Heliyon 10 (2024) e24944

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Re-measurement and influencing factors of agricultural eco-efficiency under the 'dual carbon' target in China

Li Yang [a], Zhenyu Guan [b], Shiying Chen [c,*], Zhenhua He [d]

[a] *School of Economics and Management, Ningxia University, Yinchuan, 750021, China*
[b] *School of Information, Renmin University of China, Beijing, 100872, China*
[c] *School of Economics and Management, Zhejiang Ocean University, Zhoushan, 316022, China*
[d] *Academic Affairs Office, Xinhua College of Ningxia University, Yinchuan, 750021, China*

ARTICLE INFO

Keywords:
Carbon peaking
Carbon neutrality
Agricultural eco-efficiency
Agricultural carbon emissions
Sustainable development

ABSTRACT

Given that agriculture is both a carbon source and sink, the sustainability goals of carbon peaking and neutrality place high demands on the green and low-carbon agricultural development in China, and the exploration of a realistic path for a sustainable agricultural development is urgently needed. Under the above 'dual carbon' target, this study focused on the key issue of how to improve China's agricultural eco-efficiency (AEE) and constructed an innovative AEE indicator system that can reflect carbon constraint and coordinated agricultural economic development, resource use and ecological environment. The super-efficient slack-based measured Data Envelopment Analysis (SBM-DEA) method, which considers undesirable outputs, was applied to re-measure the AEE of 30 provinces and cities in China from 2001 to 2020, and its spatial and temporal evolution was analysed in conjunction with kernel density estimation. The Tobit regression model was used to explore various influencing factors by region. The results show that the AEE re-measurements, which take into account the 'dual carbon' requirement, are significantly better than the traditional AEE. From 2001 to 2020, China had an overall V-shaped fluctuation curve AEE, with a small decline and several inter-annual fluctuations, and exhibited a large potential to rise. China's AEE showed a spatially uneven regional development at different stages of distribution and evident multi-polar differentiation. Inter-provincial differences were observed in China's AEE, and the vicious circle of low-level green and low-carbon agricultural development was difficult to break. Urbanisation had a significant positive effect on national and eastern AEE but a significant negative effect on central AEE. The agricultural carbon offset rate had a significant effect on AEE nationally and in the three regions. Thus, the introduction of 'dual carbon' target effectively drove the development of AEE. Agricultural industry structure inhibited the improvement of AEE nationally and in the western region. Agricultural economic development hindered the national AEE improvement but promoted that of the central region, where China showed an environment Kuznets curve. Hopefully, this study can provide data support and theoretical reference for the green and low-carbon agricultural development and help achieve the 'dual carbon' target.

* Corresponding author.
E-mail addresses: yangli802306@163.com (L. Yang), zhenyu_guan@ruc.edu.cn (Z. Guan), chshy040300@126.com (S. Chen), h_zhenhua@163.com (Z. He).

https://doi.org/10.1016/j.heliyon.2024.e24944
Received 16 August 2023; Received in revised form 1 January 2024; Accepted 17 January 2024
Available online 20 January 2024
2405-8440/

1. Introduction

Since the 21st century, China's comprehensive agricultural production capacity has increased significantly, with grain production achieving 'eighteen consecutive bumper crops' from 2003 to 2021. In addition, the excessive use of various resource factors in agricultural production has caused a great deal of agricultural surface pollution, such as those of soil, water, and greenhouse gas (GHG) in the form of CO_2 [1,2]. The country has reached 'red-level' agro-ecological environment and 'bottom-line' agricultural products, issues that are gradually becoming a 'short board' for China's economic development. As agricultural pollution increases, and international calls for sustainable development rise, the promotion of ecological development in agriculture is gaining increasing attention and Chinese agriculture is gradually coming to a critical point in its return to its essential functions, transformation and upgrading.

The proposal of 'dual carbon' goal is a new opportunity to achieve sustainable development in agriculture. At the 75th session of the United Nations General Assembly in 2020, President Xi Jinping, on behalf of the Chinese government, announced the aims to achieve carbon peaking and neutrality by 2030 and 2060 ('dual carbon' target), respectively. In September 2021, the Chinese government issued the 'Opinions of the State Council of the Central Committee of the Communist Party of China on the Complete and Accurate Implementation of the New Development Concept to Do a Good Job in Carbon Dumping and Carbon Neutral Work' to accelerate green development and promote carbon sequestration and efficiency in agriculture. In June 2022, the Implementation Programme for Emission Reduction and Carbon Sequestration in Agriculture and Rural Areas, jointly issued by the Ministry of Agriculture and Rural Affairs and the National Development and Reform Commission, pointed out that the implementation of major actions to reduce pollution and carbon emissions and enhance carbon sinks should be taken as the starting point for realising a green and low-carbon transformation of the agricultural and rural production and living styles. China's Central Committee Document No. 1 in 2023 focuses on the development of ecological low-carbon agriculture. The 'dual carbon' target was introduced to address global climate change and China's sustainable development [3]. It also pointed to a new direction for agricultural development and put forward new requirements.

