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Study on agricultural carbon emission efficiency calculation and driving path of grain production department in China

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ORIGINAL ARTICLE

Abstract

Agriculture plays a pivotal role in China's environment, economy, and society, standing as a pillar in the country's shifts toward lower carbon emissions. This is important, especially in food production, where sustainable practices protect the environment and ensure food security and quality. Therefore, understanding the factors affecting carbon emission efficiency is highly practical for speeding up emission reductions and improving efficiency throughout the entire food supply chain. This study uses the Super Slacks Based Measure (SBM) model to evaluate the efficiency of carbon emissions in 30 provinces (including municipalities and autonomous regions) in China from 2013 to 2022, emphasizing the food production sector. Through the Technology Organization Environment (TOE) framework, an integrated analysis is crafted to explore ways to enhance carbon emission efficiency. The set Qualitative Comparative Analysis (fsQCA) method is applied to examine these pathways from a perspective offering unique insights tailored to the food production field. The findings reveal that agricultural carbon emission efficiency surpasses the average in half of the provinces studied, yet notable discrepancies exist among them. In the eastern regions, efficiency values tend to be higher compared to the western areas, impacting the sustainability of regional food production. The research identifies four patterns that drive agricultural carbon emission efficiency: those led by technical conditions, attention structure synergy, agriculture support structure synergy, and overall development synergy. Enhancing efficiency involves factors such as adopting technologies promoting digital economy development, investing in agriculture financially, embracing eco-friendly agricultural practices, and optimizing the agricultural industrial structure. These aspects have implications for food science and the broader agricultural sector. Additionally, the study uncovers a substitution relationship between technological and environmental conditions that influence efficiency. These findings provide an overview of the pathways that enhance provincial agricultural carbon emission efficiency from an interactive perspective. This study is helpful to expand the understanding of the TOE framework, enrich the research results in the field of low-carbon agriculture, provide insights for provinces in the stage of efficiency improvement, and provide theoretical support for carbon emission reduction in grain production in various provinces. The research aims to guide policymakers, food scientists, and agricultural stakeholders in China toward optimizing carbon efficiency in food production systems to support global climate change mitigation efforts while ensuring food supply.

Keywords: agricultural carbon emission efficiency; configurational analysis; fuzzy-set Qualitative Comparative Analysis (fsQCA) Method; Technology–Organization–Environment (TOE) framework

Introduction

Food security is essential for human welfare and is a critical issue for the nation's economy and people's livelihoods, serving as the foundation of national stability and development (Rosegrant and Cline, 2003). Agriculture is a contributor to greenhouse gas emissions, making up around 23% of total human-induced emissions globally. This significant portion highlights farming practices' role in the world's carbon footprint and underscores the importance of targeted actions and sustainable innovations within the sector. The United Nations Intergovernmental Panel on Climate Change noted that global climate change may speed faster if the agricultural production process does not interfere with carbon emissions. This can impact global food security and possibly jeopardize human survival (Khojasteh *et al.*, 2024).

Although China's grain output has exceeded 1.3 trillion jin for 8 consecutive years, the large-scale agricultural production model characterized by high input and high consumption has generated significant negative externalities (Yin *et al.*, 2024b). According to the 2018 National Greenhouse Gas Inventory Report, agricultural greenhouse gas emissions are the second most significant source of greenhouse gas emissions after industry, accounting for approximately 15% of the nation's total greenhouse gas emissions. Agricultural air pollution is a significant issue that must be addressed (Gu *et al.*, 2023). At the same time, changes in agricultural carbon emissions have not only affected China as a whole but also have had widespread global effects (Zhu and Huo, 2022). It is crucial because China's agriculture must keep up with a growing population and intricate food supply chain while lessening its environmental impact (Yin *et al.*, 2024c). Tackling this issue calls for solutions such as using low-carbon technologies, promoting farming methods, and enacting policies that encourage environmentally friendly agriculture. By taking these steps, China can help reduce carbon emissions and set an example for agricultural development worldwide (Huang *et al.*, 2019).

Researchers have noted that there is a synergistic relationship between food security and agricultural carbon emission at the levels of policies, carbon sequestration and emission reduction, increasing production and carbon sequestration, and increasing production and emission reduction (Chen *et al.*, 2021; Jiang *et al.*, 2017). Improving agricultural carbon emission efficiency can enhance the efficient utilization of resources and energy, and thereby boost the quantity and quality of food production. Simultaneously, the implementation of the national food security strategy prioritizes crop enhancement, water conservation, fertilizer reduction, pesticide minimization, and the cultivation of high-yielding new varieties, all aimed at reducing greenhouse gas emissions. These measures collectively contribute to enhancing agricultural carbon emission efficiency. China needs to focus on reducing carbon emissions while maintaining or increasing agricultural production to meet the needs of an expanding population, all while minimizing unnecessary carbon output. Therefore, to ensure food security, it is essential to reduce redundant agricultural carbon emissions and improve emission efficiency in agriculture. This will ultimately achieve a mutually beneficial outcome for both food security and the dual carbon targets in agriculture.

To achieve this goal, scholars have conducted numerous studies focused on agricultural carbon emission efficiency. DEA method (Zhang *et al.*, 2018), Malmquist index model (Majiwa *et al.*, 2018), and SBM method (Huang *et al.*, 2021) are widely used in the calculation of agricultural carbon emissions. Kwon *et al.* (2017) used the DEA method to measure the carbon emission efficiency of 12 European countries, which showed that Germany was the most efficient country. According to the conclusion, some suggestions were put forward to effectively reduce the potential level of carbon dioxide. Wang and Feng (2021) chose DEA and Malmquist index models to calculate the agricultural carbon emission efficiency in China. The results showed that the overall agricultural carbon emission efficiency in China was 0.654, which showed an overall upward trend, but there were significant regional differences.

In terms of influencing factors, green technology (Deng and Zhang, 2024), digitalization (Grimsby, 2024), government concern (Raza *et al.*, 2023), environmental regulation (Guo *et al.*, 2022), and industrial structure (Shi and Chang, 2023) have all been proved to affect the efficiency value. Some scholars primarily analyze single factors using a linear approach. Fan and Li (2022) found a "U" relationship between heterogeneous environmental regulation and the carbon emission efficiency of the grain production industry. Agricultural mechanization, farmland management scale, and technological progress also affect the improvement of agricultural carbon emission efficiency (Cheng *et al.*, 2023; Zhou *et al.*, 2023; Zhu *et al.*, 2022).

