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Research article

Environmental regulations and agricultural carbon emissions efficiency: Evidence from rural China

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A B S T R A C T

Reducing carbon emissions while maintaining simultaneous economic growth has been the focus of agricultural and environmental management research in recent times. To examine the influence of agricultural environmental regulations and related factors on agricultural carbon emissions efficiency, the entropy method was utilized to weigh each index and develop an index system for evaluating agricultural environmental regulations. This study utilizes the Super Slacked-Based Measure model that takes into account undesirable outputs. The research data used spans the years 2010–2019 and covers 31 provinces in China to calculate the efficiency of agricultural carbon emissions. A spatial Durbin model was employed to investigate the influence of environmental regulations and other influential factors on the efficiency of agricultural carbon emissions. The efficiency levels in the eastern region of China have consistently exceeded the national average, whereas the central region has demonstrated the lowest efficiency levels across the nation. Both the efficiency of agricultural carbon emissions and the intensity of agri-environmental regulations measured in this paper are strongly spatially autocorrelated between provinces. The environmental regulations index on local agricultural carbon emissions efficiency is significantly positive, while the effect on the agricultural carbon emissions efficiency in adjacent areas is not significant. Overall, agricultural environmental regulations effectively enhance agricultural carbon emissions efficiency, which in turn promotes technological innovation and economic growth. At the same time, local governments should actively adopt targeted strategies based on the actual situation of different regions in terms of their resource endowments and differences in the production characteristics of different crops.

1. Introduction

Global warming has become a significant problem globally due to the drastically increased levels of carbon emissions caused by human activities, leading to climatic disasters and ocean acidification [1,2]. Environmental challenges not only destroy the ecosystem, but also hurt human beings and the rate of economic development [3,4]. Other than industrial sources, the agricultural sector is the economic sector that emits the most greenhouse gases, accounting for 25% of the global perceived carbon emissions [5,6].

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In recent years, Chinese agriculture has experienced significant growth through the mechanization of farming and the widespread use of pesticides and fertilizers [7]. However, this modernization has also brought negative impacts on the environment, such as increased agricultural carbon emissions, which is a serious problem [8,9]. The academic community is currently discussing various ways to reduce agricultural carbon emissions, including reducing emission levels and achieving sustainable agricultural development by addressing economic issues [10,11]. Research has shown that policies can affect agricultural carbon emissions from six different sources [12]. Current research also focuses on factors that influence agricultural carbon emissions efficiency, such as cropping management practices, local economic development levels, farmers' use of technology, and agricultural specialization [13–15]. It is important to note that reducing carbon emissions while increasing economic output and achieving sustainable development is a crucial issue [16,17].

Exploring carbon efficiency in this period is crucial to the development of green agriculture in China. The simultaneous advancement of emission reduction and economic growth, along with the enhancement of carbon efficiency, holds great significance in achieving carbon neutrality by 2060 [18–20]. A scientific measure of carbon efficiency, which compares the actual level of carbon emissions with the minimum level of carbon emissions, can indicate the potential for improvement in current carbon emissions [21,22]. Simultaneously, comprehending the impact of numerous factors on agricultural carbon emissions efficiency (ACEE) enables scientists to recognize the challenges and impediments involved in emissions reduction. Production characteristics are among the factors that could affect the efficiency of agricultural carbon emissions (cropping structure, irrigation, and the strength of the land scale) [21], natural characteristics (climate fluctuation, disaster occurrence, etc), economic development strengths (regional development level, industrialization, trade openness, etc) and social factors (level of urbanization, human capital, etc) [18,21].

Many studies currently focus on the influencing mechanisms of the above-mentioned factors. Environmental regulations are also key elements influencing agricultural carbon emissions efficiency [23]. However, there have been scant studies on the influence of environmental regulations on the efficacy of agricultural carbon emissions. Various environmental policies have been proposed in China to promote ecological improvements, reduce carbon emissions, and increase the efficiency of agricultural carbon emissions [24]. Specifically, the establishment of an appraisal framework for environmental regulations in agriculture and the investigation of its impact on the diverse stages of agricultural production would assist in realizing the objective of reducing carbon emissions. Since the 'low carbon economy' idea was initially proposed, environmental protection and sustainable development have become increasingly attractive. Environmental regulations play an important function in the government's efforts to promote emission reductions, enhance the environment, and restructure economic development patterns. The implementation of these policies has had a catalytic effect on technological innovation, thereby promoting economic development and transformations in the agricultural sector [25–28]. It is critical to examine how agricultural environmental regulations (AER) on agricultural carbon emissions efficiency (ACEE) are crucial in achieving emission reductions, promoting sustainable agriculture, and ensuring the development of agricultural modernization.

To explore how agricultural environmental regulations affect agricultural carbon emissions efficiency, analyzing agricultural production inputs and outputs is essential. Firstly, the government uses AER to encourage farmers to abandon inefficient production techniques and to adopt more advanced production technologies. Incorporating new technologies into farming practices drastically improves the efficiency of farmers' production inputs, leading to a reduction in production costs. The unit yield of agricultural goods may be increased through advanced production technologies, leading to larger economic output. Furthermore, advanced technologies can help to mitigate environmental pollution and emissions by addressing environmental concerns at all stages of production. Agricultural production pollution levels and carbon emissions are considered non-desirable outputs that can diminish agricultural carbon emissions efficiency. The existing theories argue that environmental regulations require pollution treatment by the target group, as well as actions such as purchase behaviors or technology development that will eventually bring economic burdens to farmers [29–31]. At the same time, pollution control leads to producers not being able to produce at optimal levels, which results in low production efficiency [32,33]. However, as explained by the Porter hypothesis, they believed AER makes it more difficult for environmental management but AER also reduces emissions of agricultural pollution. Moreover, adopting environmental regulations improves the technology level, optimizes factors of production, and upgrades outdated agricultural equipment [28,34]. As a result, farmers receive more advanced technological innovations and they become more competitive in the market, which will finally bring them profits in the long run [27]. The Porter Hypothesis argues that the economic loss brought by the "cost of compliance" effect can be compensated by the advantages of implementing environmental regulations, which will lead to rapid economic development [26].

Environmental regulations can also optimize farmers' management practices, and improving agricultural production practices can effectively reduce carbon emissions. Studies have shown that better production patterns and management practices can effectively reduce agricultural carbon emissions [13]. Environmental regulations can guide and optimize farmers' production practices by increasing the degree of agricultural production services, resulting in higher economic income for farmers. Environmental restrictions can increase agricultural operators' knowledge of the environment on all levels and lower carbon emissions during each operator's agricultural production process. The relationship between agricultural carbon emissions and economic growth is intricate and diverse, making it difficult to assess the effects of a single statistic. Most approaches to evaluating how strictly environmental regulations are enforced are focused on mitigating carbon emissions from industry and overlook agricultural carbon emissions. However, since the industrial sector is where the majority of carbon emissions come from, examining the response of carbon emissions to regulation alone is not representative of the degree to which regulation affects agricultural carbon emissions. The current study has a research gap since there is no measurement of the impact of environmental regulation on agricultural carbon emissions and no construction of indicators for the agricultural environmental regulation component.

