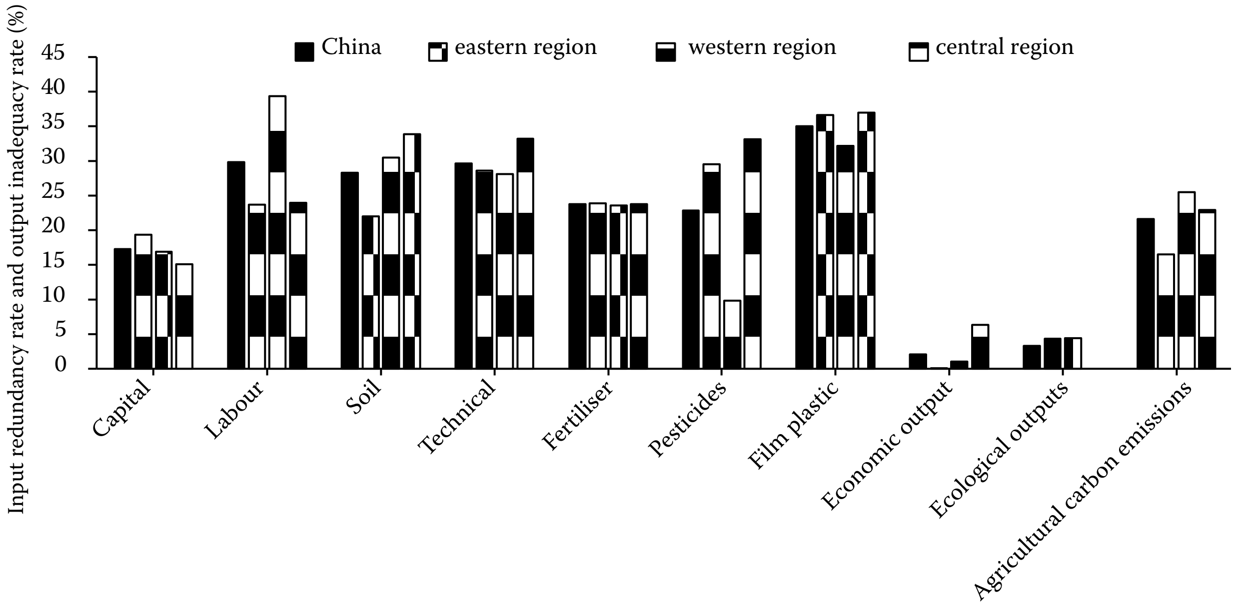

Figure 2. The redundancy rate of input and the inadequacy rate of output for agricultural carbon emission efficiency

Source: Authors' own processing

labour, resulting in diminished labour productivity and energy efficiency due to the relative shortfall in technological sophistication and automation. The major factors contributing to the decline in ACEE in the central region included film and land inputs. As a predominant agricultural hub in China, the central region witnessed excessive land development. The absence of effective crop rotation may contribute to a reduction in soil organic carbon storage, exacerbating the deterioration of carbon emission efficiency.

The analysis indicated a relatively low rate of inadequacy in agricultural economic and ecological output. This implies that the deficiencies in these outputs were not the primary cause for the loss of ACEE. Instead, the key factors linked to the decline primarily stemmed from resource inputs and unexpected outcomes.

Analysis of the coordinated development level

Overall analysis. The average coordination level between farmers' income and agricultural carbon emission efficiency in China from 2005 to 2021 was determined based on the measurement outcomes from the coupling coordination model, shown in Figure 4. Assessment of the coupling coordination trend revealed

