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RESEARCH ARTICLE

Examination of the relationship between agricultural carbon emission efficiency and food quality and safety: from the perspective of environmental regulation

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Abstract

An important breakthrough in the coordinated development of China's low-carbon goals and food security strategies is agricultural development oriented toward quality, safety, green, and low carbon. This study integrated command-control and market-incentive environmental regulation (ER), agricultural eco-efficiency (ACEE), and food quality and safety (FQS) into a unified theoretical framework. The unexpected output-oriented Super-SBM model was used to calculate the ACEE of China's provinces and cities from 2011 to 2020 and test the bidirectional causality between ACEE and FQS through the system generalized moment estimation model. A dynamic panel smooth transition (PSTR) model was used to explore the nonlinear impact mechanisms of different types of ERs on ACEE and FQS. The results showed that there was a long-term, two-way causal relationship between ACEE and FQS. The impact of environmental regulations on ACEE and FQS has a nonlinear relationship. Among them, the role of market-incentivized ER is more significant. Therefore, building an inter-regional coordinated development mechanism, improving the utilization rate of agricultural resources such as fertilizers and pesticides, and coordinating the positive effects of different types of ERs are the keys to improving the ACEE and ensuring the coordinated development of FQS.

Keywords Environmental regulation · Agricultural eco-efficiency · Food quality and safety · Panel smooth transition model

Introduction

Agriculture is the foundation of the national economy. It not only undertakes the function of natural ecological regulation but also plays an important role in ensuring national food security (Sheng Jiping et al. 2021). However, the Food and Agriculture Organization (FAO) of the United Nations released a report at the 26th United Nations Climate Change Conference stating that in the past three decades, greenhouse gas emissions from global agricultural production and food systems have increased by 17%, and carbon emissions from agricultural and food system accounted for 31% of the global anthropogenic carbon emissions in 2019 (Chao Feng and Shan 2020). In the same year, China's total agricultural carbon emissions reached 9,406,721 tons, of which carbon emissions from agricultural energy use, agricultural material input, and rice planting accounted for 14.21%, 26.38%, and 25.95%, respectively. It can be seen that agriculture has a huge potential for carbon emission reduction and plays a role in achieving carbon peak and carbon neutral targets (Zhang et al. 2019; Pang et al. 2020).

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Since the twenty-first century, Chinese government departments have repeatedly emphasized the promotion of green and low-carbon agricultural development. The "13th Five-Year Plan" in 2016 proposed that while ensuring food security, agricultural production should be transformed into a resource-saving, environmentally friendly, and efficient agricultural modernization path, which provides a win–win development for promoting low-carbon agriculture and improving food quality and efficiency (Searchinger et al. 2018). In the report of the 20th National Congress of the Communist Party of China for 2022, accelerating the green transformation of the development mode and promoting green and low-carbon development were emphasized again.

Therefore, quantifying the relationship between agricultural carbon emission efficiency (ACEE) and food quality and safety (FQS) and exploring the means and paths to promote the coordinated development of the two are the keys to the effective implementation of China's low-carbon agriculture and food security strategy. In 2021, the Central Committee of the Communist Party of China and the State Council issued the "Opinions on Completely, Accurately and Comprehensively Implementing the New Development Concept and Doing a Good Job of Carbon Neutrality at Peak Carbon Peak," emphasizing the importance of green agricultural development, carbon sequestration, emission reduction, and efficiency increase. In 2022, the Ministry of Agriculture and Rural Affairs and the National Development and Reform Commission jointly issued the "Agricultural and Rural Carbon Sequestration Implementation Plan," which provides guidelines and implementation paths for low-carbon agricultural development in China. In addition, the national carbon emission trading market will officially open in 2021, and the means of ER will be more abundant. It is worth noting that although the methods and channels of ER are more diversified, this does not mean that implementation efficiency will increase accordingly. More attention should be paid to the classification and applicable scenarios of ERs and combined with the current development background; we should promote the formation of a win–win situation of "dual carbon" goals and food security.

Literature review

The ACEE and FQS are important elements of green, low-carbon, and sustainable development in the agricultural sector. The ACEE is the ratio of the ideal minimum carbon emission to the actual carbon emission under the given conditions of input and output, which to a certain extent reflects the level of agricultural productivity under the given carbon emission constraints (Zhou and Han 2010; Wang and Feng 2019). At present, the main methods for measuring ACEE include the unexpected output SBM model and DEA-Malmquist index decomposition (Lee 2021; Yang et al. 2022).

Research on the ACEE has mainly focused on dynamic changes, influencing factors, and spatial correlations (Zhu and Huo 2022; Xiong et al. 2020; Yin et al. 2022). Effective countermeasures for agricultural carbon sequestration and emission reduction are provided by discussing regional heterogeneity, spatial spillover effects, and redundancy. In addition, agricultural green and low-carbon development includes not only the improvement of ACEE but also FQS. The FQS requires not only food and clothing but also higher-quality agricultural products to upgrade the consumption structure (Hurmuzache et al. 2015). Therefore, under the current development situation, in which grain yield is guaranteed and the ecological environment needs to be protected in the new era, it is necessary to correctly handle the dialectical and unified relationship between food security and low-carbon agriculture and promote a higher level of quality and green development (Shen et al. 2022). Because agricultural producers and operators are often economic entities that seek to maximize profits, it is currently unfeasible to rely completely on agricultural operators to independently reduce carbon emissions. Therefore, the improvement of ACEE and guarantee of FQS must be regulated by ER (Rude and Weersink 2018).

Generally, the improvement of ACEE and the guarantee of FQS are important for ensuring sustainable development of agriculture, and ER is an important means of macro-control. At present, there have been many achievements in local research, but there are still deficiencies. First, in terms of the theoretical framework, there have been many studies on ER, but most have focused on the one-way impact of regulatory means on research subjects (Altman 2001; Chen et al. 2018; Huang and Tian 2023). Second, in terms of the selection of research subjects, there are many studies on the impact of ER on the carbon emission intensity of cities and industries; however, less research has been conducted on the impact of ER on ACEE (Zhang and Song 2021; Lena et al. 2022; Xie et al. 2023). Third, in terms of research indicators, existing studies have explored the dynamic relationship between ER and food security, but the relevant indicators have mainly focused on food quantity security, and insufficient attention has been paid to FQS (Andrade and Satorre 2015; Tenorio et al. 2020).