It is still unclear whether agricultural environmental regulations can be utilized as a tool to encourage Chinese economic development through coercive or incentive measures to reduce environmental pollution, promote technological innovation, and ultimately improve the ACEE. The development of an assessment index system for agricultural environmental regulations and the investigation of its effects on the ACEE in China remain unresearched topics. Indicators must be developed for the section that addresses the lessening of agricultural carbon emissions. This research aims to assess the ACEE of each region and province in China from 2010 to 2019 using data from all 31 provinces. An evaluation index system for the intensity of AER, using two dimensions of ex-ante and ex-post, is constructed. The analysis also examines the interactions between regions to deepen the meaning of their impact on ACEE. The paper's conclusion and any pertinent policy suggestions will be presented at the end.

2. Data and method

2.1. Data description

In recent years, China's agricultural economy has experienced a rapid pace of development. Not only have agricultural production and farmers' incomes surged significantly, but there has also been an excessive exploitation of agricultural resources. The continual excessive use of pesticides and fertilizers can result in soil degradation, and the emergence of environmental issues is becoming increasingly evident. Based on data availability, this paper's scope encompasses 31 provinces in China, representing 97.80% of the population and 99.38% of the cropland [35,36]. Agricultural environmental regulation is measured by constructing a system of environmental regulation evaluation indicators. The following variables are mainly involved: the investment in pollution control, the investment in environmental protection, the number of released policies, the agricultural expenditure, the number of management staff, the agricultural carbon emissions, the amount of agricultural pollution, the sewage treatment, and the domestic waste treatment. The agricultural carbon component encompasses carbon emissions stemming from the production and utilization of pesticides, fertilizers, and agricultural films in agricultural production, as well as the fossil fuel consumption associated with agricultural machinery operation, soil organic carbon depletion due to plowing, and the utilization of fossil fuels in irrigation. Agricultural capital, agricultural labor, and agricultural land are also involved in the measurement of carbon emission efficiency in agriculture. Each of the explanatory variables used in this study to calculate the degree of environmental regulation and ACEE was obtained from the various national and local statistical yearbooks from 2011 to 2020. Several variables were gathered from the regional statistical yearbooks. Additionally, the number of local carbon emissions policy releases was obtained from the PKULAW website.

2.1.1. Measurement of agricultural environmental regulations index

The command-and-control regulations refer to the type that the government directly supervises and demands polluters to meet relevant standards based on existing laws and regulations [28,37,38]. The incentive-based regulations refer to the type with price-based tools including financial investment and environmental protection subsidies, as well as property rights-based tools such as carbon emission trading [37,39]. Voluntary regulation participation refers to the way of reducing pollution behavior by relying on initiatives carried out by social groups such as industry associations [39]. All three categories can effectively reduce environmental pollution from different perspectives.

To evaluate the intensity of AER, existing studies are mainly classified into single-index problems and composite-index problems. Single-index problems are further classified into cost-based AER and performance-based AER [40]. The cost-based AER includes the number of local environmental policies issued and the cost-to-expenditure ratio for treating pollutant emissions [41,42]. In contrast, the performance-based AER uses pollutant emissions and the pollutant disposal tax as the level of AER [43]. Since environmental regulations are diverse and continuous, using a single evaluation index may cause a large deviation from the actual situation. A remedy to this problem is to combine these two indicators by multiplications [27,28]. However, this strategy does not offer a thorough analysis of the whole scope of environmental control. Moreover, it is more comprehensive and specific to measure the intensity of AER by constructing an environmental regulation evaluation index system. To more effectively assess how environmental legislation influences agriculture, all indicators related to the agricultural environment and carbon emissions regulation are consolidated to provide a comprehensive measure of agricultural environmental regulation. Drawing on existing information, this study represents the implementation of environmental regulation by constructing a system of indicators for evaluating AER.

The evaluation layers used to build the environmental regulation evaluation index system can be divided into two groups: the command-and-control environmental regulations and incentive-based environmental regulations. According to the full-process control theory, when evaluating environmental regulations, some scholars incorporate the implementation, effectiveness, and results of environmental regulations into their evaluation index system [40]. As an example, the effectiveness of environmental regulation transformation can be evaluated by using indicators such as relative pollution emissions, sulfur dioxide removal rate, and industrial soot removal rate from the previous year. Peng et al. integrated three indicators of environmental regulation: measures, impacts, and efficiency to build an evaluation index system and classified them into five aspects: economic type, administrative type, emission type, health type, and efficiency type.

According to the full-process control theory, this paper divides the entire evaluation indicators into ex-ante indicators and ex-post indicators. Three primary indicators include measure indicators, impact indicators, and efficiency indicators. These three indicators offer a comprehensive assessment of the strength of agricultural environmental regulation. Moreover, the three primary indicators are further subdivided into nine secondary indicators. After preprocessing the data, the value of each variable is calculated using the entropy method. Weights are assigned to the outcomes to evaluate the intensity level of agricultural environmental regulations [44]. The ex-ante component encompasses five facets: investment in environmental governance, funding for rural environmental protection, number of local carbon emission policies issued, agricultural expenditure, and rural environmental managers. Investment in environmental governance is a robust indicator of the importance placed on environmental governance by the region. Funding for rural environmental protection reflects the financial resources allocated by the government to agricultural energy. The number of local carbon emission policies issued signifies the relevance and strength of local policies aimed at mitigating carbon emissions. Agricultural expenditure reflects all local costs associated with agriculture-related construction and can represent local input into agricultural development. The number of individuals managing rural energy institutions is also considered a factor in quantifying environmental regulation. Ex-post evaluation indicators include four categories: agricultural carbon emissions, relative emissions of agricultural pollution, sewage treatment, and domestic waste treatment, which reveal the outcomes of environmental regulation and are included in the indicator system. Table 1 and Fig. 1 provide a full description of the classification of environmental regulation evaluation indicators, as well as the calculation and evaluation of their values.

2.1.2. Super-SBM-undesirable model

The initial step of this study involves determining the ACEE of all 31 provinces in China. Compared to other methods of calculating efficiency, the Data Envelopment Analysis method can evaluate the efficiency without setting the production function form and it has a wide range of applications [45–47]. A non-angular and non-radial SBM model in 2001, can effectively address the issue of radial DEA models not reflecting objective reality [48]. However, when using the SBM for the efficiency calculation, the effective decision-making units are presented as 1, and comparing different efficient decision-making units is not possible [49,50]. To overcome this problem, Tone proposed the Super-SBM-Undesirable Model, which takes into consideration the presence of undesired outputs [51]. To account for non-desired outputs such as agricultural carbon emissions and surface pollution, this article employs a super-efficient SBM model that incorporates these outputs into the estimation of the efficiency of China's agricultural carbon emission production [52–54].