Unlike industries such as manufacturing and energy, agriculture has both attributes of a carbon source and sink. According to the Third National Communication on Climate Change of the People's Republic of China submitted in 2019, GHG emissions from the agricultural sector account for nearly 8.3% of the total in China, making it the largest source of non-CO_2 GHG emissions. However, when considering the indirect carbon emissions from the associated industries involved in agricultural resources, such as pesticides and fertilisers, this figure is notably an underestimate. In addition, agriculture itself has a strong capacity to sequester carbon and increase sinks, which can effectively mitigate carbon emissions [4]. Thus, agriculture can contribute to carbon neutrality by reducing carbon emissions and increasing carbon sinks to offset emissions that are more difficult to reduce.

From the above realities, green development of agriculture is highly consistent with carbon emission reduction, an important element in promoting ecological civilisation and a grip to achieving peak carbon and carbon neutrality. Finding a mechanism to reduce emissions and increase sinks, the environmental and economic benefits of sustainable development of agriculture have become a pressing issue in China. Therefore, a practical analytical framework for assessing the level of agroecological development under the 'dual carbon' target must be determined. AEE is a useful evaluation indicator for the coordinated advancement of agricultural economics, resource usage, and ecological environment since it can precisely assess the amount of green, ecological, and sustainable growth of agriculture [5].

In view of such goal, this study applied the highly efficient slack-based measured data envelopment analysis (SBM-DEA) model to determine the AEE of 30 provinces in China (Hong Kong, Taiwan, Macau and Tibet were excluded due to incomplete data) based on the 'dual carbon' objective and the perspective of integrated management of agro-ecological environment in 2001–2020. Compare the superiority of the re-measurement results and analyse the spatial and temporal characteristics of AEE in China as a whole, in regions and in provinces. By using the Tobit model, the key factors affecting AEE in China and the eastern, central and western regions are analysed. This research provides scientific basis and suggestions for AEE enhancement and high-quality agricultural development under the new situation.

This study has three main contributions. Firstly, the introduction of the 'dual carbon' target not only puts forward new requirements for China's agricultural green development and ecological civilisation construction but also makes AEE research under the 'dual carbon' target a new issue in this new phase. Based on existing literature and policy context, this study constructed a theoretical model for AEE assessment that is consistent with China's national context. The study rethinks how Chinese agriculture can take the 'dual carbon' target as an opportunity to develop a green and low-carbon method under multiple unfavourable conditions. Secondly, it innovatively incorporates agricultural carbon emissions and sequestration as carbon constraints and agricultural surface pollution as environmental constraints into the AEE evaluation index. Given the in-depth identification of the 'carbon peaking' and 'carbon neutrality' ecological concepts, the various production factors of agricultural ecosystems and requirements of sustainable development strategies, a set of AEE indicators has been constructed to objectively reflect the new role of agriculture in the context of 'dual carbon' requirements and fully measure the economic and resource efficiency of agriculture and the coordinated advancement of agricultural economy, resource use and ecological environment. A comparative analysis of 'dual carbon' AEE and traditional AEE is also presented. Thirdly, the influencing elements of AEE at the national and regional levels were further tested using the Tobit model. Several key factors that have been neglected in traditional AEE studies were examined, and the agricultural carbon offset rate (ACOR) was selected to analyse the effect on the proposed 'carbon peaking' and 'carbon neutrality' on AEE.

2. Literature review

2.1. Meaning and application of AEE

Compared with single indicators of environmental resources or emissions, eco-efficiency more comprehensively and accurately reflects the overall performance of ecological governance and the meaning of ecological civilisation construction [6,7]. To accurately assess of the true value of agro-ecosystems, eco-efficiency has been extended to agriculture and has become an important indicator of ecological civilisation and green and sustainable agricultural development [8]. Based on previous research and an understanding of the concept of eco-efficiency [9], we take AEE to mean that, in order to produce more and better-quality products and services with the least amount of resource consumption, environmental pollution, and carbon emissions while staying within the carrying capacity of the agro-ecosystem. AEE adhered to the essential eco-efficiency connotation and embodied the ecological and economic dimensions of sustainable agricultural development. In addition, the aims are to bring forth more agricultural carbon sinks, to harmonise the link between agricultural inputs and outputs, economic and environmental benefits and to promote green, low-carbon, sustainable agricultural development.

Studies on AEE have been applied mainly at the national [10,11], provincial [12], specific regional [13], city [14,15] and community levels [16]. The DEA has become the most common evaluation method for AEE due to its capability to determine the efficiency of multi-input and multi-output systems and effectively handle non-parametric boundaries [17,18]. Although DEA methods were used to evaluate AEE in many studies, the results were inconsistent [19]. [19] used SBM and Theil index to assess the level and spatial pattern of AEE development in 31 Chinese provinces from 2003 to 2013 [20]. [20]applied a SBM model, which considers undesired outputs, to assess AEE in 27 EU countries in 2008–2017 and argued that the DEA model that considers undesired outputs produces results that are closer to reality than models that do not. The SBM model, which considers non-desired outputs, has gradually become the mainstream model for measuring AEE due to its capability to incorporate negative externality outputs and effectively address the input–output slack.