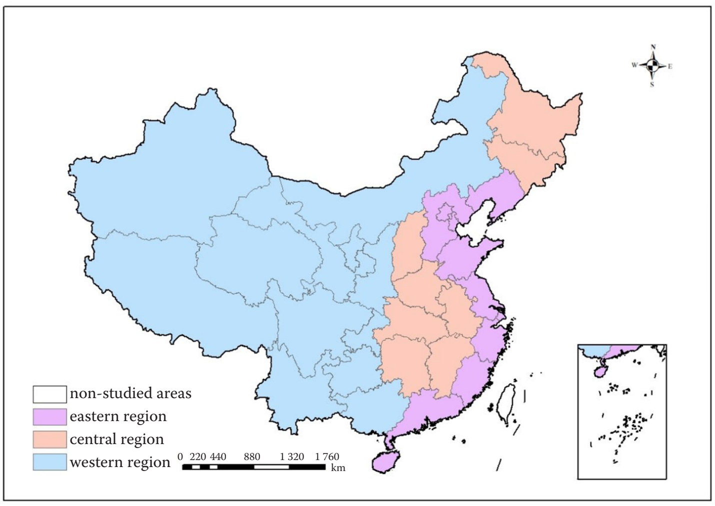

Figure 3. Division of China into eastern, central and western regions

Source: Authors' own processing based on standard map No. GS(2023)2767 on the standard map service website of the Ministry of Natural Resources of China

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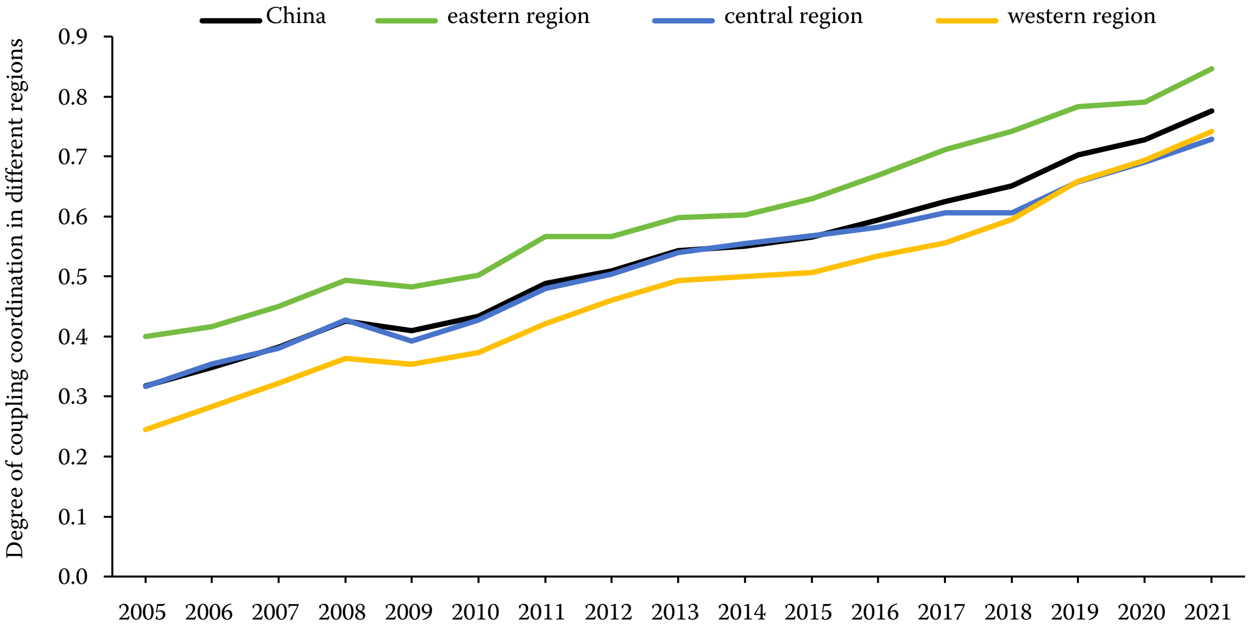

Figure 4. Coupling coordination in China from 2005 to 2021

Source: Authors' own processing

a fluctuation and enhancement in levels of coupling coordination, ranging from 0.318 to 0.775. Over the years, China transitioned from mild disorder between 2005 and 2007 to primary and intermediate coordination grades between 2017 and 2021, respectively. Regionally, there has been progressive improvement in coupling coordination levels: ranging from 0.40, 0.32, 0.24 in 2005 to 0.85, 0.73, 0.74 in 2021 for the eastern, central, and western regions, respectively, with growth percentages of 112.5%, 125%, and 208.3%. The western region exhibited substantial growth, with the central region following suit, while the eastern region experienced more subdued progress.