The model defines that there are n decision units with input vector $x \in R^m$, desired output vector $y^e \in R^a$, and non-desired output vector $y^n \in R^b$. We defined the matrix: $X = [x_1, x_2, \cdots, x_n] \in R^{m\times n} > 0$, $Y^e = [y_1^e, y_2^e, \cdots, y_n^e] \in R^{a\times n} > 0$ and constructed the Super-SBM-undesirable Model based on non-desired outputs. See equation (1)- (5) for details.

$$\rho^* = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{D_i^-}{x_{i0}}}{1 - \frac{1}{a+b}\left(\sum_{r=1}^{a}\frac{D_r^e}{y_{r0}^e} + \sum_{h=1}^{b}\frac{D_h^n}{y_{h0}^n}\right)} \tag{1}$$

$$x_{i0} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j - D_i^- \; D_i^- > 0, \forall i \tag{2}$$

$$y_{r0}^e \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_{rj} + D_r^e, D_r^e > 0, \forall r \tag{3}$$

$$y_{h0}^n \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_{hj} - D_h^n, D_h^n > 0, \forall h \tag{4}$$

$$1 - \frac{1}{a+b}\left(\sum_{r=1}^{a}\frac{D_r^e}{y_{r0}^e} + \sum_{h=1}^{b}\frac{D_h^n}{y_{h0}^n}\right) > 0 \tag{5}$$

$$D_i^- > 0, D_r^e > 0, D_h^n > 0, \lambda_j > 0, \forall i, j, r, h$$

ρ^* is the calculated efficiency value. D^-, D^e, and D^n are the slack variables for inputs, desired outputs, and undesired outputs, respectively. λ is the weight vector, and the subscript 0 indicates the decision-making unit.

Before calculating the agricultural carbon emissions (ACEE), setting up a logical input and output system is required. Firstly, various approaches utilized in existing research work should be comparatively analyzed thoroughly. Additionally, the availability, comparability, and variability of the raw data should be considered in the analysis of ACEE. This paper established an indicator system of eight input variables, one desired output variable, and two non-desired output variables. Interpolation was used to complete missing

Table 1
Details of the indicators at each level.

Secondary Indicators	Explanation
Investment in pollution control (+)	Investment in environmental pollution control/GDP of the region
Investment in environmental protection (+)	Government funding for rural energy
Number of released policies (+)	Number of local carbon emissions policies issued in the year
Agricultural expenditure (+)	Regional agricultural expenditures
Number of management staff (+)	Number of rural energy management agencies
Agricultural carbon emissions (-)	The proportional amount of CO2 emissions from the agricultural sector
Amount of agricultural pollution (-)	The relative pollution level from the agricultural sector
Sewage treatment (+)	Sewage treatment plant centralization rates
Domestic waste treatment (+)	Rate of safely discarding household garbage

In the table (+) and (−) indicate positive and negative indexes respectively.

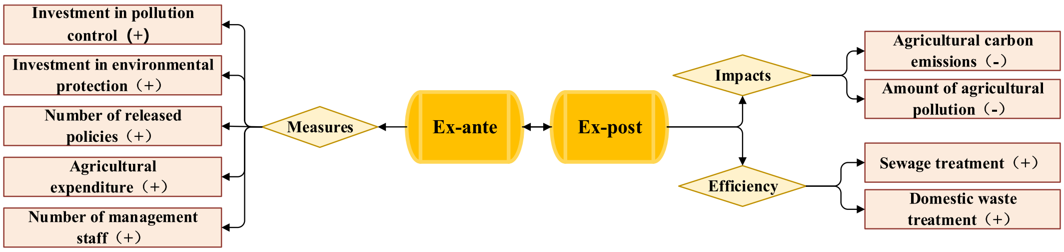

Fig. 1. Evaluation index system of agricultural environmental regulations.

data caused by official statistics. In Fig. 2, descriptive statistics are shown.

The entropy approach was used to calculate agricultural non-point source pollution. The loss coefficient and residue coefficient were obtained from Yuan Pei [55]. Agricultural carbon emissions were calculated using the data from six emission sources shown in Fig. 2, while the emission coefficients were obtained from Li Bo and Yuan Pei's research findings [55,56].

2.2. Spatial econometric model

Given the potential spatial correlation between AER and ACEE, the analysis of influencing factors necessitates the inclusion of spatial econometric methods [57]. To account for the spatial spillover effects of AER on ACEE, we employ a spatial panel model as our analytical methodology [58]. The spatial panel model for this study can be expressed as equation (6)- (7).

$$Y_{it} = \beta ed_{it} + \lambda control_{it} + \alpha WY_{it} + \theta Wed_{it} + \gamma Wcontrol_{it} + u_{it} \tag{6}$$

$$u_{it} = \varphi Wu_{it} + \varepsilon_{it} \tag{7}$$

where W is the weight matrix; β, λ, α, θ, γ are the effects of local AER, local control variables, the agricultural carbon emissions efficiency in adjacent areas, AER in adjacent areas, and the impacts of control variables in adjacent areas on the local carbon emission efficiency, respectively. φ is the interaction effect in adjacent areas. If θ, γ, and φ are 0, the model is a spatial lag model (SAR); if α, θ, and γ are 0, the model is a spatial error model (SEM); if φ is 0, the model is a spatial Durbin model (SDM) [59].

This paper selects six explanatory variables and we study how they influence agricultural carbon emissions efficiency (ACEE). The agriculture environmental regulatory (AER) is the primary explanatory factor. The other five explanatory variables including rural public investment (PI), degree of industrialization (IN), degree of agricultural disaster (AD), industrial structure (IS), and the level of economic development (ED) are used as control variables. Table 2 displays the calculation methods, data sources, and descriptive statistics.

3. Results

3.1. Agricultural environmental regulation intensity

The provinces of the nation have been classified into four regions in this article: the eastern, central, western, and northeastern

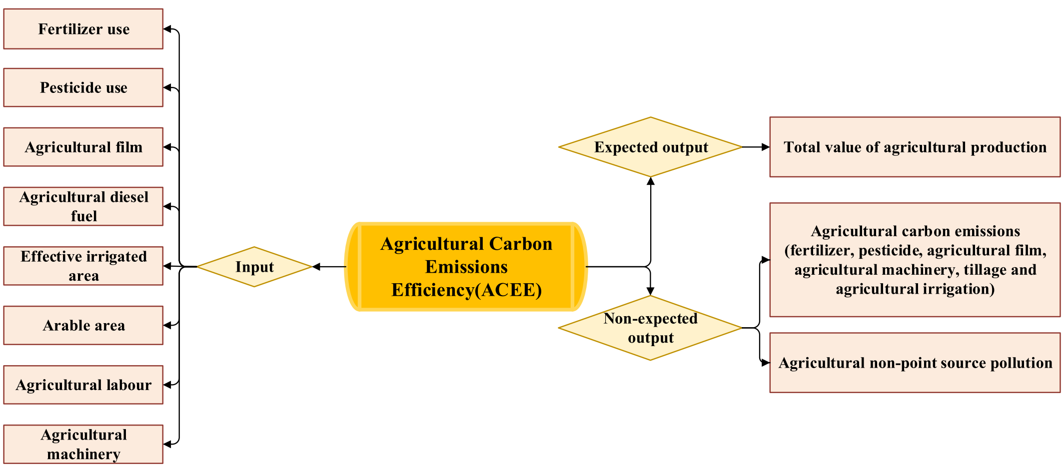

Fig. 2. Indicators of agricultural carbon emissions efficiency (ACEE).