Therefore, based on the statistical panel data of 30 provinces in China from 2011 to 2020, this study expands the existing research: First, in terms of theoretical framework, this study innovatively integrates ER, ACEE, and FQS into the same research framework and conducts in-depth research on theoretical mechanisms. Compared with previous studies, this study has been supplemented and improved. Second, based on the win–win goal of "double carbon" and food security, it explores the macro-control role of ER and the dynamic mutual feedback relationship between ACEE and FQS. This provides data support for macro policy guidance. Third, it verifies the nonlinear relationship between different types of ERs on ACEE and FQS and provides a policymaking reference for the green, low-carbon, and sustainable development of the agricultural sector and identified the impact pathways of environmental regulation, which helps to explore the new era of "double carbon" strategy and the coordinated development path under the dual strategic guaranteed goal of food security.

The remainder of this paper is structured as follows: The second section is the theoretical analysis and research assumptions. The third section is the data sources and research methods. The fourth section is the result analysis. The final section is the conclusion and discussion.

Theoretical analysis and research hypothesis

Food security is a major strategic issue in a country's economic development, social stability, and national security (Aquino et al. 2021). In recent years, under the background of sustainable development goals, the traditional food security concept oriented by "grain quantity" has been continuously adjusted and made breakthroughs, and "food quality and safety (FQS)" has gradually become one of the important indicators of the new concept of food security (Yang et al. 2019). The ACEE refers to achieving rapid economic growth with less carbon emissions and lower energy consumption. At present, it is mainly measured by the carbon emission intensity of agricultural inputs in academia (Jinkai Li et al. 2023). The measurement of FQS is closely related to the pass rate of the quality inspection. This primarily focuses on production. Reducing the use of chemical fertilizers and pesticides is important for ensuring FQS (Yongming Han et al. 2023). Therefore, there is a close relationship between the ACEE and FQS (Kotsanopoulos and Arvanitoyannis 2017). On the one hand, the improvement of ACEE will help optimize the agricultural carbon emission reduction mechanism; promote the efficient input technology of agricultural materials, such as fertilizers and pesticides; reduce the intensity of greenhouse gas emissions from crops; internalize the benefits of carbon emission reduction (Zhang 2021); and reduce the harm to the quality and safety of agricultural products caused by the abuse of agricultural materials. Therefore, improving ACEE is an important engine for FQS (Ericksen et al. 2009). On the other hand, to improve the FQS assurance system, it is first necessary to establish standard constraints on agricultural inputs such as chemical fertilizers and pesticides at the end of production, fundamentally reducing the over-reliance on agricultural inputs, thereby reducing heavy metal pollution and pesticide residues. Therefore, ensuring the goal of FQS will help drive the green transformation of agricultural production, stimulate the internal development momentum of low-carbon agriculture, and reduce agricultural carbon emissions. ACEE and FQS promote and complement each other, which is conducive to forming a benign synergy effect and promoting the mutual benefit and win–win of "low carbon" and "food security." The path of action is shown in Fig. 1. Based on the above analysis, H1 was proposed for testing.

H1: There is a bidirectional causal relationship between ACEE and FQS.

ER is heterogeneous in ACEE. On the one hand, based on the "Porter hypothesis," moderate ER stimulates technological innovation (Porter and Vanderlinde 1995). Under the constraints of command-control ERs, as carbon emitters face the dual pressure of carbon emission reduction and cost effect, they often choose to strengthen the research and development of clean technologies, reduce the input of highly polluting materials in the industry, and reduce the pollution of local carbon emitters in the production process emissions, thereby increasing agricultural productivity and strengthening the "innovation compensation" effect, and

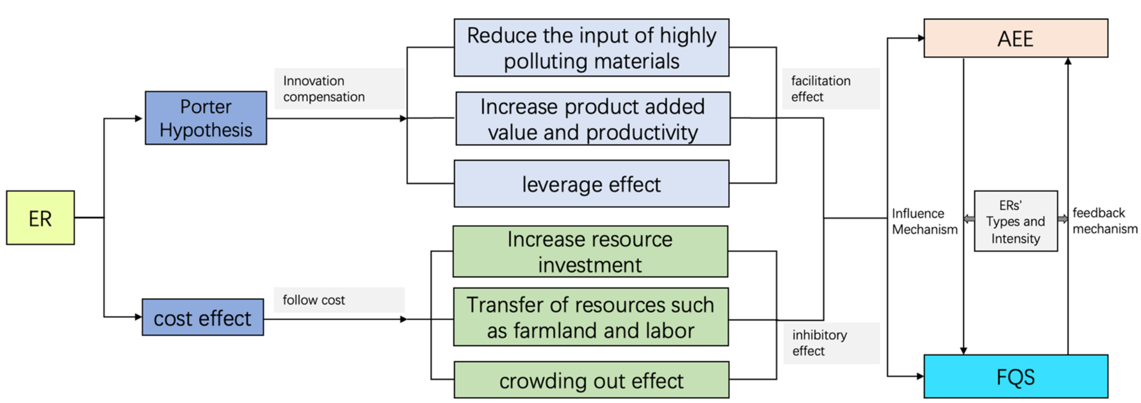

Fig. 1 Framework diagram of the logical relationship between ACEE, FQS, and ER

then achieve the purpose of improving ACEE (Yuan and Xiang 2018; Teets et al. 2021). However, command-control ER may have a negative effect on regional ACEE. Based on the viewpoint of "following the cost" to maximize profits and compensate for the additional "cost effect" produced by ERs, carbon emitters will choose to expand resource input and output, resulting in larger-scale carbon emissions (Barbera and Virginia 1990). In this context, market-incentivized ER is a more coordinative and important method to assist strict command-control ER. In addition, under strict ERs, the power of carbon emission entities to update technology is limited by the cost of technology research and development (Ramanathan et al. 2016; Hou et al. 2020), and generally choosing to only reduce emissions to the minimum carbon emission limit required by the government, insufficient attention has been paid to the ACEE. Based on the above analysis, we propose that H2 should be tested.