However, some gaps still need to be addressed for a more precise and thorough analysis. Firstly, in terms of the carbon emission efficiency measurement index system, the majority of the previous studies have overlooked the aspect of crop carbon absorption. Secondly, in the calculation method, the DEA model and SBM method were commonly employed in previous studies to measure agricultural carbon emission efficiency. However, the DEA model faces limitations in addressing unexpected output and slack in the production process, while the SBM method is unable to further distinguish decision-making units with efficiency values of 1, which somewhat compromises the accuracy of agricultural carbon emission efficiency calculations. Third, in exploring how to improve the efficiency of agricultural carbon emissions, most studies on the impacts of practices on carbon emissions use methods such as linear regression. While these methods offer insights, they are often limited by focus and sample selection of each study, resulting in varying conclusions across different scenarios. Additionally, these approaches need help to capture the interactions and causal relationships among the multiple factors affecting agricultural carbon emission efficiency. The elements that drive efficiency enhancements are often intertwined in ways that adequately challenge research methodologies to explore these interconnections. While existing literature has identified factors influencing carbon emission efficiency, there needs to be more cohesion in selecting these variables and forming a coherent theoretical foundation. This shows the necessity for an integrated framework that systematically organizes and investigates the factors influencing carbon emission efficiency.

In light of these considerations, the incremental contributions of this paper can be underscored in the following ways. Firstly, this paper introduces the concept of carbon absorption into the index system used to gauge carbon emission efficiency. By incorporating this neglected factor—emphasizing the role of crops in carbon sequestration—the assessment of carbon emission efficiency becomes more precise and reflective of the true environmental footprint of agriculture. Secondly, the super-efficiency SBM model is employed to enhance the accuracy of measuring agricultural carbon emission efficiency. Thirdly, to solve the problems of dispersion and disorder of existing influencing factors, based on the TOE framework, the pathway to enhancing agricultural carbon emission efficiency is investigated across three dimensions: technology, organization, and environment, utilizing the fuzzy set qualitative comparative analysis (fsQCA) method.

This study improved the index system of agricultural carbon emission efficiency and enriched the related research of agricultural carbon emission from the perspective of configuration. Introducing TOE framework, this structure helps elucidate the connections among these variables, presenting a more thorough comprehension of the catalysts for efficiency. QCA method enables an analysis of the potential interactive impacts among different precursor variables, tackling the existing chaos and scattering in the factors that impact agricultural carbon emission effectiveness. This approach permits an exploration of the intricacy and the connection matching relationships between carbon emission efficiency and its influencing elements. By diving into these relationships, the research offers insights into how diverse combinations of factors can collaborate to enhance efficiency, providing a nuanced understanding of which strategies could be most impactful in different scenarios.

Therefore, the purpose of this study is to establish a more perfect evaluation index system of agricultural carbon emission efficiency, and evaluate the efficiency of 30 agricultural production departments in China from 2013 to 2022. Based on the TOE framework, this study uses the fsQCA method to explore ways to improve carbon emission efficiency and provide corresponding improvement measures. These contributions propel the field forward by delivering assessments with a unified theoretical structure and an advanced analytical method for comprehending and enhancing agricultural carbon emission effectiveness. At the same time, it supplements the research on agricultural carbon emission efficiency from the perspective of food security, which is helpful to provide policy implications for improving food production efficiency in China.

Theoretical Basis

The TOE framework, proposed by Tornatzky and Fleischer in 1990, initially focused system transformation on three dimensions: technology, organization, and environment (Abed, 2020). In the context of China, the application field of the TOE framework has been continuously expanded. Developing low-carbon agriculture and achieving "dual carbon" goals require joint efforts from aspects such as technology level, organizational conditions, and industrial structure. The factors affecting agricultural carbon emission efficiency are mostly encompassed within the technological, organizational, and environmental dimensions, and the TOE framework facilitates the integration of these factors. Secondly, the ability to innovate in green technology is a core element in enhancing agricultural carbon emission efficiency (Zhang *et al.*, 2024), and the essence of the TOE framework is technology application, which highly matches. Therefore, introducing the TOE framework into the context of China's agricultural carbon emissions, starting from the main elements affecting agricultural carbon emission efficiency, is of practical significance in seeking pathways to enhance agricultural carbon emission efficiency and achieving "dual carbon" goals.

In the context of ensuring food supply and enhancing the growth of high-quality agricultural output, this study introduces a comprehensive analysis framework using the Technology Organization Environment (TOE) model. Specifically focusing on agriculture and crop cultivation, this research aims to delve into the factors influencing carbon emission efficiency within the crop sector, which plays a crucial role in the overall agricultural system.

The framework unravels the relationships between progress organizational strategies and environmental aspects that collectively impact carbon emissions in crop production. By concentrating on crop farming practices, this study seeks to offer insights into how agricultural methods, innovations, and policies can be fine-tuned to boost carbon efficiency while preserving or enhancing crop yields.

This targeted examination is important to China's objectives of ensuring food security and sustainable progress. Given that the crop industry plays a role in both food provision and carbon emissions generation, there are challenges and opportunities for enhancing carbon efficiency in this sector. Using the TOE framework, the research not only uncovers the influencers of carbon efficiency in crop cultivation but also investigates ways to efficiently manage and utilize these elements to promote the growth of a sustainable agricultural industry that is both productive and eco-friendly.

Technology Dimension

Primarily includes two antecedent conditions: agricultural green technology innovation and the development level of the digital economy. Green technology innovation can help agricultural operators improve energy efficiency, reducing carbon emissions. Green technology innovation can reduce per unit energy consumption through green design, process improvement, and the application of green innovation technology in the agricultural planting production process, such as green agricultural input creation technology, high-yield and efficient agricultural machinery, and agronomy integration technology, green low-carbon planting, and pollution control technology, can effectively reduce the undesirable outputs of agricultural carbon emission efficiency. The majority of domestic and international scholars' research indicates that green technology innovation is a core factor in addressing carbon emissions and environmental issues, helping to "reduce quantity and improve quality" of carbon emissions (Deng and Zhang, 2024; Sethi *et al*., 2024). The digital economy is a new economic form characterized by green, innovative, and shared attributes. It gradually integrates into the entire process of food production in the agricultural field and, directly reduces carbon and enhances efficiency in agriculture (Grimsby, 2024). On one hand, the development of the digital economy reduces the constraints of information asymmetry, allowing agricultural operators to make wiser decisions about planting activities and the input of agricultural production factors through digital platforms, thereby improving labor productivity and agricultural carbon emission efficiency. On the other hand, the development of the digital economy reduces geographical limitations, enabling a large number of rural laborers to migrate to cities and land to be transferred to a few people for a large-scale operation, which helps promote intensive, mechanized, automated, and intelligent cultivation. Utilizing digital information technology in the production and planting process can enhance environmental control capabilities and the mechanization level of plant protection operations, promote the widespread adoption of field operation technology equipment (Yin *et al*., 2024d), precision production, and management models, make agricultural input more efficiently used, improve production benefits while reducing carbon emissions (Mei *et al*., 2023).