The above observations demonstrate a positive trend in the coordinated development of FI and ACEE in China. The western region is showing promising progress, whereas the central and eastern regions need to enhance efforts on multiple fronts to speed up the advancement of coordination between the two systems.

Analysis of spatial variation and sources of variation. Compared with the standard Gini index, the Dagum Gini coefficient had good decomposition performance, which could take into account the distribution status of the sub-sample and the cross overlap between the samples, to achieve the complete identification of the contribution to the overall regional disparity. Therefore, this paper calculated the decomposition results of the Dagum Gini coefficient for China and various regions from 2005 to 2021 based on the research of related scholars (Dagum 1997), to further reveal the spatial differences in the level of synergistic development of farmers' incomes and agricultural carbon emission efficiencies in China and various regions and the sources of the differences. The results are shown in Table 3.

There was an overall decreasing trend in the difference between FI and ACEE, ranging from 0.180 to 0.055. Regionally, the coordinated development levels in the eastern, central, and western regions of China indicated a fluctuating downward trend. The Dagum Gini coefficient decreased most significantly in the western region, reaching 0.194, while decreasing by the lowest margin in the central region at 0.036. This divergence can be attributed to the western region's infrastructure enhancements, factor flow improvements, and regional integration, which helped to close the gap (Fan et al. 2011). Conversely, limited policy support and technological dissemination spaces in the various regions of the central area led to slower synchronization in development levels among provinces. The Dagum Gini coefficients for the eastern, central, and western regions displayed a fluctuating downward trend. The 'east-central' decline was approximately 0.062, corresponding to a decrease rate of around 52.99%; the 'east-west' decline measured about 0.154, with a decrease rate estimated at 74.71%; and the 'central-west' decrease was around 0.136, with

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Table 3. Decomposition results of Dagum Gini coefficients for China and its regions

Year	China	Intra-regional			Inter-regional			Contribution percentage		
		eastern	central	western	east-central	east-west	central-west	intra-regional	inter-regional	supervariable density
2005	0.180	0.105	0.081	0.239	0.116	0.207	0.183	27.461	63.062	9.478
2006	0.154	0.098	0.107	0.161	0.113	0.165	0.154	26.987	58.144	14.869
2007	0.128	0.088	0.070	0.146	0.095	0.144	0.119	28.191	61.075	10.734
2008	0.121	0.090	0.087	0.116	0.098	0.130	0.113	27.975	58.897	13.128
2009	0.123	0.079	0.071	0.135	0.096	0.135	0.112	27.608	59.361	13.031
2010	0.107	0.053	0.071	0.112	0.077	0.116	0.102	25.081	64.716	10.203
2011	0.112	0.069	0.068	0.117	0.084	0.122	0.105	26.500	61.990	11.510
2012	0.092	0.055	0.073	0.100	0.074	0.095	0.094	28.316	52.178	19.506
2013	0.089	0.050	0.072	0.105	0.068	0.092	0.095	28.985	50.286	20.729
2014	0.089	0.051	0.072	0.107	0.066	0.092	0.097	29.719	49.012	21.269
2015	0.100	0.067	0.078	0.114	0.079	0.105	0.104	29.922	50.853	19.225
2016	0.088	0.047	0.066	0.093	0.069	0.092	0.087	26.713	59.884	13.403
2017	0.090	0.057	0.060	0.079	0.074	0.096	0.076	25.376	64.701	9.923
2018	0.088	0.053	0.062	0.082	0.079	0.090	0.075	25.934	58.845	15.222
2019	0.073	0.037	0.062	0.066	0.067	0.070	0.066	25.122	56.002	18.876
2020	0.059	0.035	0.047	0.056	0.055	0.057	0.055	26.795	53.079	20.127
2021	0.055	0.032	0.045	0.045	0.055	0.052	0.047	24.504	61.697	12.799
Mean	0.103	0.063	0.070	0.110	0.080	0.109	0.099	27.129	57.870	14.943

Source: Authors' own processing

a decrease rate recorded at 74.36%. Results in Table 3 revealed that during the assessment period, the contribution percentage of inter-regional deviations was 57.870. This implies that inter-regional variations represent the primary root cause of the development gap.