Scholars have begun to pay more attention to the scientific rigor and logic of the selection of input-output indicators as a result of the DEA model's application to AEE, and two lines of thought have been introduced. Firstly, factors of production (e.g. land, labour, machinery, water, fertiliser, pesticide, agricultural film) are used as input variables that involve indicators, such as total area of crop sown, agricultural workers, total power of agricultural machinery, agricultural fertiliser application; pesticide and agricultural film use. The output indicators are the expected outputs, including the total output values of agriculture, forestry, animal husbandry and fishery and the entire sector [21,22]. Secondly, the choice of input variables is similar to the first category, but the selection of output indicators distinguishes between desired and undesired outputs, with desired outputs involving variables, such as gross agricultural

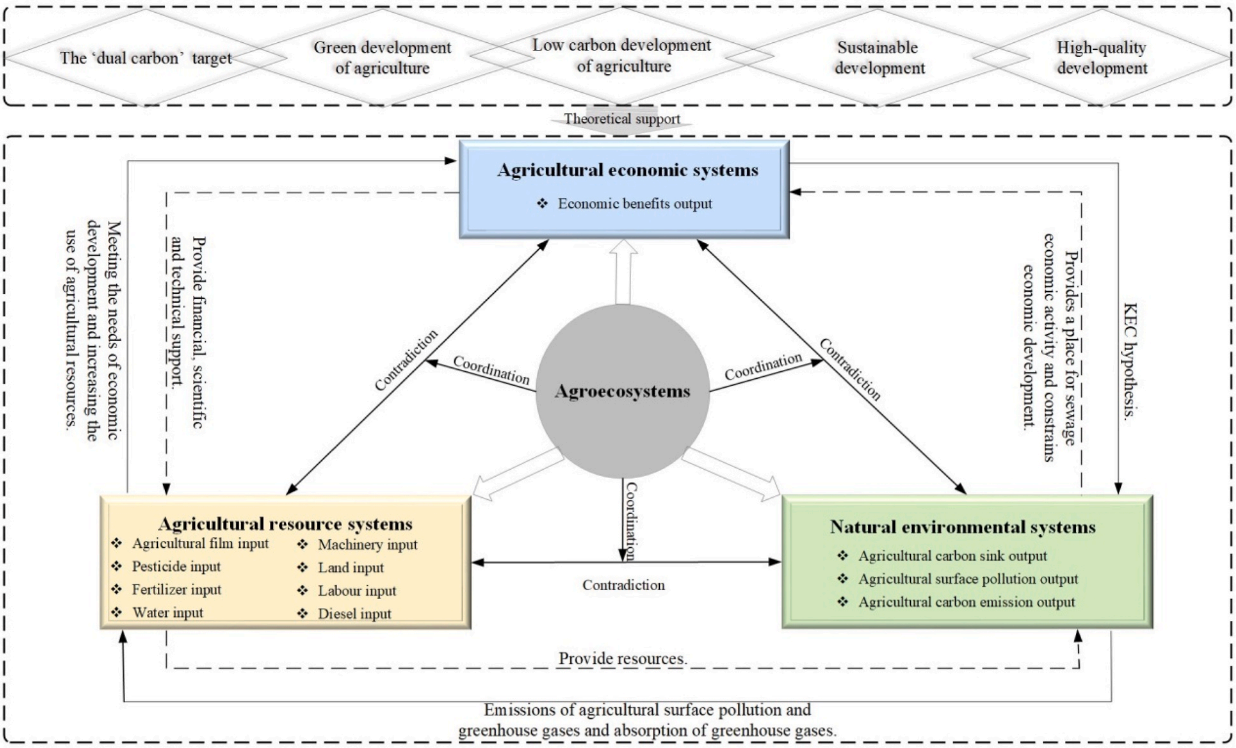

Fig. 1. The theoretical and analytical framework for AEE research in China under the 'dual carbon' target.

output, gross agricultural, forestry and fishery products, value of ecosystem services and food production [23,24], and undesired outputs involving variables, for instance, surface source pollution and carbon emissions [25–27]. Given the significant difference between AEE results considering and not considering non-desired outputs, the former is more realistic [28]; the second idea of indicator selection is receiving increasing attention from scholars.

The analysis of AEE drivers enables the scientific and effective exploration of AEE improvement paths [29]. The most applied methods are the Tobit model, grey correlation analysis, geographic probe model, augmented regression tree method, panel regression method, etc. The selection of variables affecting AEE has been explored by scholars from different perspectives [30]. [30] screened the influencing factors of AEE in terms of agriculture industry structure (AIS) using Chinese province panel data from 1978 to 2017, infrastructure conditions, development potential and input intensity, and then carried out an empirical analysis by using ordinary least squares as well as fixed and random effects model. Using panel data from 31 Chinese provinces from 2009 to 2018 [31], [31] examined the impact of environmental regulation on AEE using two-way fixed effects with endogeneity treatment and robustness testing. By using a two-stage double-bootstrap DEA technique [32], [32] experimentally evaluated the impact of climate change on AEE in China. Applying data from China for 2009–2018 [33], [33] used a Tobit model to analyse the effects of urbanization composite index and indicators on AEE in 30 Chinese provinces and cities.