H2: Different types of ER measures have a nonlinear relationship with the ACEE according to changes in regulation intensity.

ER is an important tool for ensuring FQS, and its functional path is mainly divided into two aspects. On the one hand, by promoting the progress of agricultural technology and reducing the input of highly polluting materials in agriculture, ERs help curb pollution-intensive production, increase the added value and output rate of agricultural products, stimulate the "leverage effect" of technology-empowered agriculture, and drive green agricultural development, thereby ensuring FQS (Kuiper and Cui 2021). Simultaneously, strict command-control ERs are conducive to curbing the entry of highly polluting capital into the market and forcing an upgrade of the industrial structure (Ploeg 2012; Asadullah and Kambhampati 2021).

Under the conditions of market-incentive ER, the high returns of organic agricultural products induce food producers to take the initiative to apply clean technology in all aspects of agricultural production, reducing the input of agricultural chemicals and pesticide residues in agricultural production, thereby promoting FQS (Jiang et al. 2022). On the other hand, the cost effect brought about by ERs limits the incentive effect. The increase in food production and labor costs leads to the transfer of farmland and labor resources, which has a "crowding-out effect" on the research and development of green agricultural technologies (Reinhard et al. 1999; Zhao and Sun 2016), which may reduce the degree of FQS. Based on the above analysis, this study proposes H3.

H3: Different types of ER measures have a nonlinear relationship with FQS according to changes in regulation intensity.

Overall, environmental regulation is a "double-edged sword" for agricultural carbon emission efficiency and food security, which can improve agricultural carbon emission efficiency and food quality safety by reducing polluting inputs and increasing value-added products, but it can also reduce agricultural carbon efficiency and curb the improvement of food quality and safety by increasing resource inputs and transferring resources such as labor and land. At the same time, agricultural carbon emission efficiency and food quality and safety affect each other, and the intensity of the impact will vary depending about environmental regulations.

Data and methods

Variable interpretation and data sources

Variable interpretation

Explained variables ① Agricultural carbon emission efficiency (ACEE): the measurement of ACEE reflects the relationship between agricultural input and output. This study drew on the experience of Guo et al. and used the unexpected output Super-SBM to measure the ACEE (Niu et al. 2022). The higher the value, the higher the ACEE level. The specific input–output data and variable descriptions are shown in Table 2. ② Food quality and safety (FQS): in recent years, China's food security goals have changed from quantity-oriented to quality-safe. From the perspective of production, source control, green prevention, and control measures are important for improving the FQS. Reducing excessive investment in agricultural materials, such as pesticides, and reducing pesticide residues are an important criterion for measuring food quality. Therefore, this study referred to the methods of Yang and Lei (Yang Jianli 2014) and measured the pesticide residues per unit of grain output. Specifically, it was calculated by multiplying the pesticide residue coefficient by the ratio of pesticide use to grain crop yield. Because the lower the pesticide residues, the higher the degree of FQS; therefore, the opposite was true for the regression analysis coefficient.

Explanatory variables ① Market-incentive environmental regulation (market incentive ER): existing studies mostly use indicators such as pollution production intensity, investment in pollution control projects, enterprises' collection of pollutant discharge tax, and issuance of trading pollutant discharge permits to measure ER variables (Penghao Wang 2023). There are a few ER variables that control agricultural nonpoint source pollution. Because market-incentive ERs are mainly used as the characteristics of regions actively adjusting through market means, this study used the indicators of the collection of annual sewage charges by key monitoring enterprises in regions to measure the intensity of market-incentive ER (Yin et al. 2015). ② Command-control environmental regulation (command-control ER): command-control ER is often an important means for a country or government to control and regulate using mandatory policies and regulations. Because of the difficulty in measuring the implementation strength of rules and regulations in various regions and based on the scientific nature and availability of data sources, this study used the number of environmental protection laws and regulations, local regulations, and environmental protection standards issued by various regions as an index to measure the order-controlled environmental regulations (Zhang et al. 2022).

Control variables ① Natural disaster (*DISA*): natural agricultural disasters have a direct or indirect impact on the food cultivation environment, which affects grain production capacity. In this study, the proportion of disaster-affected areas to the total sown area of crops was used to measure the degree of the disaster. ② Urbanization level (*URBL*): the level of urbanization involves the replanning of urban and rural land-use structures, which affects the scale of production and the effective supply of grain. This study used the proportion of the urban population to the total population of each region to measure the level of urbanization. ③ Agricultural workforce education level (*EDU*): the cultural level of the labor force directly affects the effect of environmental protection publicity. It plays a role in promoting the use of new agricultural production factors and the improvement of production macro conditions. The proportion of the illiterate population aged 15 and above in each region was measured as a negative indicator of the labor culture level. ④ Income distribution (*IND*): the urban–rural income distribution reflects the comparative benefits of grain, and optimizing the structure of income distribution is conducive to improving farmers' enthusiasm to grow grain. This study used the ratio of urban per capita disposable income to rural per capita net income to measure income distribution. ⑤ Rural economic status (*RURS*): rural economic development often achieves growth by sharing the profits of the entire industrial chain, which plays a role in promoting farmers' food production and environmental protection initiatives. This study measured the level of rural economic status based on the proportion of added value of the primary industry in the regional GDP. ⑥ Research and development investment (*RD*): actively promoting technological innovation in the green food industry will help improve the transformation of scientific and technological achievements, as well as food quality and safety. This study measured the level of investment in science and technology by calculating the ratio of science and technology expenditure to the total fiscal expenditure of the region.