Characteristics of the spatial evolution of CCD

To further study the spatial evolution pattern of the coordinated development, the Moran's I index of 31 provinces from 2005 to 2021 was calculated. The results are shown in Table 4. The values of Moran's I fluctuated between 0.131 and 0.360, all were significant at least at the 10% level, indicating a high degree of spatial dependency of coordinated development levels among different provinces in geographic positions, and the presence of spatial agglomeration effects.

The previous global spatial auto-correlation analysis failed to display the spatial correlation features among provinces. Therefore, we utilised Moran scatter plots to perform a local spatial auto-correlation analysis. The selected years were 2005, 2010, 2015, and 2021.

Examining Figure 5 reveals that the regression slopes of the Moran scatter plots over the four years were consistently positive. This exemplifies a notable spatial clustering trend in the integrated progress of farmers'

Table 4. Global Moran index of coupling coordination degree between agricultural carbon emission efficiency and farmer's income from 2005 to 2021

Year	I	$E(I)$	SD	Z	P
2005	0.203	−0.033	0.089	2.647	0.008
2006	0.252	−0.033	0.092	3.116	0.002
2007	0.182	−0.033	0.082	2.633	0.008
2008	0.179	−0.033	0.088	2.410	0.016
2009	0.288	−0.033	0.089	3.626	0.000
2010	0.360	−0.033	0.091	4.324	0.000
2011	0.300	−0.033	0.090	3.718	0.000
2012	0.266	−0.033	0.090	3.314	0.001
2013	0.236	−0.033	0.090	2.981	0.003
2014	0.250	−0.033	0.089	3.174	0.002
2015	0.269	−0.033	0.090	3.374	0.001
2016	0.306	−0.033	0.090	3.784	0.000
2017	0.312	−0.033	0.090	3.833	0.000
2018	0.250	−0.033	0.090	3.137	0.002
2019	0.231	−0.033	0.090	2.937	0.003
2020	0.134	−0.033	0.087	1.913	0.056
2021	0.131	−0.033	0.088	1.853	0.064

I – Moran's index; E – normal distribution expectation of the global Moran's index Z – test statistic of the Moran's index
Source: Authors' own processing