Organizational Dimension

The analysis mainly looks at two factors; government spending, on agriculture and the emphasis on friendly initiatives by the government. The progress of agriculture heavily relies on government aid with financial support and policy guidance playing roles in improving carbon emission efficiency in the sector.

To start with investments in agriculture are crucial for supporting practices adopting technologies and making infrastructure upgrades that help decrease carbon emissions in farming. Government funds can aid in researching and developing low-carbon farming methods offering subsidies for eco practices and facilitating the shift to sustainable agricultural systems. This financial backing is essential for offsetting the costs of these changes and encouraging adoption among farmers and agricultural entities.

Additionally, prioritizing development demonstrates a commitment to sustainability in agricultural policies. By concentrating on eco-initiatives, the government can encourage organizations to embrace low-carbon practices through support, favorable policies, and institutional development. Measures like providing subsidies for technologies offering tax benefits for sustainable farming methods and establishing regulations that prioritize environmental advantages all contribute to reducing carbon emissions from agriculture.

When the government pays attention to it, the agricultural sector can work toward goals promoting a culture of sustainability that becomes part of the industry's operation.

These two important factors—government spending and attention—are essential for pushing agriculture toward being carbon. They offer the needed support and incentives for businesses to embrace practices that ultimately help improve how efficiently agricultural carbon emissions are managed. By investing resources and policy focus in growth, the government plays a key role in shaping a future for sustainable agriculture and ensuring that the industry contributes positively to efforts against climate change (Yang *et al.*, 2022). Firstly, fiscal expenditure related to agriculture can ensure the continuity of scientific and technological research and development for agricultural enterprises and related institutions (Guo *et al.*, 2022). Agricultural technology has significant sociality and public goods characteristics, and fiscal expenditure related to agriculture can effectively increase the research and development intensity of high and new technology in the regional agricultural industry, share research and development risks, guide funds to key links, and help improve agricultural carbon emission efficiency. Secondly, fiscal expenditure related to agriculture is beneficial to support rural development, such as small farm water conservancy, agricultural technology promotion, soil and water conservation subsidies, plant protection subsidies, and rural afforestation subsidies, which can improve agricultural production efficiency, thereby reducing carbon emissions and increasing carbon use efficiency. Government attention to green development reflects the local government's emphasis on agriculture and agricultural carbon reduction efficiency. As the "visible hand," the central government enacts relevant policies, which local governments implement, directly influencing the allocation of local government attention to green development and thereby affecting local government decision-making behavior and governance effectiveness in carbon reduction. Local governments, as promoters and implementers of central government policies, and their attention to green development can reflect the overall implementation of government environmental policies (Chen *et al.*, 2024).

Environmental Dimension

This mainly includes two antecedent variables: environmental regulation and rationalizing agricultural industrial structure. Environmental regulation, government-led, intervenes directly or indirectly in enterprise behavior to prevent and control environmental pollution issues (Fan and Li, 2022; Wang *et al.*, 2024). Environmental regulation can bring about environmental pressure for carbon reduction and the improvement of carbon emission efficiency (Yin *et al.*, 2024a). The impact mechanism of different environmental regulations on carbon emission efficiency varies. Environmental regulations are classified based on their intensity into command, market-based, and voluntary regulations. Mandatory regulations are compulsory and function by controlling carbon emission sources to lower emissions and enhance emission efficiency. Market-based regulations influence the behavioral choices of grain producers through incentives, subsequently affecting carbon emissions. Voluntary environmental regulations involve producers taking voluntary steps toward carbon reduction, such as consciously reducing the usage of chemical fertilizers and pesticides, employing high-tech methods in agricultural production, and enhancing the unit efficiency of carbon utilization.

Existing research shows that China's environmental regulation policies play an important role in reducing carbon dioxide emissions (Liu *et al.*, 2020). The continuous improvement of environmental regulation can promote the reduction of carbon emissions and carbon intensity. The way agricultural industries are structured impacts how resources are distributed and how they affect carbon emissions (Shi and Chang, 2023). Changes in the structure of industries can influence the levels of carbon emissions. Different agricultural sectors have characteristics. How resources are distributed among them directly affects their carbon footprints. Crop production contributes to carbon emissions in agriculture because it relies heavily on factors like fertilizers, water, and energy. So, any changes in the structure related to crop production will lead to shifts in carbon emission efficiency within agriculture. For example, if resources are redirected from crop production to more sustainable practices or less carbon-intensive industries, overall carbon emissions can be lowered, improving emission efficiency.

Furthermore, restructuring the industry is important for fostering the integrated development of sectors within agriculture. This integration can help enhance the use of resources, boost productivity, and reduce waste and environmental impact.

By creating connections between sectors within agriculture, such as combining crop farming with animal husbandry, agroforestry, or renewable energy production, we can use resources and lower the environmental impact of farming activities.

This shift needs to be maximized for the benefits of both nature and finances. It also drives improvements in how efficiently agriculture emits carbon. As the structure of industries advances, it encourages the adoption of methods and technologies that promote sustainability. These changes help achieve the overarching aim of cutting down on carbon emissions while keeping or even boosting output, thereby contributing to the goals of protecting the environment and fostering economic progress.

To sum up, restructuring industries enhances the efficiency with which agriculture emits carbon. By redistributing resources and merging sectors, agriculture can embrace sustainable practices, make smarter use of resources, and ultimately lessen its environmental impact. This approach aligns with objectives focused on well-being and economic advancement. Figure 1 shows the TOE multilevel analysis framework constructed in this paper.

Research Methods and Data Sources

Data sources

The sample for this study consists of 30 provinces (cities, autonomous regions) in China, with data sourced from the "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Industrial Statistical Yearbook," statistical yearbooks of various provinces, local government work reports, and green patent applications from the CNRDS database and the State Intellectual Property Office from 2013 to 2022. Due to severe data limitations, Hong Kong, Macao, Taiwan, and the Tibet region are not included in the study. Additionally, to prevent price factors from interfering, the annual output values were converted using 2012 as the base year for comparable prices.

Technical condition variables
Agricultural green technology innovation is measured by the number of applications for green invention patents and utility models in agriculture (Li *et al*., 2024). Green patents are committed to reducing energy consumption, improving the ecological environment, promoting high-quality economic development, and achieving carbon reduction goals. The number of patent grants needs to catch up compared to patent applications, making the volume of patent applications more credible. The development level of the digital economy affects the mechanism of carbon emission occurrence. The development level of the digital economy in various provinces is measured by constructing an indicator system from multiple dimensions and using principal component analysis to calculate the digitalization index.