This study selected panel data of 30 provinces, municipalities, and autonomous regions in mainland China from 2011 to 2020 (excluding Tibet, where data are seriously missing) for empirical research. All the above data were from "China Statistical Yearbook," "China Environment Statistical Yearbook," "China Environment Yearbook," "China Rural Statistical Yearbook," "China Population and Employment Statistical Yearbook," "China Urban Statistical Yearbook," and various provinces' Statistical Yearbook; pesticide residue coefficient refers to "Handbook of Pesticide Loss Coefficient in the First National Survey of Pollution Sources." Missing data were filled in using interpolation.

Variable statistical description

As shown in Table 1, over the past 10 years, ACEE and FQS in China have maintained a relatively high level. The difference between command-control ER and market-incentivized ER is relatively large, showing an imbalance in the implementation of policies, regulations, and market incentives among different regions in China.

Research methods and models

Calculation method of ACEE

Calculation of agricultural carbon emissions This study drew on Li's method and used the emission factor method to measure agricultural carbon emissions (Li and Li 2022). Emission-factor approach is one of the carbon emission estimation methods proposed by the IPCC, and it is also a method widely used in academia. For each carbon emission source of the research subject, activity data and carbon emission factors were constructed, and the product of the two was

Table 1 Descriptive statistics of related variables for 30 Chinese provinces from 2011to 2020

Variable	Obs	Mean	Std. Dev	Min	Max
ACEE	300	12.783	1.042	9.764	14.185
FQS	300	1.146	0.120	1.018	1.650
Command-control ER	300	3.803	4.037	0.000	29.000
Market-incentive ER	300	64,217.220	55,178.850	2848.600	350,000
DISA	300	0.150	0.115	0.005	0.619
URBL	300	59.007	12.218	35.030	89.600
EDU	300	7.847	3.910	2.110	24.800
IND	300	2.635	0.432	1.850	3.980
RURS	300	9.732	5.162	0.300	26.200
RD	300	2.095	1.468	0.389	6.757

used as the estimated value of the carbon emission of the research subject. This study built a calculation method for agricultural carbon emissions based on carbon sources, such as chemical fertilizers, pesticides, agricultural film, diesel, irrigation, and plowing.

$$E = \sum E_i = \sum T_i \times \delta_i \tag{1}$$

where E is the total amount of agricultural carbon emissions, E_i is the carbon emission from the *i-type* carbon source, T_i is the carbon emission from the *i-type* carbon source, and δ_i is the carbon emission coefficient of the *i-type* carbon source. Based on a comprehensive consideration of the relevant literature, the sources and coefficients of agricultural carbon emissions are summarized in Table 2.

Calculation method for ACEE based on unexpected Super-SBM output Combined with relevant research, the input indicators of agricultural carbon emission efficiency were determined from the four dimensions of labor force, capital, land, and agricultural materials. The output indicators were determined from the two dimensions of expected output and nonexpected output, as shown in Table 3. Based on this, a Super-SBM model of unexpected output was constructed.

Causality test method based on system generalized moment estimation

A causal relationship may exist between the ACEE and FQS in the theoretical analysis. However, ordinary panel regression models cannot identify possible individual heterogeneity problems, omitted variable biases, measurement errors, or potential endogeneity problems, whereas system generalized moment estimation (GMM) models can correct these problems. Therefore, based on dynamic panel data, this study drew on related research (BS 1998; Chen Yuke and Jingrong 2022) and used the GMM model to test the causal relationship between ACEE and FQS. Under this analytical framework, the lagged value of the explained variable was used as the instrumental variable for estimating the model. The specific system model for testing the ACEE and FQS is as follows:

$$\begin{aligned} lnACEE_{i,t} = &\sum\nolimits_j^m \alpha_i lnACEE_{i(t-j)} \\ &+ \sum\nolimits_j^m \beta_i lnFQS_{i(t-j)} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{2}$$

$$\begin{aligned} lnFQS_{i,t} = &\sum\nolimits_j^m \alpha_i lnFQS_{i(t-j)} \\ &+ \sum\nolimits_j^m \beta_i lnACEE_{i(t-j)} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Table 2 Agricultural carbon emission sources, coefficients, and reference sources

Carbon source	Carbon emission factor	Reference source
Fertilizer	0.896 kgC/kg	Oak Ridge National Laboratory (West and Marland 2002)
Pesticide	4.934 kgC/kg	Oak Ridge National Laboratory (West and Marland 2002)
Agricultural film	5.180 kgC/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University (Tian et al. 2011)
Diesel fuel	0.593 kgC/kg	2013 IPCC United Nations Intergovernmental Committee of Experts on Climate Change (W 2013)
Irrigation	266.48 kgC/hm^2	Reference related literature (Duan et al. 2011)
Plowing	312.6 kgC/km^2	Reference related literature (Li Bo and Haipeng 2011)

Table 3 The undesirable output SBM model index system for measuring ACEE

Index	Category	Variable	Units	Explanation
Input	Labor input	Labor	10^4	Proportion of rural individual employment
	Capital input	Machinery	10^4 kw	Agricultural machinery investment
		Irrigation	10^4 hm^2	Effective irrigation area
	Land input	Sown area	10^4 hm^2	Crop sown area
	Agricultural inputs	Chemical fertilizer	10^4 kg	Fertilizer application amount
		Pesticide	10^4 kg	Pesticide application amount
		Agricultural film	10^4 kg	Amount of agricultural plastic film
		Diesel	10^4 kg	Application amount of agricultural diesel
Output	Desirable output	Total output value of agriculture, forestry, animal husbandry, and fishery	10^8 yuan	Total grain output
	Undesirable output	Agricultural carbon emissions	10^4 kgc	Total agricultural carbon emissions

where i, t, j represent different regions, years, and lag orders, respectively. $lnACEE_{i,t}$ and $lnFQS_{i,t}$ are the explained variables of models (1) and (2), respectively. $lnACEE_{i,t}$ and $lnFQS_{i,t}$ are the explanatory variables in the model. μ_i represents unobservable individual effects, and $\varepsilon_{i,t}$ is the residual term.