Table 2
Descriptive statistics of the regression variables.

Variables	Definition	Mean	Std. dev.	Min	Max	Source
AER	As mentioned above	53074050	37915640	1442483	164371900	China Agricultural Statistical Report, Peking University Law website [60], Statistical bulletins of national economic and social development of various regions
ACEE	As mentioned above	0.5347899	0.2491414	0.1163657	1.124174	China Rural Statistical Yearbook, China Statistical Yearbook
PI	Agricultural fiscal expenditures/ Total fiscal expenditures	0.115	0.032	0.041	0.203	China Rural Statistical Yearbook
IN	Industrial value-added/Regional GDP	0.441	0.086	0.162	0.59	China Statistical Yearbook
AD	Area of crops affected/Total area sown	0.159	0.119	0.006	0.695	China Rural Statistical Yearbook
IS	Production value of agriculture, forestry, animal husbandry, and fishery/Regional GDP	0.517	0.088	0.338	0.74	China Statistical Yearbook
ED	Regional GDP/Regional year-end population	5.176	2.61	1.323	16.421	China Statistical Yearbook, China Statistical Abstract

regions. This research has also produced an index for measuring the degree of agricultural environmental regulation. As depicted in Fig. 3(a), the agricultural environmental regulation index has exhibited a steady increase over the years, indicating a general upward trend in the intensity of environmental regulation across the country. The central region consistently occupies the lowest position on the index, while the northeastern region has experienced a significant increase. From 2010 to 2015, the eastern region had a faster rate of growth in environmental regulation, which was then followed by a significant decline between 2015 and 2016 before increasing once more. The western region consistently maintains a higher position on the index.

3.2. *Agricultural carbon emissions efficiency (ACEE)*

This paper utilizes MATLAB 2021b to compute the ACEE, using the Super-SBM-undesirable model.

Fig. 3(b) demonstrates that between 2010 and 2015, the national average value for the ACEE increased rather steadily. Although the speed of increase slowed down between 2015 and 2017, exponential growth picked up in the following two years.

Fig. 3 illustrates the dynamic changes of ACEE for each region, with lines of different colors representing their corresponding regions. The graph illustrates that the ACEE in the Eastern part of China has consistently been higher than the national average. Throughout the 2010–2019 period, the ACEE in the Western part of China has remained slightly below the national average, but the gap has decreased in recent years.

The ACEE in the Northeastern part of China exhibited steady growth from 2010 to 2015, while there was a significant decline in 2016. However, it started to rise again from 2017 to 2019. The ACEE in Central China has consistently been below the national average, with its growth rate increasing since 2017–2019.

The temporal and spatial representation in Fig. 4 illustrates the variation in ACEE for each province from 2010 to 2019. From Fig. 4, the eastern part of China has a higher level of agricultural sustainability than the other provinces. Much more developed than other regions in China, provinces in the Eastern part of China are equipped with more advanced agricultural production techniques. At the same time, economically developed areas are usually chosen as primary pilot regions for certain government policies. Therefore, more local farmers in these provinces are educated and they are likely to adopt more appropriate strategies when issues happen. The Western

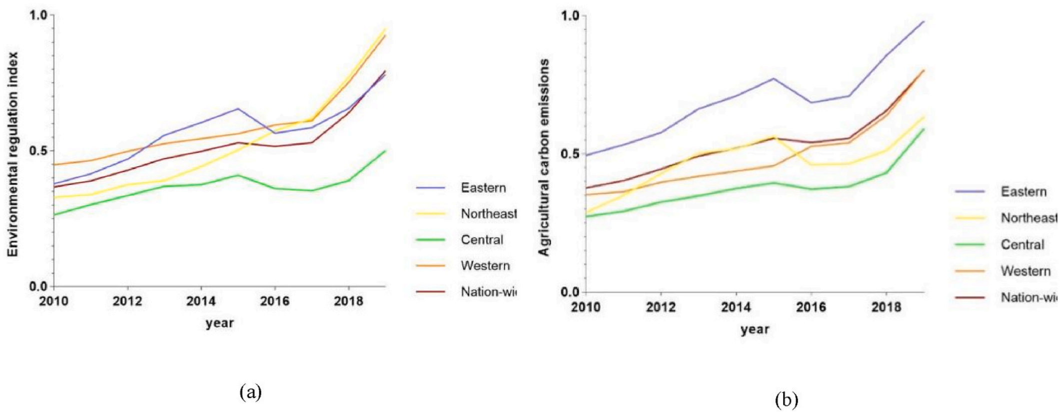

Fig. 3. Changes in environmental regulation index and agricultural carbon emissions efficiency by province, 2010–2019.

part of China is comparatively less economically developed than other regions and also has a lower level of agricultural economy and development of rural habitat. However, the amount of pollution driven by agricultural output in Western China is minimal. The northeastern part of China and Central China has a lower degree of agricultural modernization and land intensification, resulting in less efficient agricultural carbon emissions. High land utilization brought on by Central China's dense population limits the growth of the ACEE.

The average ACEE for each province and region during the study period is presented in Table 3. Table 3 demonstrates that during the study period, the ACEE varied significantly among the 31 provinces in China (excluding Hong Kong, Macao, and Taiwan). The highest mean value of efficiency is 0.944 in Beijing, followed by 0.937 and 0.809 in Shanghai and Jiangsu, respectively. Gansu and Shanxi exhibit low ACEE, with values of 0.237 and 0.251, respectively. In Anhui, agricultural carbon emissions have the lowest efficiency (0.235).

The ACEE values show a noticeable disparity across various regions in China. The central region, which includes densely populated provinces, should strive to improve the modernization of agriculture and technological developments, reducing carbon emissions and responding positively to national policies. The Western part of China should focus on upgrading agricultural production techniques to promote regional economic development.