2.2. Review and theoretical framework

The reviewed literature indicates the benefits of AEE research, but four areas can still be improved. Firstly, the issue of AEE improvement from the perspective of 'dual carbon' targets is an extension of AEE in the field of low-carbon economy, which has received less attention in previous literature. Secondly, the existing AEE input–output indicator system is lacking in breadth and precision, as the ecological concept of carbon neutrality is not fully reflected in AEE studies. The choice of environmental constraint indicators in the existing literature is mostly based on agricultural surface pollution and the findings of several scholars on agricultural carbon emissions, whereas relatively limited results combine the two and consider agricultural carbon sequestration. Thirdly, identifying the drivers of AEE (direction and magnitude) has been one of the most important research topics in AEE research and the most debated area of research. In the process of analysing the drivers of AEE, scholars have obtained numerous results from different perspectives through various models, but few have considered factors such as the ACOR. As a result, the proposed 'carbon peaking' and 'carbon neutrality' shows no effect on China's AEE. Fourthly, research that systematically examines the above elements within the same framework is lacking.

This study attempted to make the following extensions. Firstly, a theoretical model for AEE assessment was constructed to meet China's national conditions (Fig. 1). The model takes into account the country's 'carbon peaking' and 'carbon neutrality' targets and the Chinese strategic requirements for low-carbon, green, sustainable and high-quality agricultural development of related natural, economic and resource subsystems. The three sub-systems were considered as a whole. Only by taking a holistic approach and simultaneously coordinating the relationship between resource use, value growth and environmental protection can we truly optimise agro-ecosystems in the new context. Secondly, according to the multi-input and output characteristics of the DEA model and with reference to existing literature and data, agricultural carbon emissions and sequestration were used to express the hard requirements of the 'dual carbon' target. In addition, based on AEE connotations, we innovatively include agricultural carbon emissions, carbon sequestration and surface pollution as environmental elements in the model with full consideration of the major national policies and programmes. Comparative analysis of remeasured AEE and traditional AEE. Thirdly, the impact of major national policies and regional heterogeneity on AEE was fully considered, ACOR was included as one of the affecting elements, and empirical analysis was done to determine the extent and direction of various influencing factors on AEE throughout China as well as in the eastern, central, and western areas.

3. Methodology and data collection

3.1. Methodology

3.1.1. Measurement of AEE: Super-efficiency SBM-DEA with undesirable output

The DEA method of non-referential productivity measurement was first put forth by Ref. [34]. By examining the boundaries between input and output variables, DEA determines the relative effectiveness of decision units and generates efficiency. Traditional DEA models can be categorized into two groups: radial models such as CCR [34] and BCC [35] and non-radial models such as SBM [36]. Undesirable by-products, such as wastewater, exhaust gases, and CO_2, are continually produced throughout the actual production process and have an impact on efficiency. Desirable production should grow while undesired output should decrease to maximize economic efficiency. To deal with the latter [37], further extended the SBM while [38] constructed a super DEA model, which effectively remedied this problem by allowing efficiency comparisons between DMUs. Therefore, following previous studies, the super-efficient SBM-DEA model, which takes into account undesired outputs, was applied to re-measure the AEE of Chinese provinces in light of the 'dual carbon' target.

Assume a production system that has n decision units, each of which has m input units that create desirable (S_1) and undesired outputs (S_2) in the form of three input-output vectors: inputs, desired (S_1), and undesired (S_2) [39]. The three input–output vectors can be represented as $x \in R^m$, $y^g \in R^{S_1}$, $yb \in R^{S_2}$, where the matrices X, Y^g and Y^b are:

$$X = [x_1, x_2, \cdots x_n] \in R^{m\times n}, Y^g = \left[y_1^g, y_2^g, \cdots y_n^g\right] \in R^{S_1\times n}, Y^b = \left[y_1^b, y_2^b, \cdots y_n^b\right] \in R^{S_2\times n}.$$

Assuming that $X > 0$, $Y^g > 0$ and $Y^b > 0$, the range of production options is found:

$$P = \left\{ \left(x, y^g, y^b\right) \middle| x \geq X\theta, y^g \geq Y^g\theta, y^b \leq Y^b\theta, \theta \geq 0 \right\}, \tag{1}$$

in Eq. (1), actual desired output is lower than the ideal desired output at the frontier and the actual non-desired output is higher [40, 41]. Given the set of production possibilities, the SBM model based on Tone's SBM model that adds the undesirable output into the evaluation decision unit (x_0, y_0^g, y_0^b) is shown in Eq. (2):

$$\rho = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{S_r^b}{y_{r0}^b}\right)}, s.t. \begin{cases} x_0 = X\theta + S^- \\ y_0^g = Y^g\theta - S^g \\ y_0^b = Y^b\theta - S^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \theta \geq 0 \end{cases} \tag{2}$$