Analysis method based on dynamic panel threshold model

In practice, ERs are often used to restrict ACEE and FQS. To further test the impact of command-control ER and market-incentive ER, explore the differences in the impact of heterogeneous ER on ACEE and FQS and improve the reference of the research results. This study used the panel smooth transition (PSTR) model (Gonzalez et al. 2017) to test the nonlinear impact mechanism of different types of ERs on ACEE and FQS. ACEE and FQS, with a one-period lag, were incorporated into the PSTR model. The dynamic PSTR model was constructed as follows:

$$lnACEE_{i,t} = \mu_i + \alpha ACEE_{i,t-1} + \beta_0 ER_{i,t} + \beta_i X_{i,t} + \left(\alpha ACEE_{i,t-1} + \beta_0 ER_{i,t} + \beta_i X_{i,t}\right) h\left(q_{i,t}; \gamma; c\right) + \varepsilon_{i,t} \tag{4}$$

$$lnFQS_{i,t} = \mu_i + \alpha FQS_{i,t-1} + \beta_0 ER_{i,t} + \beta_i X_{i,t} + \left(\alpha FQS_{i,t-1} + \beta_0 ER_{i,t} + \beta_i X_{i,t}\right) h\left(q_{i,t}; \gamma; c\right) + \varepsilon_{i,t} \tag{5}$$

where i and t represent the region and year, respectively. $X_{i,t}$ is a set of control variables. $h\left(q_{i,t}; \gamma; c\right)$ is a continuous and bounded transition function. $q_{i,t}$ is the conversion variable. γ is a smoothing parameter. If $\gamma = 0$, there is no nonlinearity; if $\gamma \geq 1$, there is nonlinearity, and the PSTR model can be used. c is the location parameter, μ_i is the individual fixed-effect item, and $\varepsilon_{i,t}$ is the random disturbance item.

Results

Spatiotemporal difference analysis of ACEE

According to the ACEE calculation model, the change index of the ACEE in the provinces and regions of the country over the past ten years was obtained, as shown in Table 4.

The average ACEE value fluctuated slightly between 2011 and 2017 in China, and the overall trend first decreased and then increased. The main reason for this is that, from 2011 to 2017, agricultural development tended to be oriented toward agricultural inputs. High inputs, such as chemical fertilizers, pesticides, agricultural films, and diesel fuel, have led to continuous growth in agricultural carbon emissions. However, the expected output, such as the total agricultural output value, does not show a proportional increase. In 2017, the Ministry of Agriculture issued the "Action Plan for Agricultural Film Recycling." As an important source of agricultural carbon emissions, the recycling and resource utilization of agricultural films have greatly improved. The constraints on low-carbon development in China have gradually increased. The ACEE gradually recovered.

The average ACEE in Eastern China was the highest, whereas that in Central China was low. The eastern region mainly includes economically developed provinces, such as Beijing, Tianjin, Shanghai, and Shandong. The level of economic development and technology promotion rate was relatively high, the input–output rate of agricultural materials was high, and the ACEE was relatively high. The central region has a large plain area and is important for agricultural production in China. It was dominated by grain crops and had a high density of planted grains. Therefore, to promote food production, more agricultural inputs such as fertilizers and pesticides were invested in these areas. Moreover, the technological and economic level of development that relies on the agricultural output value lags behind that of the developed eastern regions, resulting in a low ACEE. On the one hand, with the increase in the area of land transfer in recent years, the planting scale and ACEE have gradually increased. On the other hand, the scale of grain planting in the western region is small, focusing on the development of economic crops. The regional ecology is better, and the level of agricultural carbon emissions is relatively low.

Analysis of the causal relationship between ACEE and FQS

This study used system GMM to estimate the causal relationship, and System Eqs. (1) and (2) were estimated. The test results are presented in Table 5. In Eq. (1), the explained variable is ACEE, and the explanatory variable FQS passed the test at the 1% significance level; in Eq. (2), the explained variable is FQS, and the explanatory variable, ACEE, and the lagged values of each period were significant at the 1% level. Simultaneously, the AR (2) test P values of Eqs. (1) and (2) were 0.567 and 0.405, respectively, and the assumption that the disturbance term has no autocorrelation was established. The P values of the Hansen test were 0.713 and 0.975, respectively, indicating the hypothesis that all selected instrumental variables are valid. Therefore, there is a bidirectional causal relationship between ACEE and FQS. The system GMM model does not have overidentification constraints, and the testing methods and results are true and reliable. This conclusion validates H1.

Specifically, FQS had a positive effect on ACEE and passed the test at the 1% significance level, as the estimation results of Eq. (1) show. From a theoretical perspective, high-quality and safety requirements for grain can help force grain producers and operators to optimize the efficiency of agricultural inputs, such as fertilizers and pesticides, through multiple constraints, such as government and consumers. From the perspective of the entire agricultural industry chain, the input of low-efficiency