Organizational condition variables
The government is the core organizational condition for improving agricultural carbon emission efficiency, which can promote carbon emission efficiency improvement through various means such as administrative orders and financial support, with financial support having a more stable effect, measured by the expenditure on agriculture, forestry, and water affairs in various provinces. At the same time, government attention to agricultural green development is beneficial in guiding various agricultural entities to engage in green production and reduce carbon emissions, represented by the frequency of keywords in government work reports (Tu *et al*., 2024).

Environmental condition variables
Environmental regulation can achieve the goal of improving carbon emission efficiency through the "technology innovation compensation effect" (Chen *et al*., 2024). The investment amount in industrial pollution control reflects the government's determination to protect resources and control environmental pollution, represented by the ratio of industrial pollution control investment to the value added of the secondary industry. This ratio is positively correlated with the intensity of environmental regulation in that region. The transformation and upgrading of the industrial structure help achieve the strategic goal of carbon reduction, measured by the total agricultural output value ratio to the total output value of agriculture, forestry, animal husbandry, and fishery (Shi and Chang, 2023).

The measurement methods and data sources for each antecedent variable are shown in Table 1.

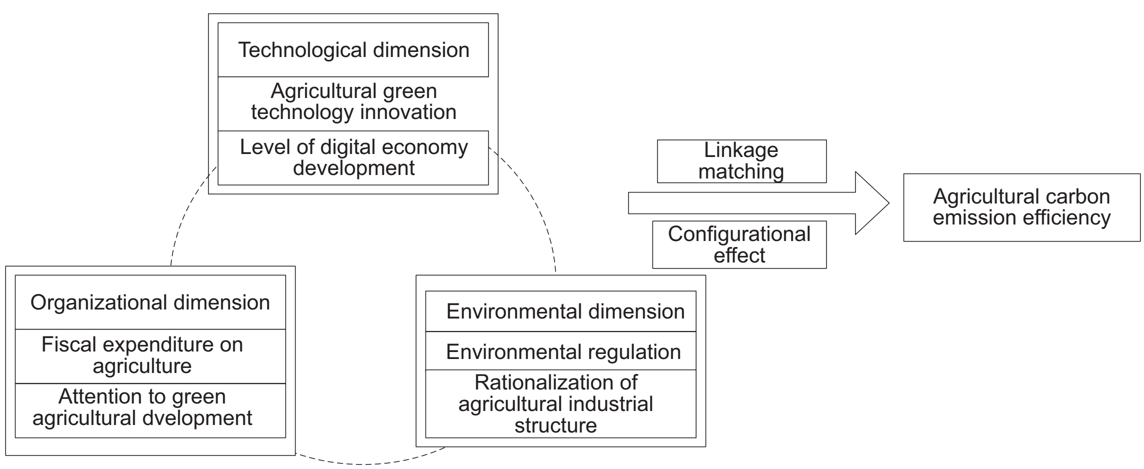

Figure 1. TOE multilevel analysis framework.

Table 1. Measurement methods and data sources for antecedent variables.

Variable		Measurement method	Data source
Condition variable	Agricultural Green Technology Innovation	Number of applications for agricultural green invention patents and utility models from 2013–2022 by province	CNRDS database, State Intellectual Property Office
	Level of Development of the Digital Economy	Digitalization index	China Statistical Yearbooks
	Fiscal Expenditure on Agriculture	Local fiscal expenditure on agriculture, forestry, and water affairs	Provincial Statistical Yearbooks
	Attention to Green Agricultural Development	The sum of frequencies of green agriculture keywords in government work reports	Provincial Government Work Reports
	Environmental Regulation	Investment in industrial pollution control/value added to the secondary industry.	China Industrial Statistical Yearbooks and Provincial Statistical Yearbooks
	Rationalization of Agricultural Industrial Structure	Total agricultural output value/Total output value of agriculture, forestry, animal husbandry, and fishery	China Rural Statistical Yearbooks
Outcome Variable	Agricultural Carbon Emission Efficiency	Agricultural carbon emission efficiency evaluation index system	China Statistical Yearbooks, China Rural Statistical Yearbooks, and Provincial Statistical Yearbooks

Research methods

Super-SBM model

The Super SBM model successfully addresses the limitation of the traditional radial DEA model, which only provides relative efficiency values between 0 and 1, by handling slack variables and efficiency assessments. However, it falls short of effectively ranking decision-making units. While the DEA model typically focuses solely on anticipated output, the Super SBM model considers expected and unexpected outputs. With the ability to distinguish between decision units with efficiency values of just one and more than one, the Super-SBM model accounts for undesirable output and produces more accurate calculation results. It is well-suited for handling efficiency measurement problems involving multiple input and output variables. It is frequently required to consider the negative environmental repercussions (nonanticipated outputs) and the economic benefits (expected outputs) while studying green development. The agriculture sector must increase economic revenue and decrease carbon emissions, which requires balancing input, expected output, and nonexpected output. This model can be applied to measuring agricultural carbon emission efficiency. To better reflect the differences in agricultural carbon emission efficiency in different provinces, the Super-SBM model under fixed scale (CRS) was selected. The calculation steps are as follows:

This paper selects six carbon emission sources based on existing research: fertilizers, pesticides, agricultural film, diesel, land plowing, and agricultural irrigation. The coefficients for each type of crop farming carbon emission source mainly come from data released by authoritative organizations such as the Intergovernmental Panel on Climate Change (IPCC) (Edenhofer *et al.*, 2014). The formula for agricultural carbon emissions is constructed as:

$$E = \Sigma E_i = \Sigma T_i Q_i \tag{1}$$

The expression of agricultural carbon absorption is as follows:

$$S = \sum\sum_{i=1}^{k} S_i = \sum_{i=1}^{k} s_i Y_i (1-r) / HI_i \tag{2}$$

The expression of constructing agricultural net carbon sink is as follows:

$$C = S - E \tag{3}$$

Where E is the carbon emissions from crop farming; E_i is the carbon emissions from the i-th carbon source; T_i is the quantity of the i-th carbon source; Q_i is the carbon emission coefficient of the i-th carbon source; S is the carbon absorption by crops; S_i is the carbon absorption by a certain crop; k is the number of crop types; s_i is the carbon absorption rate of crops; Y_i is the economic yield of crops; r is the water content of the economic part of crops; Hii is the economic coefficient of crops; C is the net agricultural carbon sink.