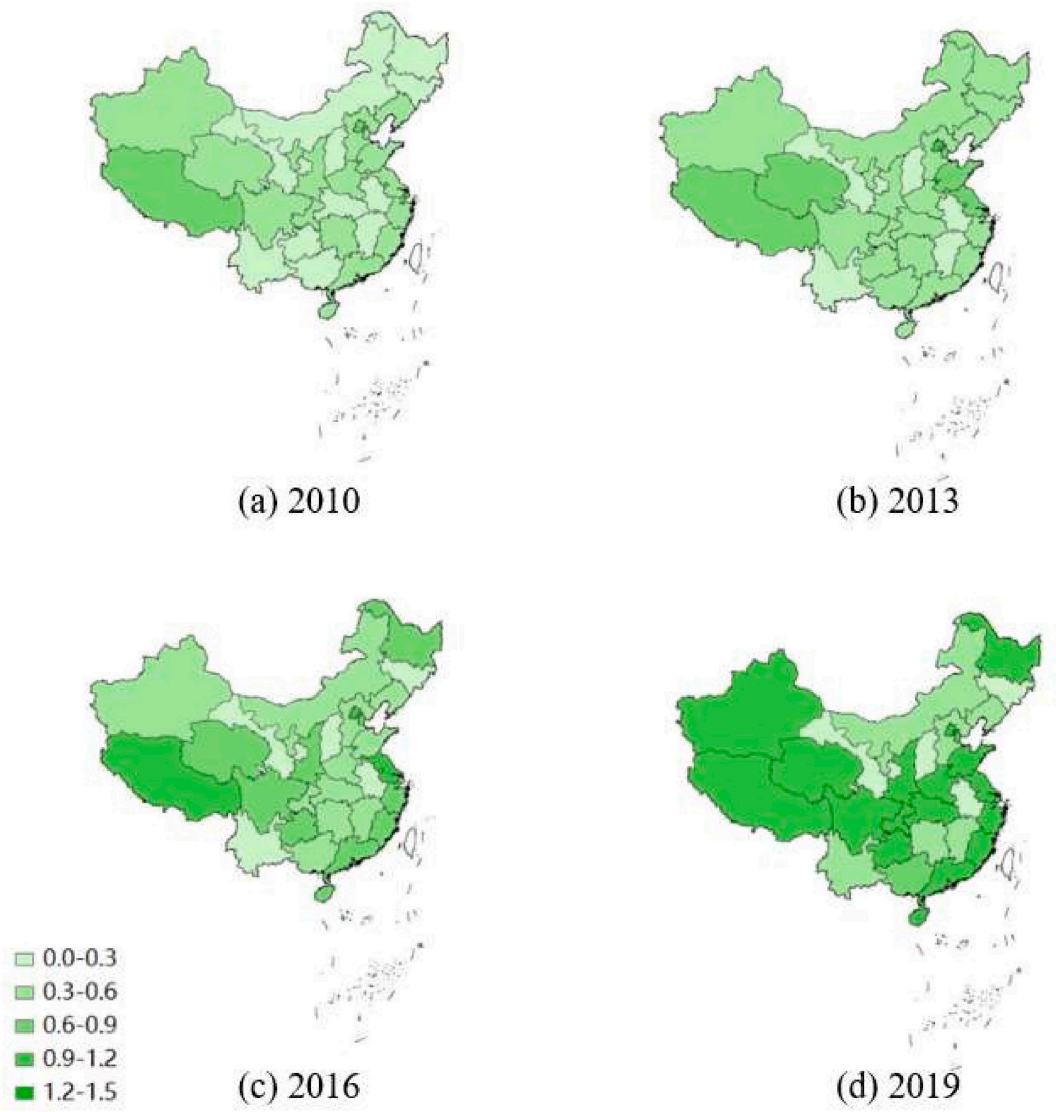

Fig. 4. Temporal and spatial variation in agricultural carbon emissions efficiency by region, 2010.

Table 3
The average value of ACEE for 31 provinces from 2010 to 2019.

Province	Mean value	Province	Mean value
Beijing	0.944	Heilongjiang	0.600
Tianjin	0.710	Jilin	0.302
Hebei	0.393	Liaoning	0.516
Shandong	0.686	**Northeast**	0.473
Jiangsu	0.809	Chongqing	0.498
Shanghai	0.937	Sichuan	0.623
Zhejiang	0.576	Guangxi	0.410
Fujian	0.658	Guizhou	0.526
Guangdong	0.622	Yunnan	0.274
Hainan	0.653	Shaanxi	0.612
Eastern	0.699	Gansu	0.237
Shanxi	0.251	Inner Mongolia	0.336
Henan	0.584	Ningxia	0.394
Hubei	0.492	Xinjiang	0.620
Hunan	0.400	Qinghai	0.642
Jiangxi	0.314	Xizang	0.758
Anhui	0.235	**Western**	0.494
Central	0.379	**Nation-wide**	0.536

3.3. Global spatial auto-correlation test

The global Moran's I analysis conducted using the Geoda software revealed a consistently positive and statistically significant correlation ($p < 0.05$) in terms of ACEE from 2010 to 2019. The global Moran's I of the agricultural environmental regulation intensity was found to be significant ($p < 0.01$) [61]. The ACEE is influenced by factors such as natural elements, industrial structure, and local economic development. Due to their similar geographical and climatic characteristics, adjacent regions are not independent of each other.

3.4. Analysis of factors affecting ACEE

3.4.1. Main results

Before conducting the regression analysis, we transformed the values by taking their logarithm to make them smoother [62,63]. Table 4 shows the results of the multiple covariance test, showing that variance inflation factor (VIF) values below 10 and a mean value of 1.46. There's no multi-collinearity problem present. The LM test and the robust LM test were performed first in this paper [64,65]. As shown in Table 5, both the LM value and the robust LM value of the SEM pass the test ($p < 0.001$) under the spatial adjacency matrix, while the robust LM value of the SAR also passes the test ($p < 0.01$).

Table 6 indicates that all three Hausman tests are significant at the 1% level, suggesting that the selection of the fixed effects model is appropriate. Given that all of the results are significant at the 1% level, the results of the LR tests show that none of the models can be reduced to either an SEM or a SAR. Table 6 presents the results obtained using three models: SDM, SAR, and SEM. The goodness of fit is only 0.3485 and 0.0034 for the SAR and the SEM, respectively, while the SDM's score is greater, suggesting its appropriateness for calculation. The SDM demonstrated a strong positive impact of the SAR at the 1% level, demonstrating that the ACEE in nearby provinces significantly influences the ACEE value in a particular province.

3.4.2. Direct vs. indirect

The point estimates applied in the fixed effects SDM ignore the interaction terms between adjacent provinces, therefore the individual coefficients may not accurately reflect the effects between the variables [66,67]. Partial differentiation is utilized to classify the impacts of each explanatory variable on the value of ACEE into direct, indirect, and total effects [66,67]. Table 7 shows the results.

A coefficient of 0.566 indicates that the direct effect of the AER on the ACEE is statistically significant (p 0.05). This suggests that AER can enhance the productivity of local agricultural carbon emissions. The findings are consistent with the research hypothesis and show that implementing AER can dramatically reduce local pollution and carbon emissions, and it also improves local carbon

Table 4
Multicollinearity test.

Variables	VIF
AER	1.330
PI	1.800
IN	1.400
AD	1.260
IS	1.110
ED	1.860
Mean VIF	1.460

Table 5
LM and robust LM tests.

LM test	Statistic	df	P value
Lagrange multiplier (error)	11.069	1	0.001
Robust Lagrange multiplier (error)	19.258	1	0.000
Lagrange multiplier (lag)	2.392	1	0.122
Robust Lagrange multiplier (lag)	10.581	1	0.001

Table 6
Estimation results.