Table 4 Change index of ACEE in China's provinces from 2011 to 2020

Area	Year										
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average
Beijing	1.186	1.208	1.262	1.308	1.288	1.275	1.277	1.252	1.173	1.076	1.230
Tianjin	1.072	1.031	1.033	1.030	1.040	1.039	0.673	1.420	1.373	1.503	1.121
Hebei	0.573	0.565	0.660	0.508	0.460	0.441	0.386	0.413	0.400	0.413	0.482
Shanxi	0.423	0.405	0.414	0.405	0.328	0.365	0.334	0.315	0.321	0.345	0.366
Inner Mongolia	1.107	0.617	0.550	0.532	0.432	0.462	0.437	0.393	0.354	0.364	0.525
Liaoning	1.068	1.103	1.069	1.033	1.006	0.800	0.615	0.581	0.578	0.537	0.839
Jilin	0.628	0.595	0.545	0.523	0.477	0.392	0.260	0.253	0.258	0.289	0.422
Heilongjiang	0.517	0.585	0.611	0.666	1.021	1.042	1.044	1.061	1.033	1.037	0.862
Shanghai	1.074	1.055	1.035	1.020	0.567	0.487	0.529	0.510	0.461	0.420	0.716
Jiangsu	1.010	1.023	1.013	1.007	1.033	1.019	1.005	0.682	0.642	0.596	0.903
Zhejiang	1.024	1.016	1.004	0.577	0.580	1.011	1.007	0.615	0.563	0.520	0.792
Anhui	0.529	0.499	0.518	0.527	0.538	0.475	0.439	0.388	0.420	0.405	0.474
Fujian	1.096	1.099	1.122	1.117	1.142	1.119	1.125	1.112	1.121	1.117	1.117
Jiangxi	0.578	0.563	0.631	0.619	0.545	0.621	0.535	0.537	0.568	0.557	0.575
Shandong	0.608	0.575	0.613	0.606	0.570	0.515	0.492	0.458	0.427	0.412	0.528
Henan	0.594	0.582	0.664	0.631	0.598	0.562	0.522	0.431	0.430	0.472	0.549
Hubei	0.732	0.730	0.730	0.708	0.725	0.738	0.688	0.673	0.637	0.625	0.699
Hunan	1.153	1.189	1.211	1.199	1.226	1.167	1.211	0.571	1.110	1.031	1.107
Guangdong	1.139	1.146	1.147	1.151	1.152	1.152	1.151	1.142	1.154	1.152	1.149
Guangxi	1.123	1.049	1.066	1.063	1.167	1.039	1.065	1.074	1.053	1.051	1.075
Hainan	1.401	1.354	1.271	1.361	1.315	1.304	1.358	1.351	1.220	1.289	1.322
Chongqing	1.021	1.010	1.026	0.719	0.601	1.011	0.780	0.686	0.771	1.001	0.863
Sichuan	1.140	1.134	1.093	1.141	1.241	1.089	0.836	0.777	1.008	0.860	1.032
Guizhou	1.009	1.036	1.069	1.134	1.229	1.250	1.285	1.331	1.340	1.325	1.201
Yunnan	0.500	0.475	0.477	0.463	0.429	0.426	0.466	0.561	0.629	1.001	0.543
Shaanxi	1.164	1.135	1.135	1.143	1.150	1.186	1.183	1.158	1.178	1.161	1.159
Gansu	0.330	0.322	0.340	0.315	0.295	0.285	0.250	0.266	0.291	0.281	0.297
Qinghai	1.146	1.212	1.284	1.233	1.284	1.303	1.310	1.165	1.129	1.199	1.226
Ningxia	0.544	0.468	0.447	0.445	0.517	0.455	0.452	0.468	0.402	0.436	0.463
Xinjiang	1.157	1.202	1.076	1.151	1.058	1.055	1.059	1.003	1.005	0.551	1.032
East	1.023	1.016	1.021	0.974	0.923	0.924	0.874	0.867	0.828	0.821	0.927
Central	0.738	0.682	0.694	0.687	0.706	0.686	0.654	0.570	0.619	0.618	0.665
West	0.890	0.888	0.883	0.860	0.867	0.895	0.847	0.824	0.861	0.868	0.868
Average	0.888	0.866	0.871	0.845	0.834	0.836	0.792	0.755	0.768	0.768	0.822

carbon-emission materials was compressed, and the expected output value of agricultural material input was increased, thereby improving the ACEE. By combining the regression coefficients of FQS with a lag of one period and three lags, it can be seen that FQS requirements have a long-term positive impact on regional ACEE, and the impact is superimposed. Therefore, FQS requirements are a long-term dynamic evolution process and not a short-term constraint behavior. China should formulate long-term dynamic response strategies based on the actual situation in the region to improve the degree of food quality and safety assurance.

ACEE had a significant positive impact on FQS and passed the test at the 1% significance level, as the estimation results in Eq. (2) show. ACEE focuses on the perspective of production through the rational input of agricultural materials, the use of organic fertilizers, and scientific and technological means to reduce undesired outputs, such as carbon emissions, improve the overall efficiency value, and then improve the level of FQS. Among them, the ACEE with a one-period lag had a greater impact coefficient on the FQS and then gradually weakened. This means that the impact of ACEE on FQS has a hysteresis, and the hysteresis effect will gradually weaken over time.

Overall, there was a significant two-way causal relationship between ACEE and FQS in the long term and short term. Exploring the coordinated development mechanism

Table 5 Test results of causal relationship between ACEE and FQS

Variable	(1) Explained variable *lnACEE*		(2) Explained variable *lnFQS*	
	coef	Std. error	coef	Std. error
lnACEE	–	–	0.028***	0.003
$lnACEE_1$	–	–	0.109***	0.003
$lnACEE_3$	–	–	0.038***	0.004
lnFQS	0.670***	0.133	–	–
$lnFQS_1$	1.858**	0.103	–	–
$lnFQS_3$	2.351***	0.106	–	–
AR(2)	0.567		0.405	
Hansen	0.713		0.975	

of the two is of great significance for the long-term sustainable development of agriculture.

Nonlinear effects of heterogeneous ER

Nonlinear test

The PSTR model first tested the nonlinear relationships between the variables. The Wald, Fisher, and LRT tests were used to test the nonlinearity of models (3) and (4). The results are summarized in Table 6. When $H_0 : \gamma = 0; H_1 : \gamma = 1$, models (3a) and (3b) rejected the null hypothesis with a significance level of 1%; when $H_0 : \gamma = 1; H_1 : \gamma = 2$, model (4a) rejected the null hypothesis at a significance level of 10%, while model (4b) rejected the null hypothesis at a significance level of 1%. The results showed that both models (3) and (4) have nonlinear effects, meaning that when command-control and market-incentive ER are used as threshold variables, there are significant nonlinear effects on ACEE and FQS. The PSTR model was used for the linear effects. Simultaneously, according to the estimation results, both models (3) and (4) have an optimal threshold parameter, $m = 1$.