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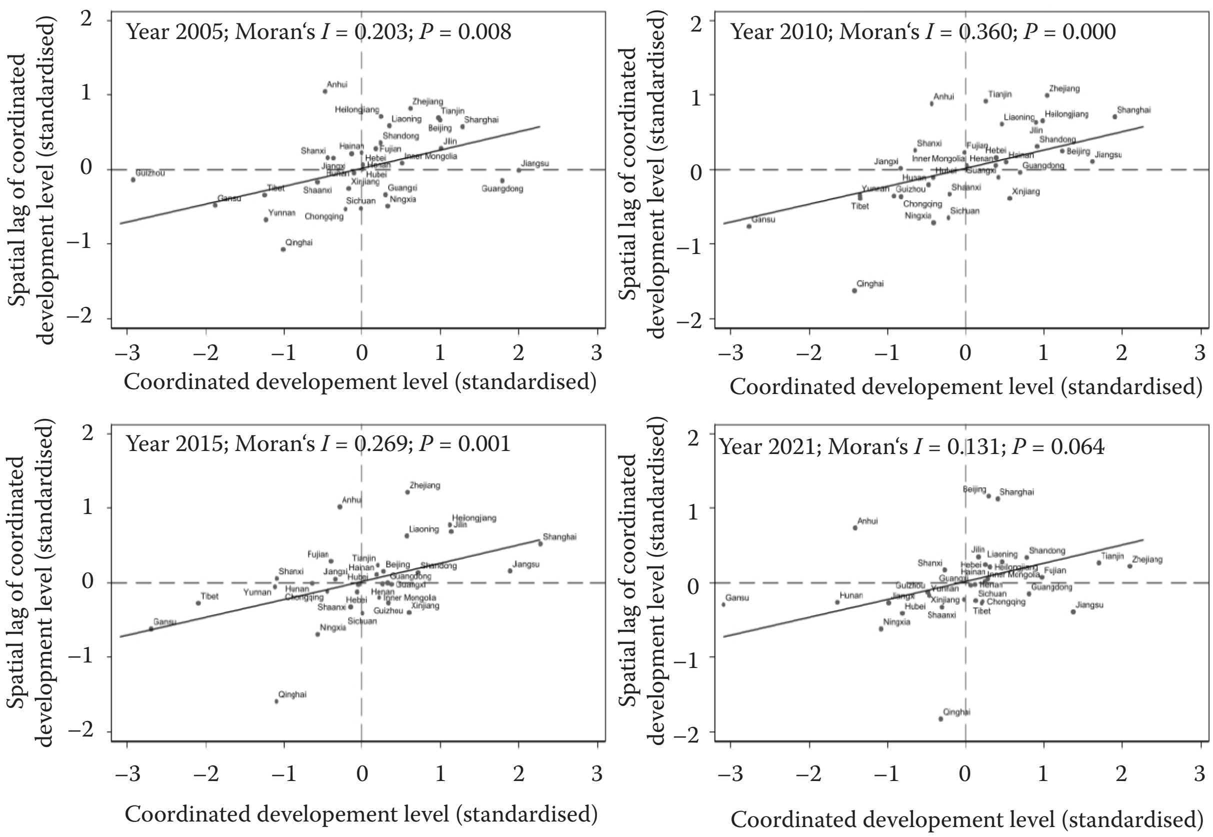

Figure 5. Moran scatter plots of the coordinated development levels for the years 2005, 2010, 2015, and 2021

Source: Authors' own processing

income and agricultural carbon emission efficiency, demonstrating the pattern where high values aligned with other high values and low values aligned with low values. The high-high clusters predominantly clustered in the eastern region, where provinces rich in agricultural resources and with relatively advanced economies facilitated progress in agricultural modernization and scalability, setting a model for neighbouring provinces. On the contrary, several provinces in the central areas, in conjunction with numerous provinces in the southwest and northwest, formed areas characterised by low values. These localised regions might face challenges stemming from limited agricultural resources, carbon-intensive planting patterns, or economic constraints, resulting in a lower level of cooperation progress. Notably, minimal fluctuations were observed between 2005 and 2021, underscoring a spatial clustering phenomenon reinforcing the concept of 'the weak remaining weak'. Thus, it is imperative to strategise and navigate approaches to enhancing farmers' income and agricultural carbon emission efficiency collaboratively on a regional scale.

Trend forecast of coordinated development levels

The traditional Markov chain revealed the development characteristics of the synergistic development level of farmers' income and agricultural carbon emission efficiency at different levels in different regions by discretising the continuous data into K types, and calculating the probability distribution and evolutionary trend of each type under the condition that both time and state are discrete. To forecast the long-term trend of collaborative development level growth, we referenced a relevant study (Quah 1996) and performed additional analysis using the traditional Markov chain method. Initially, we categorised the collaborative development status space into four groups using the quartile grouping technique to define the Markov transition matrix of collaborative development levels, presented in Table 5.

Table 5's diagonal elements signify the likelihood of maintaining farmers' income and agricultural carbon emission efficiency coordination unchanged, while the off-diagonal elements express the probability of transitioning between different coordination

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Table 5. Traditional Markov chain transition probability matrix of coordinated development level