where $S = (S^-, S^g, S^b)$ represents the slack in inputs, desired outputs and undesired outputs. The objective function value of ρ is the efficiency of the decision unit that ranges between $[0,1]$. For a given decision unit (x_0, y_0^g, y_0^b), it is valid if and only if $\rho = 1, S^- = S^g = S^b = 0$. If $0 \leq \rho < 1$, the evaluated unit is inefficient, and the inputs and outputs need improvements. Being non-linear, the model is not conducive to efficiency calculation. The non-linear equations are made linear by means of the Charnes–Cooper transformation, the equivalent form of which is given in Eq. (3):

$$T = mint - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}, s.t. \begin{cases} \left\{ 1 = t + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{s_1} \frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{S_r^{gb}}{y_{r0}^{gb}}\right) \right. \\ x_0 t = X\mu + S^- \\ y_0^g t = Y^g\mu - S^g \\ y_0^b t = Y^b\mu - S^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \mu \geq 0, t > 0 \end{cases}. \tag{3}$$

The super-efficiency model's basic idea is to exclude DMUs when evaluating efficiency. The inefficient DMU is evaluated with the same production frontier and therefore provides the same efficiency value as in the traditional DEA model. However, with the same efficiency value, the effective DMU has a proportional increase in inputs that is noted as the value of the super-efficiency evaluation. Given that the production frontier is shifted back, compared to the conventional DEA model, the efficiency value is greater. Eq. (4) shows the super-efficient SBM-DEA model as follows:

$$\rho^* = min \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\overline{x_i}}{x_{i0}}}{\frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{\overline{y_r^g}}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{\overline{y_r^b}}{y_{r0}^b}\right)}, s.t. \begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} \theta_j x_j \\ \overline{y}^g \leq \sum_{j=1,\neq k}^{n} \theta_j y_j^g \\ \overline{y}^b \geq \sum_{j=1,\neq k}^{n} \theta_j y_j^b \\ \overline{x} \geq x_0, \overline{y}^g \leq y_0^g, \overline{y}^b \geq y_0^b, \overline{y}^g \geq 0, \theta \geq 0 \end{cases} \tag{4}$$

where the objective function value of ρ^* is the efficiency value of the decision unit and can be larger than 1. Similar to Eq. (3), further variables are specified. The above models assume a constant size.

3.1.2. Study of the dynamic distribution of AEE: kernel density estimation

An essential non-parametric method for describing the pattern of random variable distribution is known as kernel density estimation. It can be used to estimate the trend of sample location changes and has the advantage of having no assumptions about data distribution; only the sample data are used as a reference, which has strong robustness, to study its distribution characteristics [42]. We investigated the dynamic evolution of the distribution of absolute differences in AEE across the nation and in three regions using kernel density estimation, focusing on presenting the location, dynamics, extension and polarisation of the AEE distribution. It was assumed that random variable X's density function would be:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - \overline{x}}{h}\right) \tag{5}$$

Eq. (5) is the basic model for nuclear density analysis. N represents the number of provinces, X_i is the AEE of each province, $\overline{x}$ indicates the mean AEE of each province, $K(\bullet)$ indicates the kernel density, and $\hbar$ indicates the window width.

3.1.3. Analysis of factors influencing AEE: Tobit model

The AEE obtained through the DEA model is influenced by other factors in addition to the selected input–output indicators. Further analysis can be carried out to measure the direction and strength of the factors affecting AEE under the 'dual carbon' target. The AEE of the DMU is evaluated as the dependent variable and the influencing factors are evaluated as independent variables in a regression model we develop using the super-efficiency SBM-DEA model. The coefficients of independent variables were used to determine the direction and strength of the influencing factors on AEE. With 0 as the lowest bound, the AEE as measured by the DEA model is unlikely to be negative. Therefore, the Tobit model was used to address this restricted dependent variable to avoid the least squares method from yielding consistent estimates [43]. We constructed the basic Tobit model as shown in Eq. (6):

$$Y_{kt} = \begin{cases} Y_{kt}^* = \alpha + \beta X_{kt} + \varepsilon_{kt}, Y_{kt}^* > 0 \\ 0, Y_{kt}^* \leq 0 \end{cases}, \tag{6}$$

where Y_{kt} is the truncated dependent variable of decision unit k in period t, that is, the AEE of the K th province in time t, Y^* is the latent variable of decision unit k in t, and X_{kt} is the independent variable used as an influencing factor of the AEE.

3.2. Variables and data sources

3.2.1. AEE input and output indicators

Promotions for agro-ecological development center on the plantation industry. Based on the DEA model's multi-input and multi-output properties, this work narrowly defined agriculture (plantation) as the research object, improved the traditional AEE indicator system based on its connotation, requirements of agricultural carbon reduction and sink increase and characteristics of agro-ecological systems; constructed an AEE evaluation indicator system that considers the strategic 'dual carbon' target (Table 1). Table 2 presents the descriptive analysis results.