It can be seen from Tables 7 and 8 that the estimation results of the core explanatory variables in models (3) and (4) are significant, but different types of ERs have heterogeneous effects on ACEE and FQS. In addition, control variables, such as disaster severity, urbanization level, labor cultural level, income distribution, rural economic status, and technological input, had significant dual-zone nonlinear characteristics on the core explanatory variables. Specifically, the impact coefficients of different types of ERs in the dual-zone system were different. The command-control type changed from significantly negative to insignificant for ACEE and insignificant to significant to positive for FQS. The market-incentive ER changed from insignificant to significant to negative for ACEE and from significant to positive to significantly negative for FQS. The conversion speeds were 1.370, 90.147, 5.895, and 1.974, respectively, with large differences.

The impact of command-control ER on ACEE in the low district system interval (threshold value was 22.196) showed a significant inhibitory effect with an increase in regulation intensity. The impact on ACEE in the high district system interval increased with the regulation as the intensity increased, and the significant inhibitory effect gradually disappeared (Table 7). This is because command-control ER coercively restricts carbon emissions through policies, laws, regulations, and other means. Generally, enterprises with a certain R&D level respond more strongly to command-control ERs. Currently, the main bodies of agricultural management in China are small- and medium-sized ordinary farmers, family farms, cooperatives, and leading enterprises. Therefore, mandatory orders not only cannot effectively optimize carbon emission reduction but also make carbon emission entities maintain the carbon emission intensity at the specified minimum, lacking the ability and motivation for technology research and development and updating and inhibiting ACEE. In the high-region system area, improving agricultural productivity and resource allocation efficiency through scientific and technological means can effectively

Table 6 Nonlinear test results

Model	Nonlinear test ($H_0 : \gamma = 0; H_1 : \gamma = 1$)			Residual nonlinear test ($H_0 : \gamma = 1; H_1 : \gamma = 2$)		
	Wald	Fisher	LRT	Wald	Fisher	LRT
Model 3a	25.573*** (0.001)	3.501*** (0.001)	26.730*** (0.000)	11.518 (0.118)	1.420 (0.198)	11.745 (0.109)
Model 3b	22.692*** (0.002)	2.911*** (0.006)	23.596*** (0.001)	2.554 (0.923)	0.297 (0.955)	2.565 (0.922)
Model 4a	13.329* (0.064)	1.747* (0.098)	13.635** (0.050)	7.210 (0.407)	0.876 (0.526)	7.298 (0.398)
Model 4b	58.383*** (0.000)	7.913*** (0.000)	64.928*** (0.000)	12.618* (0.082)	1.562** (0.047)	12.891 (0.075)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 7 The impact of two ERs on ACEE

Variable	Command-control ER		Market-incentive ER	
	Low district system	High district system	Low district system	High district system
$lnACEE_{i,t-1}$	0.834*** (13.03)	0.846*** (15.48)	−2.226*** (−3.93)	1.931*** (5.36)
$lnER_{i,t}$	−0.035* (−1.66)	−0.009 (−0.11)	−0.294*** (−2.57)	0.639*** (3.13)
lnDISA	0.132 (0.97)	0.335* (1.72)	−0.213 (−0.92)	0.013 (0.09)
lnURBL	0.058 (0.68)	0.317 (0.90)	−0.605*** (−2.77)	0.415*** (2.65)
lnIND	−0.237*** (−2.75)	0.383 (1.09)	−2.642*** (−3.11)	2.071*** (3.98)
lnRURS	0.207*** (3.80)	−0.060 (−0.91)	1.271*** (7.66)	−0.902*** (−7.59)
lnRD	−0.079* (−1.79)	−0.085 (−1.21)	1.772*** (5.28)	−1.064*** (−4.40)
γ	1.370		5.895	
c	22.196		10.455	

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Table 8 The impact of two kinds of ERs on FQS

Variable	Command-control ER		Market-incentive ER	
	Low district system	High district system	Low district system	High district system
$lnFQS_{i,t-1}$	0.989*** (57.74)	0.054*** (2.35)	1.008*** (84.62)	0.033 (1.48)
$lnER_{i,t}$	0.026 (1.56)	0.032* (1.72)	0.019*** (2.03)	0.034*** (−2.19)
lnDISA	0.010 (1.39)	−0.006 (−1.47)	0.012* (1.70)	−0.005 (−1.31)
lnURBL	0.008*** (2.12)	−0.004 (−1.19)	0.004 (1.24)	0.002 (0.46)
lnIND	0.008 (1.05)	−0.016* (−1.78)	0.001 (0.02)	0.001 (0.15)
lnRURS	−0.003 (−0.97)	0.007*** (2.44)	0.001 (0.12)	0.003 (1.05)
lnRD	−0.017* (−1.86)	0.021*** (2.19)	−0.008 (−1.10)	0.007 (1.01)
γ	90.147		1.974	
c	0.692		10.519	

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

promote an increase in the total output value of agriculture, forestry, animal husbandry, and fishery and reduce agricultural carbon emission intensity. Therefore, command-control ER has no significant positive impact on ACEE, and H2 does not hold.

Market incentive ER had a significant inhibitory effect on ACEE in the low district system interval (threshold value was 10.455) and had a certain promoting effect on ACEE.

For ACEE, when the intensity of the market-incentive ER is weak, carbon emitters will reduce the input intensity of chemical fertilizers and pesticides in the short term to obtain subsidies according to the actual situation, but this will not affect the total output value of agriculture, forestry, animal husbandry, and fishery. There was no promotional effect, which may have even been reduced. Therefore, it inhibited the improvement in the ACEE. When the intensity of market-incentive ER is strong, ordinary business entities will actively choose new clean technologies to meet their long-term interests, and the technological innovation motivation of business entities with strong scientific research will be enhanced. Under the condition of a high regional system, an increase in the intensity of ER plays a positive role in ACEE. Therefore, H2 holds for market-incentive ER measures.