This study takes the agricultural production systems of various provinces as decision-making units. Define matrices as follows:

$$X = [x_1, x_2, \cdots, x_n] \in R^{m \times n} > 0 \tag{4}$$

$$Y^a = [y_1^a, y_2^a, \cdots, y_n^a] \in R^{e \times n} > 0 \quad (5)$$

$$Y^b = [y_1^b, y_2^b, \cdots, y_n^b] \in R^{f \times n} > 0 \quad (6)$$

In the matrices, R is the set of real number vectors, *and* m, e, and f represent the number of elements in inputs, desired outputs, and undesired outputs, respectively.

The Super-SBM model is expressed as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{e+f}\left(\sum_{j=1}^{e} \frac{s_j^a}{y_{r0}^a} + \sum_{k=1}^{f} \frac{s_k^b}{y_{h0}^b}\right)} \quad (7)$$

$$s.t.\begin{cases} \sum_{j=1, j \neq t}^{n} \mu_j x_{ij} - s_i^- \leq x_{it} \\ \sum_{j=1, j \neq t}^{n} \mu_j y_{kj}^a + s_i^- \geq y_{r_0}^a \\ \sum_{j=1, j \neq t}^{n} \mu_j y_{hj}^b - s_h^b \leq s_h^b \\ 1 + \frac{1}{e+f}\left(\sum_{k=1}^{e} \frac{s_k^a}{y_{r_0}^a} + \sum_{h=1}^{f} \frac{s_h^b}{y_{h_0}^b}\right) > 0 \\ \mu, s^-, s^a, s^b \geq 0 \end{cases} \quad (8)$$

Where ρ^* represents the efficiency value of the research objective, i is the i- th input index, $j(t)$ is the $j(t)$-th decision unit, x^t is the input factor, y^a is the expected output, y^b is an undesirable output, μ is a non-negative weight vector, S^- represents the relaxation variable of the input, S^a represents the relaxation variable of the expected output, S^b represents the relaxation variable of the undesired output.

Qualitative comparative analysis method

In the 1980s, University of California sociology professor C.C. Ragin devised qualitative comparative analysis, or QCA (Schneider and Rohlfing, 2013). This approach combines the benefits of both qualitative and quantitative analysis and is based on Boolean computation. According to this study, the QCA approach can offer an "equivalent" route with several choices for areas with varying resource endowments. 30 provinces are the subject of the study, and the QCA method solves the single problem that multiple regression analysis can only examine large samples. To investigate the relationship between various conditional configurations and result variables, the qualitative and quantitative methodologies are integrated. Based on configuration theory and traceability logic, it identifies the critical elements important in specific circumstances. To sum up, the QCA method is more suitable for this study. Given data characteristics, fsQCA method is selected for specific analysis.

Results and Analysis

Measurement of agricultural carbon emission efficiency across regions

The system used an indicator system to assess the efficiency of carbon emissions in agriculture, and Matlab software was utilized to measure this efficiency in 30 provinces from 2013 to 2022. Matlab calculations and analysis were conducted to effectively evaluate carbon emission efficiency in regions.

The findings outlined in Table 2 offer insights into the fluctuations of carbon emission efficiency during the study period. These results show how each province managed and optimized its methods to reduce carbon emissions while enhancing productivity.

The data displayed in Table 2 allow for trend identification, regional differences assessment, and pinpointing areas for improvement. By analyzing these outcomes, policymakers and stakeholders can gain an understanding of the factors influencing efficiency levels across provinces, enabling them to devise customized strategies for boosting carbon efficiency within China's agricultural industry.

This thorough examination not only sets a standard for performance but also paves the way for future enhancements supporting China's overarching objectives of sustainable agricultural progress and carbon footprint reduction.

Overall, the agricultural carbon emission efficiency across the country is relatively high. From 2013 to 2019, the agricultural carbon emission efficiency showed a clear upward trend, followed by a slight downward trend after 2019 and a slow increase again in 2022. This indicates that China has achieved significant results in agricultural carbon reduction. From a regional perspective, China's agricultural carbon emission efficiency is uneven, showing the characteristics of high in the east, and low in the west. From the perspective of provinces, the efficiency values of different regions are quite different. Heilongjiang, Jiangsu, Fujian, Guangdong, Guangxi, Sichuan, Guizhou, Shaanxi, and Xinjiang provinces (autonomous regions) showed no redundancy in carbon emissions during the agricultural production process, indicating an effective state. This means these nine regions have been at the best production frontier for a long time, with optimal input-output efficiency in agriculture. This variation can be attributed to the planting structure and agricultural resource endowment. Heilongjiang benefits from fertile soil, ample arable land, and advanced modernization. Jiangsu excels in agricultural science and technology innovation. In regions where rice cultivation holds

Table 2. Agricultural carbon emission efficiency of 30 provinces (municipalities, autonomous regions) in China, 2013–2022.