Input indicators were divided into seven main categories: employed persons in agriculture, discounted by employed persons in the primary sector x (total agricultural output value/total agricultural, forestry, animal husbandry and fishery output value); total area sown to crops that shows the actual area cultivated in agricultural production; the total power of agricultural machinery, which reflects modernisation; effective irrigated area, where agricultural water is mainly used as a proxy; amount of fertiliser applied, amount of pesticides and agricultural film used; and the amount of agricultural diesel used, which is the main source of pollution in agricultural production.

Output indicators were separated into two groups: desired and undesirable. For the desired output to total agricultural output value, the data were adjusted to that at constant prices in 2001 to exclude the effect of price changes. Agricultural carbon sequestration involves constructing an agricultural carbon sink accounting system represented by major crops (rice, maize, soybean, tobacco and other major cash crops) and estimating it based on different types of carbon sequestration factors (referring to those prepared by the Department of Afforestation and Greening Management of the State Forestry Administration of China).

Undesired outputs: Agricultural carbon emissions, which were selected agricultural inputs (pesticides, fertilisers, agricultural films and diesel fuel), tilled land, rice cultivation and agricultural irrigation were estimated by multiplying the corresponding emission factors by the corresponding indicators. The comprehensive index of agricultural surface source pollution was determined using the entropy method to combine four types of indicators, namely, nitrogen (phosphorus) loss from fertilisers, phosphorus loss, pesticide residues and agricultural film residues. Nitrogen (phosphorus) loss equal to the amount of its applied fertiliser is multiplied by the fertiliser loss factor; pesticide and agricultural film residues are equal to their use. Geographical discrepancies were thoroughly taken into consideration by referring the pertinent coefficients to the First China Pollution Census Agricultural Coefficients Manual.

Table 1
AEE evaluation index system under the 'Dual Carbon' targets.

First indicators	Secondary indicators	Variable and description
Inputs	Labour input	Agricultural employees
	Land input	Total planting area of crops
	Machinery input	Total power of agricultural machinery
	Water input	Effective irrigation area
	Diesel input	Agricultural diesel use
	Fertiliser input	Application amount of agricultural chemical fertiliser
	Pesticide input	Pesticide usage
	Agricultural film input	Consumption of agricultural film
Desirable outputs	Economic benefits	Total agricultural output value
	Agricultural carbon sink	Agricultural carbon absorption
Undesirable outputs	Agricultural carbon emission	Agricultural carbon emissions
	Pollution emission	Comprehensive index of agricultural non-point source pollution
Carry-over	Asset investment	Rural fixed asset investment

Table 2
Descriptive statistics of the data.

Variable	Unit	Average	Maximum	Minimum	Standard
Agricultural employees	10^4 people	504.927	2202.374	11.434	384.275
Total planting area of crops	10^3 hm^2	5333.403	14910.100	92.000	3629.218
Total power of agricultural machinery	10^4 kW	2897.151	13353.020	93.970	2722.257
Effective irrigation area	10^3 hm^2	2029.645	6177.590	109.243	1536.303
Agricultural diesel use	10^4 ton	64.724	487.030	1.700	64.804
Application amount of agricultural chemical fertiliser	10^4 ton(net amount)	177.398	716.090	6.100	137.843
Pesticide usage	10^4tons	5.271	17.346	0.123	4.202
Consumption of agricultural film	10^4 tons	7.130	34.352	0.064	6.396
Total agricultural output value	10^8 CNY	739.083	3177.069	26.131	564.871
Agricultural carbon absorption	10^4 tons	2302.027	8692.019	37.826	1853.170
Agricultural carbon emissions	10^4 tons	2545.645	6047.393	58.612	1815.736
Comprehensive index of agricultural non-point source pollution	/	0.212	0.674	0.007	0.145
Rural fixed asset investment	10^8 CNY	1035.739	8828.537	6.318	1144.337

3.2.2. *Influencing factors of AEE*

Numerous factors influence AEE. In this study, we mainly referred to previous literature such as [3,44]; thought on data accessibility and the realistic situation and finally selected UR, agricultural disaster rate (ADR), agricultural carbon offset rate (ACOR), agricultural industry structure (AIS) and economic development level of agriculture (EDLA). An empirical analysis of the influences of these six factors on AEE was performed.

UR. UR affects agricultural resource inputs that in turn affect its output and pollution, and thereby AEE. As the UR increases, urban civilisation gradually spreads to the countryside, and farmers' ecological awareness gradually increases. On the one hand, UR can promote agricultural and rural economic development, as argued by Ref. [45]. [46] reported similarly that UR could boost the revenue of farmers. While on the other hand, UR may have a negative effect on agricultural and rural development. UR is expressed in terms of urban population/year-end resident population.

ADR. The degree of agricultural damage is a critical external environmental factor affecting AEE environment. The more severe the agricultural disaster, the greater the loss of agricultural factor inputs, which in turn may negatively affect AEE [47]. ADR is expressed as the area of affected crops/total planted area.