	SDM		SAR		SEM	
Variables	Coeff.	Z-value	Coeff.	Z-value	Coeff.	Z-value
ln (AER)	0.455**	2.44	0.557***	3.96	0.779***	5.74
ln (PI)	0.476***	3.85	0.396***	3.32	0.020	0.14
ln (IN)	0.371*	1.72	−0.019	−0.09	0.244	0.90
ln (AD)	−0.020	−1.11	−0.013	−0.73	0.002	0.09
ln (IS)	0.449***	3.04	0.1680	1.16	0.0001	0.03
ln (ED)	0.752***	3.93	−0.133	−0.90	−0.8240	−5.28
W × ln (ER)	−0.033	−0.11				
W × ln (PI)	1.124***	5.83				
W × ln (IN)	4.009***	6.60				
W × ln (AD)	0.095***	2.61				
W × ln (IS)	0.799**	2.21				
W × ln (ED)	−2.506***	−7.33				
ρ	1.013***	12.84	−0.631***	−8.55	−0.599***	−6.57
R2	0.7835		0.3485		0.0034	
Log-likelihood	−24.3630		−99.1763		−99.1763	
Hausman	42.00***		16.01**		15.27**	
LR-err	81.24***					
LR-lag	88.99***					

*p < 0.1, **p < 0.05, ***p < 0.01.

Table 7
Total, direct, and indirect effects of explanatory variables.

	Total		Direct		Indirect	
	Coef.	z	Coef.	z	Coef.	z
ln (AER)	0.216*	1.75	0.566**	2.09	−0.35	−1.13
ln (PI)	0.794***	7.58	0.31*	1.89	0.484***	2.67
ln (IN)	2.221***	6.47	−0.533*	−1.81	2.754***	6.18
ln (AD)	0.037**	2.1	−0.049*	−1.88	0.086***	2.61
ln (IS)	0.636***	3.13	0.372*	1.79	0.264	0.86
ln (ED)	−0.893***	−6.54	1.578**	4.62	−2.47***	−6.35

*p < 0.1, **p < 0.05, ***p < 0.01.

efficiency in terms of undesired outputs. In terms of the desired output, AER raises the level of production technology, leading to higher profits. Restrictions on agricultural production by AER stimulate technological innovation, increasing the initiative of farmers and improving their competitiveness. When implementing AER, the government gives farmers more innovative farming technologies and environmentally friendly information, leading to the improvement of ACEE. Agricultural AER's indirect effect is statistically small, which means that there isn't much of a spillover effect from nearby regions to the study region. AER has a positive and significant overall impact on ACEE (p 0.1).

At the 1%, 10%, and 1% levels, respectively, the direct, indirect, and total effects of public investment (PI) on agricultural carbon emissions efficiency (ACEE) are all positive and statistically significant. The findings demonstrate that agricultural carbon emissions efficiency experienced significant growth and improvement during the study period, and this is mostly due to the large contribution made by governmental investment in agriculture. The high level of financial investment suggests that the local government is prioritizing the development of agriculture, technological innovation, and infrastructure improvements. To increase agricultural productivity and profitability, they all make a difference. The ACEE in neighboring regions is significantly improved by investments in agriculture.

The direct effect of industrialization (IN) is significantly negative, whereas the indirect and total effects are significantly positive. Industrialization can contribute to the development of agricultural technology and machinery, which raises agricultural production and economic returns. The widespread use of agricultural machinery driven by industrialization may increase the carbon emissions of agricultural production, which can negatively affect the ACEE, especially at the local level. In contrast, despite the negative direct effect on local efficiency of carbon emissions, industrialization has an overall positive effect on the Chinese ACEE. This suggests that, in general, Chinese agricultural production is still in a period driven by industrialization development, which can enhance agricultural productivity and improve agricultural carbon emissions efficiency.

Reduced sown area has a favorable impact on reducing agricultural carbon emissions, at least in terms of the direct consequences. The local agricultural carbon emissions efficiency (ACEE) is negatively impacted by the severity of agricultural disasters (AD). Agricultural disasters can lead to lower harvest per unit area of agricultural land, affecting farmers' profitability. The impact on the economy is greater than the decrease in agricultural carbon emissions, suggesting a lower level of efficiency in agricultural carbon emissions. The extent of agricultural disaster also has a large positive spillover effect on the provinces nearby's ability to reduce their carbon emissions, significant at the 1% level. When one area experiences a disaster, the supply and demand of agricultural products can shift due to the proximity of the two regions, potentially benefiting neighboring provinces that grow similar crops, and thereby improving the economic returns and efficiency of agricultural production in those provinces.

Agricultural carbon emissions efficiency (ACEE) is notably positively impacted by industrial structure (IS) at levels of 10% and 1%, respectively. Regions with a higher share of total output value from primary industries generally have a greater degree of ACEE inside the region. Firstly, regions with a higher share of the primary industry have a higher degree of land scale and efficiency of machinery utilization, which enables economy of scale and increases the profits generated from agricultural production.

With a direct effect coefficient of 1.578 and a significance level of 5%, the economic development (ED) variable significantly positively affects the ACEE in the associated area. Higher levels of economic development in a region can provide a solid material base for agricultural development. Additionally, ED has a strong favorable impact on the level of innovation in agricultural technology and rural human capital, ultimately improving agricultural productivity and ACEE. Instead, at the 1% level of significance, a negative spillover effect exists between the stage of regional economic development and the level of carbon emissions in neighboring regions, with a coefficient of -2.47. Areas with higher economic development may cause transfer of human capital from neighboring areas, generating problems such as the outflow of educated people and lower efficiency of agricultural production. Moreover, regions with greater levels of economic development may also attract more industrial and urban activities that contribute to higher levels of pollution emissions, resulting in a detrimental effect on the ACEE in neighboring regions.

4. Discussion

This research develops an assessment index method for agricultural environmental regulations, providing scientific measurements for the intensity of environmental regulations issued and quantifying their issuance. Unlike the one-dimensional measurement approach commonly adopted in most literature, this paper presents a novel "ex-ante" and "ex-post" evaluation index system for measuring the intensity of agricultural environmental regulations. This approach provides a more comprehensive method for measuring indicators of environmental regulation in agriculture. The full-process control theory and prior evaluation expertise are used to build the system. The theory of full-process control enables a comprehensive analysis of the release of environmental regulations. Besides, the system uses measures of environmental regulations and other effect indicators as evaluation indicators, which significantly improves the previous limitations of data selection and singularity of indicators [68]. Using single-type indicators and choosing different indicators within the evaluation index system may bring inconsistent results to the analysis. The inconsistency can be alleviated by the newly added indicators. The industrial sector is responsible for the vast bulk of carbon emissions, prior studies on carbon emission reduction through environmental regulation cannot be directly applied to the scenario where environmental regulation affects agricultural carbon emissions. To accurately evaluate the influence of environmental regulations on the efficiency of agricultural carbon emissions, this paper selectively incorporates pertinent indicators from the agricultural sector, thereby enhancing the precision and dependability of the experiment. It is possible to more accurately assess the impact of environmental regulations on agriculture by focusing on their specific publication related to the agricultural sector, rather than attempting to measure all environmental regulations in general. Due to the existence of these two attributes, this approach is more comprehensive and focused, and the creation of comprehensive and targeted indicators to assess AER is one of the contributions of this paper.