Provinces (Municipalities)	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean
Beijing	0.46	0.46	0.54	1.03	1.10	1.10	1.11	1.15	1.11	1.11	0.92
Tianjin	0.66	0.71	0.71	0.83	1.11	1.02	1.14	1.22	1.27	1.21	0.99
Hebei	0.59	0.59	0.65	0.71	0.78	0.84	1.02	0.92	0.94	0.96	0.80
Shanxi	0.41	0.43	0.54	0.50	0.54	0.53	0.58	0.59	0.59	0.55	0.53
Inner Mongolia	1.10	1.10	0.85	1.13	0.83	1.24	1.26	1.30	0.79	0.85	1.05
Liaoning	0.87	0.81	0.76	0.85	0.81	0.75	0.82	0.81	0.80	0.77	0.81
Jilin	1.12	1.13	1.13	1.16	1.24	0.69	1.20	1.17	1.19	1.18	1.12
Heilongjiang	1.15	1.19	1.27	1.28	1.37	1.36	1.42	1.41	1.47	1.51	1.34
Shanghai	0.62	0.78	1.07	1.08	1.07	1.17	1.17	1.14	1.14	1.17	1.04
Jiangsu	1.18	1.20	1.20	1.30	1.35	1.41	1.14	1.08	1.09	1.08	1.20
Zhejiang	0.70	0.79	1.11	1.15	1.08	1.08	1.15	1.05	0.71	0.69	0.95
Anhui	0.46	0.65	0.65	0.52	0.67	0.66	0.68	0.78	0.77	0.68	0.65
Fujian	1.25	1.19	1.20	1.22	1.18	1.19	1.26	1.07	1.06	1.03	1.17
Jiangxi	0.68	0.76	0.74	0.76	0.78	0.78	0.82	0.81	0.74	0.76	0.76
Shandong	0.66	0.72	0.71	0.76	0.81	0.79	0.84	0.92	0.84	0.86	0.79
Henan	0.76	0.85	0.86	0.86	1.08	1.05	1.08	0.88	0.91	0.90	0.92
Hubei	0.76	0.82	0.84	1.05	0.88	0.87	0.87	0.86	0.87	0.88	0.87
Hunan	0.84	0.74	0.82	0.84	0.81	0.77	0.85	0.83	0.88	1.04	0.84
Guangdong	1.35	1.35	1.37	1.27	1.19	1.18	1.35	1.20	1.25	1.19	1.27
Guangxi	1.10	1.42	1.32	1.45	1.30	1.26	1.30	1.28	1.29	1.28	1.30
Hainan	1.19	1.14	1.09	1.04	0.72	1.17	0.61	0.54	0.48	0.42	0.84
Chongqing	1.09	1.11	1.13	1.12	1.03	0.85	0.81	0.66	0.61	1.13	0.95
Sichuan	1.10	1.10	1.11	1.12	1.14	1.10	1.22	1.13	1.13	1.11	1.13
Guizhou	1.25	1.24	1.24	1.21	1.32	1.32	1.16	1.14	1.07	1.05	1.20
Yunnan	0.75	0.76	0.72	0.72	0.67	0.59	0.58	0.58	0.57	0.56	0.65
Shaanxi	1.37	1.38	1.37	1.29	1.33	1.30	1.13	1.28	1.08	1.13	1.26
Gansu	0.47	1.01	0.38	0.40	0.42	0.40	0.45	0.43	0.43	0.42	0.48
Qinghai	0.62	0.60	0.61	1.00	0.59	0.62	1.05	1.07	1.11	1.15	0.84
Ningxia	1.05	1.10	1.08	1.09	1.07	1.10	1.08	1.07	0.68	1.06	1.04
Xinjiang	1.33	1.24	1.29	1.28	1.30	1.33	1.32	1.33	1.36	1.40	1.32
Mean	0.90	0.95	0.95	1.00	0.99	0.98	1.02	0.99	0.94	0.97	0.97

a smaller share in the crop planting structure, methane emissions from rice fields are minimal, leading to lower the overall agricultural carbon emissions (Shi and Chang, 2023). Tianjin, Inner Mongolia, Jilin, Shanghai and Ningxia have higher efficiency values than the national average efficiency value, suggesting that these regions still need to focus on controlling carbon emissions in production. Other regions are below the national average efficiency value, with many redundant emissions, indicating a need for rational use of agricultural inputs to minimize ineffective emissions. In contrast, Anhui, Jiangxi, Shandong, Hebei, and other central agricultural provinces are largely responsible for the low agricultural carbon emission efficiency. These provinces fail to balance grain output with environmental protection in agricultural production, leading to a significant amount of invalid emissions. Thus, China should lower the rate of carbon extraction as per the features of each region.

Qualitative comparison and analysis of configuration results

Variable calibration

Using the direct calibration method (Dul, 2016), with the 95th, 50th, and 5th percentiles of the sample serving as the points of full membership, crossover, and full non-membership, respectively, to reflect the differences between the sample data and the actual situation. The thresholds for calibrating each variable are shown in Table 3, after which the fsQCA 3.0 software is used to convert them to membership values within the [0,1] interval.

The necessity of a single antecedent variable is analyzed by testing the consistency threshold. In this study, the consistency threshold was set at 0.9. The test results are shown in the following table, indicating that the consistency scores for each variable are less than the threshold of 0.9. This suggests that no single antecedent variable meets the necessary condition for high versus non-high agricultural carbon emission efficiency.

Configuration result

Further, check the configuration adequacy of each condition. Referring to existing research (Hong *et al.*, 2023), the consistency threshold was set at “0.8,” and to reduce the impact of contradictory configurations, the PRI consistency threshold was set at “0.7.” The analysis of configurations produces three solutions: complex, parsimonious, and intermediate. By comparing the parsimonious solution with the intermediate solution to identify condition attributes, variables that appear in both solutions are considered core conditions. In contrast, those only appearing in the intermediate solution are considered peripheral conditions. This formed paths with the intermediate solution as the primary and the parsimonious solution as supplementary, where condition configurations containing both intermediate and parsimonious solutions are considered core conditions. The specific results are shown in Table 5.

The results in Table 5 show that there are 6 configurations with high agricultural carbon emission efficiency (Paths 1 to 6), and their consistency is 0.853, 0.931, 0.888, 0.946, 0.893, and 0.931, respectively, which are higher than 0.800. The overall solution consistency reaches 0.848, and the 6 paths are all sufficient conditions for forming high agricultural carbon emission efficiency. It is proved that different configurations of the antecedent conditions influence agricultural carbon emission efficiency.

Path 1 indicates that when the level of agricultural green technology innovation is high, the level of digital economy development is high, the financial expenditure related to agriculture is high, the attention to agricultural green development is weak, the intensity of environmental regulation is small, and the degree of rationalization of agricultural, industrial structure is low, high agricultural carbon emission efficiency will be generated. This path is named “technical conditions-led.” This route covers 31% of the provinces, with typical cases in Shandong and Zhejiang. In provinces that follow this path, the government needs to pay more attention to the agricultural industry for green development. However, these provinces have fast high-tech development, reasonable agricultural industry structure, high resource allocation efficiency, and economies of scale effect, which makes the agricultural output corresponding to unit carbon emission constantly increase. Regions can rely on the support of new technologies such as digitalization, big data, and blockchain and take the opportunity of energy reform to comprehensively promote clean and low-carbon technologies and pollution reduction technologies to realize the monitoring and effective management of carbon emissions. There are more fiscal expenditures related to agriculture, and more financial funds flow to fertilizer, medicine, and agricultural machinery subsidies. After agricultural producers and operators get subsidies, they can use new agricultural inputs and agricultural machinery that are more green, environmentally friendly and clean, thus reducing the output of carbon emissions. At the same time, the pressure of environmental regulation is low, and the rationalization neural of rationalization

Table 3. Calibration of variables.

Outcome and condition		Calibration anchors		
		Full membership	Crossover	Full non-membership
Outcome Variable	Agricultural carbon Emission efficiency	1.33	0.94	0.51
Condition Variable	Agricultural green Technology innovation	928.785	121.150	14.290
	Level of development of the digital economy	1.981	-0.110	-0.529
	Fiscal expenditure on agriculture	1006	643	175
	Attention to green Agricultural development	80516	62795	53593
	Environmental regulation	0.0062	0.0020	0.0007
	Rationalization of agricultural industrial structure	0.699	0.514	0.407

Necessity analysis.

Table 4. Results of necessity analysis.