ACOR. The carbon peak and neutral targets have clearly set directions and goals for China's agricultural green development. The 'dual control' of total energy usage and intensity is now the main driver for green and low-carbon agricultural economic transformation [48], and it is necessary to effectively increase clean energy inputs, reduce the intensity of carbon emissions and increase efficiency in energy use. In related research, the impact of ACOR on AEE has been disregarded. The ACOR is expressed as agricultural carbon sequestration/agricultural carbon emissions.

AIS. Agriculture is the most basic industry in China's national economic development. Agriculture is essential for stable social

Fig. 2. Study area. (Note: Fig. 2 is generated based on the standard map GS (2019)1829 from the Ministry of Natural Resources of China's standard map service website, with no changes to the base map boundaries.).

development, and the only way for the nation to achieve a strong basic guarantee is through the efficient and sustained development of agricultural production. Changes in the AIS can also represent regional economic development to a certain extent [49]. The AIS is expressed in terms of total output value in agriculture and in the combined agricultural, forestry and fishery.

EDLA. Agricultural economic development is the foundation for upgrading AEE. The EKC hypothesis suggests that, in the long term, economic growth and resources have an inverted U-shaped relationship with environmental pressures; that is, during economic growth, resource and environmental pressures first show an upward trend, and as GDP per capita increases, an inflection point is reached, resource and environmental pressures shift to a downward trend, and eventually, the link between the two is broken (or decoupled). If the hypothesis holds, sustained, positive economic growth will eventually alleviate resource and environmental pressures [50]. In this study, the value of agriculture, forestry, livestock and fisheries/year-end resident population was selected to indicate the EDLA.

3.2.3. Data sources

This study uses a sample of 30 provinces (cities and districts) in China. Tibet, Hong Kong, Macau and Taiwan were excluded due to insufficient information. The time span was 2001–2020, which denotes the period from the 10th to the 13th Five-Year Plan (Five-Year Plans are an important part of China's national economic long-term strategy). The basic data were derived from the China Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, China Population and Employment Statistical Yearbook and provincial and municipal statistical yearbooks or bulletins. Individual missing data are supplemented by linear and mean interpolation methods. The regional division of eastern, central and western areas was determined according to the regulations of the China Statistics Bureau (Fig. 2).

4. Re-measurement results of AEE under the 'dual carbon' target

4.1. Re-measuring AEE versus traditional AEE

The results of the traditional AEE are compared with those of the 'dual carbon' AEE (Fig. 3), taking into account the fact that different constraints can lead to different results. There has been less focus in the literature on the multiple effects of agriculture in reducing carbon and increasing sinks and synergistically managing pollutant emissions. In order to verify the most realistic results of China's AEE under the " dual carbon" target, we compare the results of this paper's re-measurement with the results of traditional AEE measurements. The traditional AEE does not take into account both total agricultural output value and agricultural carbon absorption in the desired output, agricultural carbon emissions and comprehensive index of agricultural non-point source pollution in the

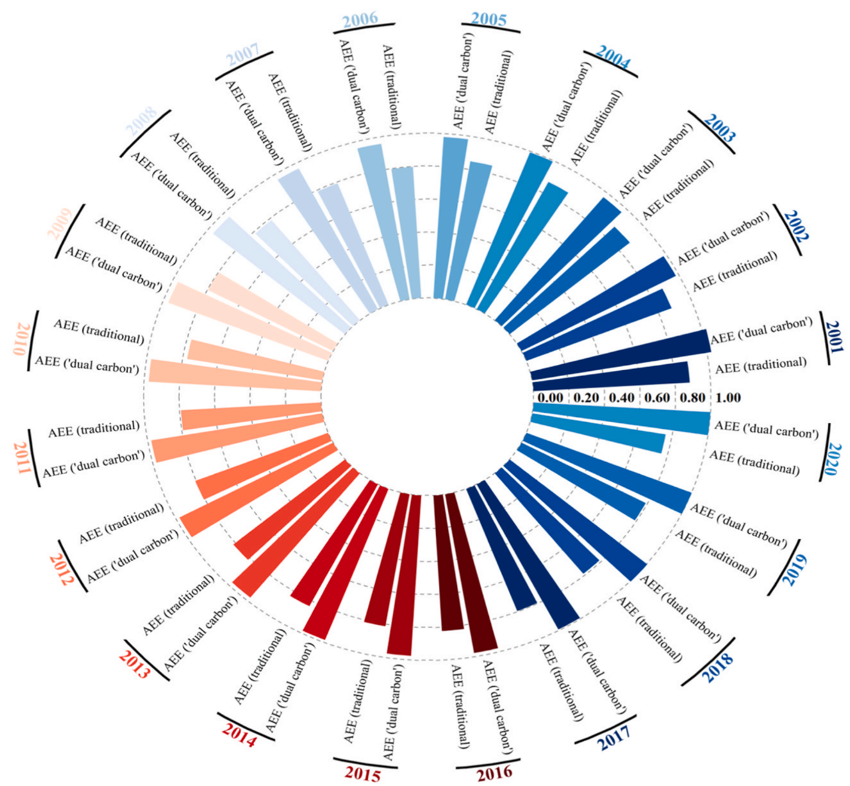

Fig. 3. Comparison of the results of a traditional AEE with those considering a 'dual carbon' AEE.

undesired output [28,30,51]. Therefore, the traditional AEE measured in this paper has only total agricultural output value as the desired output and only agricultural carbon emissions as the non-desired output.