Due to China's longstanding commitment to sustainable agriculture, it is essential to reduce carbon emissions and enhance economic benefits. How carbon emission efficiency, an excellent quantitative indicator of sustainable development, is affected is the focus of this paper. Thus, this study examines the factors affecting agriculture's ability to reduce its carbon emissions from the standpoint of agricultural environmental regulation, providing insights into the extent and scope of the result of environmental regulation on carbon emissions and aiding in China's agricultural carbon emission reduction [69]. The effectiveness of carbon emissions and environmental legislation are intricately linked. The effect of agricultural environmental regulations' "cost of compliance" increases the level of investment input and reduces overall profits [31]. According to the Porter hypothesis, the "cost of compliance" will improve the technology level and increase economic profitability. Environmental regulations can be quite effective at reducing environmental pollution in agriculture, minimizing unwanted outputs, and effectively improving the ACEE [70]. Some people believe that in recent years, the financial and material resources invested in environmental regulations have prompted a rise in the costs of environmental governance. However, technological innovations have been unable to offset the negative effects caused by increasing expenditures, which may lead to a decline in agricultural green productivity [41]. Based on the findings of the empirical study presented in this paper, agricultural environmental regulations have a significant positive effect on the local ACEE. This suggests that while the implementation of environmental regulations decreases profitability and raises the cost of agricultural production, it follows an "innovation compensation" effect in China, which leads to increased technological innovation among farmers and ultimately improves the overall ACEE. According to the literature currently available, environmental restrictions have a dynamic effect on agricultural production processes, with the "cost of compliance" effect being gradually offset by the "innovation compensation" effect [71]. Future research should prioritize analyzing the dynamic process and investigating the nuanced impacts of agricultural environmental regulations on sustainable agricultural development, to determine the optimal balance point. This finding offers guidance to regulators on how to modify their strategies for issuing environmental regulations and enhance the overall efficacy of relevant laws and regulations. This study carries significant policy implications and provides a theoretical foundation for other nations to consider implementing environmental regulation measures in the future.

Furthermore, this paper examines the impact of several other control variables on the efficiency of agricultural carbon emissions. Firstly, public investment (PI) in agriculture can significantly enhance the technological level of agriculture, leading to economic growth and increased efficiency in agricultural production. Industrialization (IN) may encourage the usage of agricultural equipment, but it can also lead to increased agricultural pollution emissions. The results of this paper show that Chinese agricultural production is currently benefiting more from industrialization. While a bidirectional causal connection exists between energy consumption and greenhouse gas emissions, industrialization exerts a moderating influence on carbon intensity [72–74]. Agricultural disasters (AD) can reduce the acreage of agriculture in a province, resulting in lower carbon emissions and reduced ACEE. Robust evidence has shown that natural disasters can directly lower carbon dioxide emissions and can also indirectly achieve this by reducing energy consumption [75]. The industrial structure is a significant factor influencing carbon emissions in agriculture, and this paper also reveals its substantial impact on the ACEE [74]. Agriculture production in the province is more advanced when the primary sector makes up a larger share of the region's overall output. The economies of scale resulting from a well-developed agricultural sector can enhance farm profitability and concurrently lower carbon emissions, ultimately leading to a more effective increase in ACEE [76]. The ACEE can be significantly improved by the level of economic development (ED). While the disparity between economic development and environmental quality becomes more pronounced during China's economic transition, higher economic development will boost agricultural incomes and reduce emissions through advanced technology adoption and cost reduction [77].

We found that ACEE currently has significant regional differences. This has similar results to previous studies [78]. The main cause of this is China's uneven economic development and the government's imperative to support poorer regions and strive for balanced development throughout the country. To mitigate carbon emissions and enhance economic efficiency, resource allocation should be optimized based on the local natural environment, production methods, social structure, and level of economic development [2,69,79]. There are notable regional variations in the ACEE, also because of disparities in both carbon emissions and agricultural surface contamination. Carbon emissions are elevated in the primary food-producing regions due to the necessity of groundwater irrigation for food cultivation, a process characterized by substantial energy consumption that consequently contributes to heightened carbon emissions [74]. Provinces that cultivate a greater quantity of crops release a higher volume of carbon emissions compared to those provinces with more modest crop cultivation [80].

From this study's findings, key policy recommendations for China arise to improve ACEE and optimize AER:

Environmental regulations must be tailored to local economic and social objectives, and customized solutions with regional traits should be implemented to attain the concurrent synergy of economic advancement and environmental preservation [80]. Regions should strive to establish a well-balanced framework of environmental regulatory portfolios to ensure the effective promotion and implementation of pertinent policies [81]. It is crucial to establish and maintain a moderate and consistent level of environmental regulations and standards while enhancing the integration of diverse policies and regulations across various sectors. The execution of policies and the strengthening of regulations should also be emphasized, rather than just the accuracy of environmental regulatory publishing. Environmental policies should be harmonized with the establishment of localized environmental protection levies to realize a symbiotic reinforcement [82]. A subsidy mechanism can be set up to address the problems of straw burning on agricultural land, pesticide and fertilizer residues, and the pollution of livestock and poultry manure. Price subsidies can be used to stimulate farmers to adopt environmentally friendly behaviors. Public environmental resources can be maintained through the establishment of property rights mechanisms.

Considering China's vast expanse, socio-economic and agricultural production traits exhibit regional variations, and ACEE is profoundly impacted by both of these factors. It is imperative to differentiate agricultural development and environmental management based on the specific resource endowment and technological level of each region. It is also crucial to optimize planting structures and varieties by local conditions to ensure food production, fortify local food production capacity, and safeguard food security. Regions characterized by lower agricultural carbon emissions should prioritize the implementation of sustainable agricultural practices, aiming to mitigate pollution and minimize resource consumption. Additionally, they should embrace innovative, efficient, and eco-friendly agricultural production techniques to modernize the agricultural sector. Conversely, regions exhibiting higher ACEE can leverage their available resources to expand agricultural development, enhance resource utilization, and effectively undertake environmental protection measures. Besides, governments should promote the development of scale economies and economic efficiency by advocating moderate-scale agricultural operations and land intensification. In regions with significant grain production, there should be a shift away from crude forms of agricultural production, and agricultural intensification should be pursued to alleviate environmental pressures. Continuous promotion of technological innovation can yield favorable inter-regional effects, driving the nation towards carbon reduction and enhanced productivity. In addition, the proportion of the agriculture, forestry, animal husbandry, and fishery sectors should be optimized according to local conditions. It should also combine the indicators of neighboring regions and work together to expand the impact of low-carbon production technologies, to achieve a joint interregional reduction of carbon emissions.