Antecedent variable	Consistency	Coverage
Agricultural Green Technology Innovation	0.735	0.642
~Agricultural Green Technology Innovation	0.615	0.654
Level of Development of the Digital Economy	0.729	0.613
~Level of Development of the Digital Economy	0.642	0.717
Fiscal Expenditure on Agriculture	0.687	0.629
~Fiscal Expenditure on Agriculture	0.613	0.616
Attention to Green Agricultural Development	0.653	0.585
~Attention to Green Agricultural Development	0.680	0.700
Environmental Regulation	0.709	0.592
~Environmental Regulation	0.622	0.700
Rationalization of Agricultural Industrial Structure	0.732	0.702
~Rationalization of Agricultural Industrial Structure	0.615	0.590

*The tilde (~) before a variable indicates the absence of that condition.

Table 5. Configurational paths for agricultural carbon emission efficiency in 30 provinces (municipalities, autonomous regions).

Category Condition variable	Technical conditions-led	Attention-structure synergy		Agriculture support-structure synergy		Overall development synergy
	Path 1	Path 2	Path 3	Path 4	Path 5	Path 6
Agricultural Green Technology Innovation	●	⨂	⨂		⊗	•
Level of Development of the Digital Economy	●	⨂	⨂	⨂	⨂	•
Fiscal Expenditure on Agriculture	●	⊗		●	●	●
Attention to Green Agricultural Development	⨂	●	●	⊗		•
Environmental Regulation	⨂		•	•	•	⨂
Agricultural Industrial Structure	⊗	●	●	●	●	●
Consistency	0.853	0.931	0.888	0.946	0.893	0.931
Original Coverage	0.310	0.375	0.435	0.364	0.401	0.317
Unique Coverage	0.092	0.067	0.039	0.031	0.024	0.050
Overall Solution Consistency				0.848		
Overall Solution Coverage				0.697		

*“⨂” indicates a core condition is missing; “⊗” indicates a peripheral condition is missing; “ ” indicates the condition does not affect the outcome; “•” indicates the presence of a peripheral condition; “●” indicates the presence of a core condition.

industrial structure is low, which means that the environmental pressure in the region is small. Developing a high-level digital economy and the government’s more agriculture-related investment will help promote carbon emission reduction.

The core conditions of Paths 2 and 3 are consistent, which means that a high level of agricultural carbon emission efficiency can be generated when the regional technology level is low, the agricultural green development attention is strong, and the agricultural industrial structure is highly rationalized. Therefore, they are combined and named “attention-structure synergy.” Path 2 covers 37.5% of the provinces, and the typical provinces following this path are Shanxi and Gansu. Route 3 covers 43.5% of the provinces, with Anhui as a typical case. In this type, the government’s high attention to the green development of agriculture and reasonable industrial structure play a leading role in promoting the improvement of agricultural carbon emission efficiency. Even in the face of insufficient technical strength, the regional agricultural carbon emission efficiency can still be improved through higher environmental pressure. Provinces following this type should improve the technical level based on maintaining a high environmental pressure; agricultural green technology innovation and digital economy development can effectively help the region to break through the technical “bottleneck,” the birth of new business forms and new models, and consolidate the foundation of green and low-carbon development. Horizontal compared paths Horizontal 2 and Path 3 that Pathr certain circumstances, less fiscal expenditure on agriculture and higher environmental regulatory pressure have an alternative effect on each other. The greater the government's investment in pollution control, the stronger the determination to improve environmental pollution, and the greater the pressure on environmental regulation. At this time, even if the fiscal expenditure on agriculture is small, the greater environmental pressure will force agricultural operators to carry out green innovation, develop green agriculture, and reduce pollution emissions.

In Paths 4 and 5, financial expenditure on agriculture and agriculture, industrial structure exists as the core conditions, digital economy development level as the core deficiency, and environmental regulation as the auxiliary conditions, combined and named "agriculture support-structure synergy." Path 4 covers 36.4% of the provinces, Path 5 covers 40.1%, and only two paths can explain 3% of the provinces. The provinces that meet this type are Jiangxi and Fujian. In the corresponding provinces of this type, environmental-solid regulatory pressure and fiscal expenditure on agriculture can make up for the need for more technical strength. The pressure of environmental regulation is relatively large, and the structure of agricultural industries is relatively reasonable, so large agricultural production linked with high pollution and high energy consumption is controlled. Agricultural producers and operators will be committed to carrying out green innovation, which can not only effectively reduce the cost of decarbonization but also provide technical support in the application of carbon dioxide, capture and storage technology research, and finally, is implemented on a large scale in the region. Government financial expenditure on agriculture can provide financial support for regional agricultural production activities, help the research and development of green technology, reduce the cost of developing green agriculture so that scientific research institutions and enterprises have more funds to invest in the improvement of green agricultural production technology and production process, and also enable agricultural producers and operators to use more low-carbon and environmentally friendly agricultural materials and techniques. Increase production efficiency per unit of carbon emissions in the planting process. By comparing Path 4 and Path 5, it is found that under certain conditions, agricultural green technology innovation and green development attention are mutually substitutive.

Name Path 6 "overall development synergy type". In Path 6, the pressure of environmental regulation is small, and other conditions exist as core or auxiliary conditions. The typical province for this route is Qinghai. To improve the efficiency of agricultural carbon emissions in provinces that meet this path, the government should significantly increase fiscal expenditure on agriculture and further adjust the agricultural industrial structure. At the same time, pay attention to the role of green technology innovation in promoting the carbon reduction rate of agriculture, and endogenous independent innovation is the core factor driving technological change and economic growth. It is necessary to continuously improve the quality of industrial development by actively distributing green and low-carbon emerging industries and taking green production increase and efficiency as the goal. Various carbon source control measures have been introduced to achieve effective control of agricultural exogenous carbon emissions and effective governance of endogenous carbon emissions.

Robustness test

In this study, we followed a method known as fsQCA, which has been used in research. We employed three methods to test the robustness: adjusting the consistency threshold, increasing the Proportional Reduction in Inconsistency (PRI) consistency, and changing the number of cases by adding or removing them. For this research, we focused on the method by raising the consistency threshold from 0.8 to 0.85. This adjustment was made to generate outcomes and validate the reliability of our conclusions.

The results of this robustness test indicated that when we increased the consistency threshold from 0.8 to 0.85, the identified configurational paths remained consistent without changes in coverage and solution consistency compared to the initial thresholds. This suggests that our findings regarding enhancing carbon emission efficiency across regions are stable and reliable. The alignment of results across thresholds strengthens the credibility of our findings, indicating that the pathways identified are dependable and provide a basis for further analysis and policy recommendations to enhance agricultural carbon emission efficiency.