The impact of command-control ER on FQS was not significant in the low district system interval (threshold value was 0.692), but the impact on FQS in the high district system interval showed a significant promotion effect with an increase in regulation intensity (Table 8). For FQS, strict control of fertilizers, pesticides, and agricultural inputs is an important way to improve security from the root. There is still a large room for improvement in the environmental management and control of China's grain production areas. Command-control ER has a significant impact on environmental and quality improvement, and the response speed is relatively fast in a period of rising dividends. Therefore, under high-institutional conditions, H3 holds true for command-control ER.

Market incentive ER had a significant effect on grain quality and safety with an increase in regulation intensity in both the low district system interval (threshold value was 10.519) and the high district system interval. This is because when initially using market-incentive ERs, the market is usually guided by incentives to regulate the market and by guiding business entities to carry out technological innovation and industrial structure adjustments to reduce and increase agricultural resources. Increase the utilization rate of inputs to ensure FQS. The green agricultural production subsidy stimulates agricultural operators to carry out green production; the subsidy effect promotes the scale of operation, and the positive promotion effect on FQS is gradually enhanced. Therefore, H3 holds.

The above analysis shows that the heterogeneity of ERs has different impacts on ACEE and FQS. Market-incentive ER had a more significant impact on ACEE and FQS. The significance of the model in the two-regional system interval shows a large difference, and the influence in the high-regional system interval is more significant. Therefore, market incentives should be combined with ERs to fully exploit the power of market regulation mechanisms.

Robustness test

To test the reliability of the analysis results, this study selected the number of environmental pollution administrative punishment cases and income from pollution discharge fees to represent command-control and market-incentive ER, respectively. It used the PSTR model to re-estimate models (3) and (4). Comparing the analysis results with Tables 7 and 8, the results of the nonlinear impact estimation on ACEE and FQS were consistent. Different types of ERs have heterogeneous impacts on the ACEE and FQS, and the models of different regional systems have significant differences. The results are consistent with the theoretical assumptions and previous analyses; thus, the empirical results of this study are robust.

Conclusion and limitation

Conclusion

Based on the background of the "dual carbon" target strategy and the food security target, this study divided the sustainable development of agriculture and rural areas into the improvement of ACEE and the guarantee of FQS. This emission system can reduce the input of high-carbon-emitting agricultural materials, such as chemical fertilizers and pesticides, thereby improving the degree of FQS assurance. However, the goal of FQS assurance is to promote the green transformation of agricultural production and stimulate the internal development momentum of low-carbon agriculture, promote each other, and form a benign interaction. The effectiveness and applicability of different types of ER methods are important factors that affect both. The following main conclusions were drawn.

First, the average ACEE value in China generally exhibits a U-shaped curve. The overall average national ACEE exhibited a slight downward trend from 2011 to 2017. This may be caused by a substantial increase in the input of agricultural materials such as chemical fertilizers, pesticides, agricultural films, and diesel. Since 2017, the ACEE value has gradually recovered with the strengthening of China's carbon emission constraints. At the same time, there are large regional differences in the ACEE. The ACEE in the developed eastern regions was higher, while the ACEE in the central regions with higher grain planting density was lower. Therefore, the research, development, and promotion of agricultural technology should be strengthened, and the utilization rate of agricultural resources, such as chemical fertilizers and pesticides, should be improved. The input of agricultural materials, such as fertilizers and pesticides, is an essential factor in ensuring the output of China's agricultural products, and the intermediate economic value created every year is as high as 100 billion yuan. However, according to data from the Ministry of Agriculture and Rural Affairs, the overall fertilizer utilization rate of China's three major staple crops of wheat, corn, and rice in 2020 was 40.2%, which is still far from the 50–60% of developed countries in Europe and the USA. Therefore, it is necessary to increase investment in agricultural research departments; improve the investment and utilization rate of agricultural materials such as grain crops, fertilizers, and pesticides; and reduce residues such as fertilizers and pesticides.

Second, there is a causal relationship between ACEE and FQS, and the mutual influence between the two is long term. Among these, the lagging effect of ACEE on FQS gradually weakened over time, and the effect of one lagging period of grain quality and safety on ACEE was the strongest. The macro-control mechanism should be strengthened to fully exploit the positive effects of different types of ERs. The applicability and effectiveness of ER should be fully explored as a rich and effective means of regulation. The state or government departments should rationally use ER means, control the command-control ER within a reasonable range, implement laws and regulations, local regulations and environmental standards, and other measures in place, and promote "from real to virtual" to achieve expectations effect. The implementation of market-incentive ERs, such as pollutant discharge taxes, should be strengthened as trading pollutant discharge permits in agricultural carbon emission reduction and increase the driving effect of incentive measures on improving ACEE. Simultaneously, we should explore a balanced and complementary ER combination system based on the situation and local conditions, improve the flexibility of implementing regulatory measures, and promote the coordinated and effective development of ACEE and FQS.

Third, the heterogeneity of ERs had a nonlinear impact on ACEE and FQS. Among these, the impact of ER on high-level district systems is more significant. Market-incentive ER plays a more significant role in promoting ACEE and FQS than command-control ER. Additionally, the relevant results passed the robustness test. To this end, an interregional coordinated development mechanism should be established to enhance the technology spillover effect in the eastern region. The developed eastern coastal areas are the backbone of green agricultural production and technological progress. The development of green agriculture in the inland areas of the central and western regions has been relatively slow. Agricultural production technology promotes the development of "from point to surface" low-carbon agriculture and realizes the active and coordinated development of the multiregional system.

Limitation

Based on a dynamic model, this study explored the relationships between ER, ACEE, and FQS. Although the research scale has been broadened theoretically, ACEE indicators are multidimensional and dynamic. This study is limited in terms of length; only the carbon emissions of the planting industry are included in the calculation, and research on the overall agricultural system needs to be deepened. In addition, FQS is only one aspect of food security. In the future, the dynamic coupling mechanism of agricultural carbon emissions and food security from the perspective of the overall agricultural system can be explored.

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