Local government departments should augment financial support to upgrade agricultural production infrastructure, such as water conservancy, thereby effectively improving the conditions for agricultural production. The degree of economic development is a pivotal contributor to local ACEE. To strengthen the local economy, local governments must also give priority to the adoption of innovative technology and human capital. Emphasis should be placed on supporting energy-saving and emission-reducing key projects and reducing the overdependence of agriculture-related industries on resources by accelerating the extension of the industrial chain and fostering new types of advantageous industries. To incentivize low-carbon agricultural production, a carbon compensation mechanism will be established post-food production to reward agricultural actors adopting low-carbon practices, thereby boosting enthusiasm for eco-friendly agricultural production.

Enhancing the agricultural literacy of workers through education is pivotal in driving the environmentally friendly development of agriculture. The disparities in carbon emissions resulting from social factors have underscored the importance of training agricultural technical personnel. A prior study revealed that the deficiency in human capital within China exerts an adverse influence on environmental pollution [77]. In rural communities, an absence of low-carbon consciousness and awareness of sustainable development can lead to significant wastage of agricultural resources and environmental degradation. Therefore, the government, universities, and research institutes should carefully select professionals and organize suitable training courses to raise the environmental awareness of grassroots agricultural practitioners and assist them in the proper use of technical equipment. Additionally, farmers should be supported in carrying out agricultural practices to effectively apply acquired knowledge in practical settings.

Investment in science and technology can efficiently mitigate carbon emissions [83]. Regarding technological innovation, given the challenges of swiftly implementing uniform technological standards nationwide, it is preferable to introduce similar technologies in regions with comparable resource endowments and geographic conditions, while also considering local factors. By fostering the exchange of key technologies aimed at bolstering food production and reducing emissions in similar regions, we can promote the transfer of technologies among neighboring areas, facilitating positive interactions. Additionally, it is crucial to strengthen the development and promotion of mechanized agricultural products tailored to the specific characteristics of Chinese agricultural production and to facilitate the widespread adoption and popularization of agricultural machinery. By intensifying our commitment to agricultural innovation, we can overcome the challenges associated with outsourcing services in technology-intensive sectors, amplify the market share for agricultural machinery services, and diminish the expenses associated with agricultural production. Integrating low-carbon principles throughout all stages of agricultural production and implementing emission reduction programs based on scientific and technological inputs are essential.

Research indicates that the Internet can play a role in carbon emissions reduction and enhancing carbon efficiency [72,84]. Therefore, on a societal level, there is a necessity to enhance the utilization of the Internet and cultivate smart agriculture. The internet can offer technical support for localized expansion of circular and eco-agriculture, rendering agricultural production precise and promoting transparency in agricultural management. It can also aid in the enhancement of integrated management systems. The Internet can also enhance integrated management systems and boost the efficacy of green supply chain management in the agribusiness sector [85].

Technological advancements, including testing soil for formulated fertilization, agricultural film recycling, and biological pest control, can efficiently reduce resource overuse and pesticide redundancy. Implementing pest monitoring technology enhances precision in pesticide application, minimizing waste. The combination of planting and breeding improves resource utilization, lowers pollution, and boosts technical efficiency in agriculture. Cleaner production methods can advance the efficient integration of farming.

5. Conclusion

This paper employs the Super-Efficient SBM Model, which takes non-desired outputs into account, to measure the agricultural carbon emissions efficiency in 31 provinces of China from 2010 to 2019. The environmental regulation intensity of each province was measured using the entropy method after constructing the evaluation index system. When developing the evaluation indicator system for environmental regulation, indicators related to agriculture were prioritized due to their relevance. An SDM was built to examine the effects of environmental regulations and other explanatory variables on agricultural carbon emissions efficiency. The discussion and analysis of the findings follow. Firstly, across the nation, the ACEE rises every year and the growth rate tends to level off from 2015 to 2017, while the growth rate increases significantly after 18 years. Within the studied period in this paper, the Eastern region of China had the greatest agricultural carbon emissions efficiency, whereas Central China had the lowest, with a remarkable gap in the ACEE nationwide. There are significant gaps in emissions efficiency among different regions, but there are significant spatial spillover effects within these areas. The study's second finding reveals that while environmental regulations positively impact the ACEE of the studied province, they have little impact on the bordering provinces' ability to reduce agricultural carbon emissions. This is because environmental rules can both encourage technical advancements and economic growth on the one hand, while lowering the level of agricultural carbon emissions on the other. Thirdly, the study discovered a link between public financial investments and industrial structure with the ACEE. However, because of the complexity of economic operations, the investigated province's efficiency of carbon emissions might also be adversely affected by industrialization and environmental damage. Additionally, these factors exhibit an association with the ACEE of adjacent regions. Advanced economic growth has a beneficial impact on the examined province's agricultural carbon emissions efficiency as well, but it hurts the ACEE in the neighboring provinces. The ACEE should be analyzed comprehensively, taking into account various influencing factors from the time and space domains. Regions with different resource endowments and development levels should be considered separately and the strategies for different stages of development should be adjusted appropriately from time to time. Environmental regulations can improve the ACEE. Hence, it is crucial to implement appropriate environmental policies that consider the production characteristics of the region, fully realizing the "innovation compensation" effect for the agricultural sector, and carrying out effective environmental management. We should improve the flexibility of the command-and-control environmental regulations and at the same time refine the responsibilities [56]. For agricultural output to be sustainable, it is imperative to boost economic growth while concurrently lowering environmental degradation. This can be done by utilizing eco-friendly technology that lessens the damaging effects of agricultural production on the environment. The less-developed regions should focus on the transformation process from labor-intensive to capital-intensive agriculture. At the same time, these regions need to focus on investment in technology and talent. On the other hand, much more developed regions should focus more on investing in low-carbon agricultural products as well as agricultural machinery with energy-saving and emission reductions. Besides, these regions should prioritize the green transformation of production practices to increase agricultural production in terms of both quality and quantity. In addition, more precise measurement of policy effects remains a focus of our future research.

6. Limitations and future research directions

This paper has some shortcomings and can be further analyzed: The assessment of environmental regulations has consistently constituted a central concern and challenge in related research. While this paper assesses the impact of environmental regulations by establishing a reasonably structured evaluation framework for AER, there is an aspiration for continuous refinement of the evaluation methodology in the future, to enhance the comprehensiveness and scientific rigor of the research. Furthermore, since farmers' conduct is highly influenced by grassroots governments, the environmental regulatory status of township governments directly impacts the management of agricultural pollution. Therefore, the implementation of environmental regulations by township-level governments is the most direct factor affecting the management of agricultural pollution. However, the existing data on grassroots governments in China is relatively incomplete and cannot provide sufficient evidence for empirical research. If we could collect this data, we would engage in more comprehensive research in this field.

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Data availability statement

The data underlying this article are available in China Statistical Yearbook (http://www.stats.gov.cn/sj/ndsj/), China Rural Statistical Yearbook (https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907997.html), and Peking University Law website (https://home.pkulaw.com/).

CRediT authorship contribution statement

Yujie Xia: Supervision, Methodology, Data curation, Conceptualization. **Hongpeng Guo:** Validation, Supervision. **Shuang Xu:** Methodology. **Chulin Pan:** Visualization, Validation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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