Conclusions and Implications

Discussion

The efficiency of the country's agricultural carbon emissions peaked. The carbon emission efficiency exhibits a "rising-falling-rising slowly and tending to be stable" pattern throughout the study period. Regionally speaking, China's carbon emission efficiency is high in the east and low in the west, and the efficiency values of various sectors of agricultural production vary significantly, which is in line with the research findings of Wang *et al.* (2024). Six paths can increase agricultural carbon emission efficiency, according to the results of the configuration analysis. This further demonstrates that the conditions are not isolated but rather cooperate to increase agricultural carbon emission efficiency, and the typical cases that correspond to the various paths differ. Therefore, to achieve balanced development and increase agricultural carbon emission efficiency based on local peculiarities, all departments involved in agricultural production should investigate suitable avenues.

Research conclusions

Specifically, the following conclusions are drawn: (1) Over the past decade, China's agricultural carbon emission efficiency has followed a "rising-flat-falling-rising" trend with notable regional variations, exhibiting high in the east and low in the west. The efficiency values in Shanxi and Gansu were far lower than those in other regions, yet around half of the provincial values were greater than the average. (2) The enhancement of agricultural carbon emission efficiency is influenced by multiple factors, with no single factor acting as a promoter. Improving agricultural carbon emission efficiency is complex, requiring the synergistic action of technology, organization, and environment. (3) The six paths can be further summarized into four types: technical conditions-led, attention-structure synergy, agriculture support-structure synergy and overall development synergy type, further illustrating that different combinations of antecedent variables have equifinal effects on improving agricultural carbon emission efficiency. The overall solution coverage is 69.7%, and regions should adapt their strategies according to provincial conditions to reduce carbon and enhance efficiency. (4) Agricultural green technology innovation, level of development of the digital economy, fiscal expenditure on agriculture, attention to green agricultural development and agricultural industrial structure play a core role in improving agricultural carbon emission efficiency. The high level of technical conditions means that the continuous improvement of farmland water conservancy facilities affects the output and income of crops and simultaneously increases the agricultural output corresponding to unit carbon emissions. More fiscal expenditure on agriculture and a reasonable agricultural, industrial structure can help the research and development of green technologies, reduce the cost of green innovation, force regions to phase out high-pollution and high-emission agricultural production technologies, promote the reform of low-carbon technologies, and contribute to regional carbon emission reduction. (5) There are two groups of potential alternative relationships: fiscal expenditure on agriculture and environmental regulation, attention to green agricultural development and agricultural green technology innovation. The main reason is that the attention to agricultural green development directly reflects the provincial government's attitude toward agricultural green development, and the level of attention affects the fiscal expenditure on the agricultural industry and the implementation of carbon emission control within the region.

Managerial implications

(1) Value green innovation and focus on internal and external synergy. Most provinces achieve high carbon emission efficiency through the combined action of technological and environmental factors. Regions with good agricultural resources, such as Heilongjiang and Jilin provinces, should promote green and low-carbon development of agriculture while continuously improving technological levels, increasing investment in green technology research and development through multiple channels, motivating innovation in the agricultural sector, and forming pathways to enhance carbon emission efficiency through transformation and substitution.

(2) Strengthen regional cooperation to break through technological barriers. The distribution of green innovation resources in China is uneven, showing a pattern of the east and south being stronger than the west and north. To alleviate this situation, relevant entities can build green technology platforms, strengthen regional cooperation, accelerate the promotion and application of green innovation technologies, fully utilize the rich green innovation resources of the eastern and southern regions, and increase technological support for the western and northern regions to form a good synergy for reducing emissions and enhancing efficiency. Additionally, the government can formulate and implement incentive policies to increase the attractiveness of green innovation talents in the western and northern regions. Quality talent can help improve agricultural carbon emission efficiency by developing efficient, low-carbon, green, innovative agronomic techniques and agricultural input products. While promoting green technology innovation and strengthening government coordination. Through government leadership, build a co-creation system for science and technology, tackle technical challenges, and achieve a win-win situation for all parties.

(3) Allocate resources rationally and choose paths according to local conditions. Based on the appropriate increase in government financial expenditure on agriculture, environmental regulation, and other aspects, the aim is to continuously improve agricultural output per unit of carbon emissions. Adjust the agricultural industrial structure according to the characteristics of each province and optimize resource allocation rationally. Regions needing more technological levels should increase investment in green agricultural research and development, while

technologically advanced areas should strengthen the application and transformation of scientific and technological achievements. Provinces should focus on identifying key areas of high carbon emissions in the agricultural industry according to their own conditions and scientific and strategic deployments to reduce carbon emissions and increase agricultural output. Provincial governments need to comprehensively consider the level of agricultural green technology innovation, digital economy development, fiscal expenditure on agriculture, focus on green agricultural development, environmental regulation, and the rationality of agricultural, industrial structure, as well as their interrelationships, to formulate carbon emission efficiency improvement plans and assess the technical, economic, and social feasibility of various driving schemes, comprehensively choosing development paths suitable for their regions.

Implications

Theoretical implications

The agricultural carbon emission efficiency of 30 Chinese agricultural production departments was computed using an assessment approach for agricultural carbon emission efficiency. Six typical antecedents are chosen and examined from three levels of technology, organization, and environment, and the fsQCA method is used to investigate agricultural green technology innovation. The TOE framework is incorporated into the configuration study of agricultural carbon emission efficiency. Digital Economy Development Level, Agriculture Fiscal Expenditure, Green Agricultural Development Attention, the combined impact of agricultural industrial structure and environmental regulations on the efficiency of agricultural carbon emissions, and identify six ways to increase efficiency. It deep dives into the meaning of the TOE framework in the context of China and enhances the research perspective on carbon emission reduction.

Practical implications

There is a significant disparity in the efficiency of agricultural carbon emissions, and the resource endowments of China's major agricultural production departments vary. To close the gap, we should select the best course of action based on the unique circumstances of each location. At the same time, we should emphasize the role of powerful provinces in encouraging radiation. Numerous configuration paths that result in high carbon emission efficiency are obtained in this study, and additional analysis shows the heterogeneous role of technology, organization, and environmental conditions in various configurations. This significantly improves the accuracy and pertinence of countermeasures to reduce carbon emissions and increase agricultural carbon emission efficiency.

Limitations and Future Prospects

Some of the data in this research are indirect data from various agricultural production departments, and there may be some inaccuracies that affect the results. There are numerous factors that affect agricultural carbon emission efficiency. In this work, only six criteria are chosen for configuration analysis of agricultural carbon emission efficiency using the TOE model, however, more components can be added in future research.

Authors Contributions

All authors contributed equally to this paper.

Conflicts of Interest

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