Region	t / (t + 1)	L1	L2	L3	L4	n
China	L1	0.765	0.235	0.000	0.000	132
	L2	0.046	0.710	0.229	0.015	131
	L3	0.000	0.023	0.738	0.238	130
	L4	0.000	0.000	0.039	0.961	103
Eastern	L1	0.787	0.213	0.000	0.000	47
	L2	0.021	0.681	0.298	0.000	47
	L3	0.000	0.065	0.652	0.283	46
	L4	0.000	0.000	0.056	0.944	36
Central	L1	0.735	0.235	0.029	0.000	34
	L2	0.059	0.647	0.294	0.000	34
	L3	0.000	0.088	0.676	0.235	34
	L4	0.000	0.000	0.000	1.000	26
Western	L1	0.706	0.294	0.000	0.000	51
	L2	0.078	0.686	0.235	0.000	51
	L3	0.000	0.000	0.760	0.240	50
	L4	0.000	0.000	0.025	0.975	40

t – year of t; L – coordinated development level; n – number of provinces with a coordinated development level of L_i
Source: Authors' own processing

levels. All main diagonal values exceeding 50% exhibited a relatively stable coordination level of farmers' income and agricultural carbon emission efficiency in China and the major regions, with limited movement. Moreover, except for the western region, the values on the main diagonal for L1 and L4 surpassed the values of L2 and L3, indicating a higher likelihood of sustainment, which points towards a converging trend. Analysis of state transition probabilities revealed that all upward transitions in China surpassed 22.9%, while downward transitions were under 4.60%, demonstrating a trend towards convergence. When farmers' income and agricultural carbon emission efficiency coordination was at level L2, a leap to level L4 is possible with a 1.5% probability. The eastern, central, and western regions showcased upward convergence trends. In the eastern region, the lowest probability of upward transition for L1 was 21.3%, followed by 29.9% and 28.3%, indicating that surpassing a specific threshold propels further progress. Focusing on the central region, the lowest probability for upward transition of L3 was 23.5%, contrasted with 26.4% for L1 and 29.4% for L2, highlighting an easier progression to a higher level when coordination levels are lower. Conversely, reaching a high development level posed challenges due to constraints. Noteworthy leapfrogging potential existed in the central region, with a 2.9% probability transitioning from L1 to L3. In the western region, the probability of rising to level L1 was highest at 29.4%, suggesting an easier adoption of advanced technologies for improving the coordinated development of farmers' income and agricultural carbon emission efficiency at lower levels.

CONCLUSION

This research focused on elucidating the efficiency of agricultural carbon emissions through the utilisation of a coupling coordination model to assess the synchronised advancement of farmers' income alongside agricultural carbon emission efficiency in China. The thorough evaluation scrutinised the extent of coordinated development across the eastern, central, and western regions of China, investigating regional disparities and emerging trends. The findings collectively recommend the following refinements:

Agricultural carbon emission efficiency in China was demonstrably increasing. Meanwhile, the correlation between farmers' income and agricultural carbon emission efficiency in China was progressively on the upsurge. Analysis of spatial disparities and their underlying factors revealed that differences in coordinated development within and among the eastern, central, and western regions tended to diminish. The interregional variations served as the principal catalyst for variations in coordinated developmental outcomes.

The spatial pattern of farmers' income and agricultural carbon emission efficiency in China displayed significant positive spatial clustering in their coordinated development levels. Findings from the Local Moran index reveal a spatial correlation of high-high and low-low clustering between provinces, with high-high cluster areas primarily situated in the eastern regions, and low-low cluster areas in the central and western regions.

China's and the east, central and west regions' CCD was more stable and less liquid. It was easier for CCD in the eastern region to break through upwards when it passed a certain threshold. The central region was more likely to develop to a higher level when CCD was at a lower level, and when the level of development was higher, it was difficult to cross the threshold due to conditions. Western region CCD was at a low level when it was easier to use advanced technology, etc. to achieve the improvement of CCD. While our research holds significant value in advancing agricultural sustainability, it includes constraints rooted in objectivity. Limited data availability solely

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enabled an examination of the trend and spatial distribution concerning the synchronized progress of farmers' income and agricultural carbon emission efficiency in China from 2005 to 2021. Given the expansive scope of agriculture encapsulating both crop cultivation and livestock sectors, potential gaps may exist in appraising agricultural carbon emission efficiency, limiting the accuracy of the calculations. Future scrutinization should aim to enhance the assessment framework, delving deeper to uncover the underlying mechanisms behind the coordinated development of agricultural carbon emission efficiency and farmers' income.

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