It is easy to see that considering 'dual carbon' AEE is significantly higher than traditional AEE. It can be seen that, on the one hand, the requirement to reduce carbon emissions and increase carbon sinks in the " dual carbon" target has had a positive impact on China's agro-ecological governance. On the other hand, against the backdrop of the serious situation facing the agro-ecological environment, the timely introduction of "dual carbon" has also provided useful guidance on how to maintain a co-ordinated approach to resource consumption, ecological protection and economic development in the process of agricultural economic development. It is not difficult to explain that the impact of a good national policy on the development of an industry is significant [52]. As a major strategic decision in line with China's national conditions, "Dual Carbon" will certainly be able to effectively promote the development of the agro-ecological industry. The dual identity of agriculture as a "carbon-reducing and sink-boosting" industry also makes the development of eco-agriculture more in line with historical and economic trends, thus contributing to the development of green and low-carbon agriculture.

4.2. Timing characterisation of AEE

This study measured the AEEs of 30 provinces (cities and districts) and the eastern, central and western regions of China according to the super-efficiency SBM-DEA model for the period of 2001–2020. Figs. 4 and 5 show the AEE by year and the trends at national and regional levels from the 10th Five-Year Plan to the 13th Five-Year Plan. At the national level, China's AEE in 2001–2020 was within 0.90–1.03. In most years, China's AEE was less than 1 and did not reach the production frontier, which implies potential areas of improvement given the country's current production inputs and environmental constraints. From 2001 to 2006, China's AEE declined gradually by 6.56 % and reached its lowest point in the past 20 years in 2006. From 2007 to 2020, China's AEE 'rebounded', but the increase was relatively small (4.44 %). Fig. 4 shows that China's AEE peaked during the period of the 10th Five-Year Plan and was very close to or above 1 until that of the 13th Five-Year Plan. Since the 10th Five-Year Plan, the Party Central Committee and the State Council have introduced policies to promote green, low-carbon and cycle development of agriculture and 'two types of agriculture'. Subsequently, China's AEE has been slowly increasing since the 11th Five-Year Plan. The policies and 'two types of agriculture' have provided 'reassuring pills' and 'strong incentives' for the development of agricultural production. However, the overall downward trend still reminds us that the harmonious development of the national agricultural economic development, ecological protection and emission reduction and exchange is still long and difficult.

In contrast to previous literature that used agricultural economic output as an index to describe AEE, the present study included agricultural carbon sinks, carbon emissions and agricultural surface source pollution as environmental constraints, and the resulting measurement findings varied from those of traditional models. The main result is that China's AEE as a whole showed a decreasing trend. On the one hand, according to Northam's stage of UR development theory, this condition was due to China's rapid UR during the study period, and its expansion gave priority to encroaching on relatively flat agricultural land with good soil conditions, which resulted in high pressure on the quantity and quality of arable land. While on the other hand, promoting pesticide and fertiliser reduction and efficiency requires considerable time [53], and the low-carbon agricultural technology remains inadequate and has a 'dual role' in enhancing agricultural carbon reduction and sequestration.

For the central, western and eastern regions, the first two showed varying degrees of decrease during the research period. Three stages were observed in general: From 2001 to 2005, the eastern and central regions alternated in second position, with the western region having the greatest AEE. From 2006 to 2010, the AEE ranking was Western > Eastern > Central. By 2011–2020, the AEE

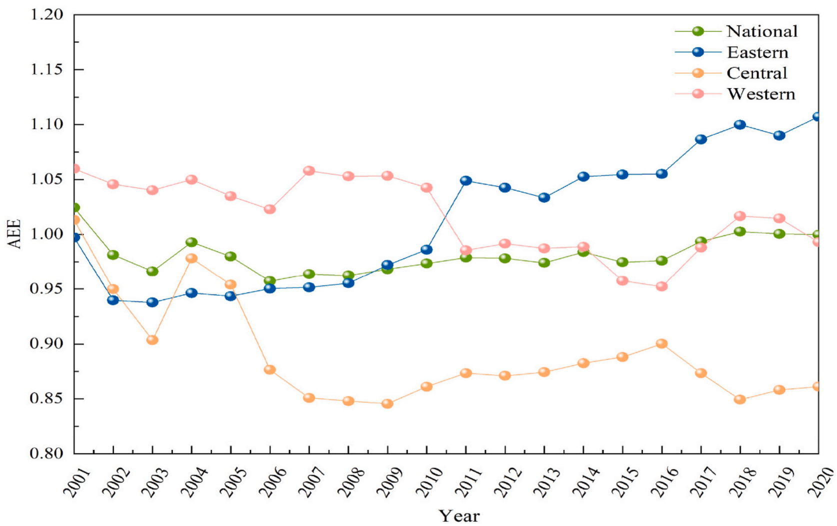

Fig. 4. Trends in AEE by period at the national and regional (east, central and west) levels (2001–2020).

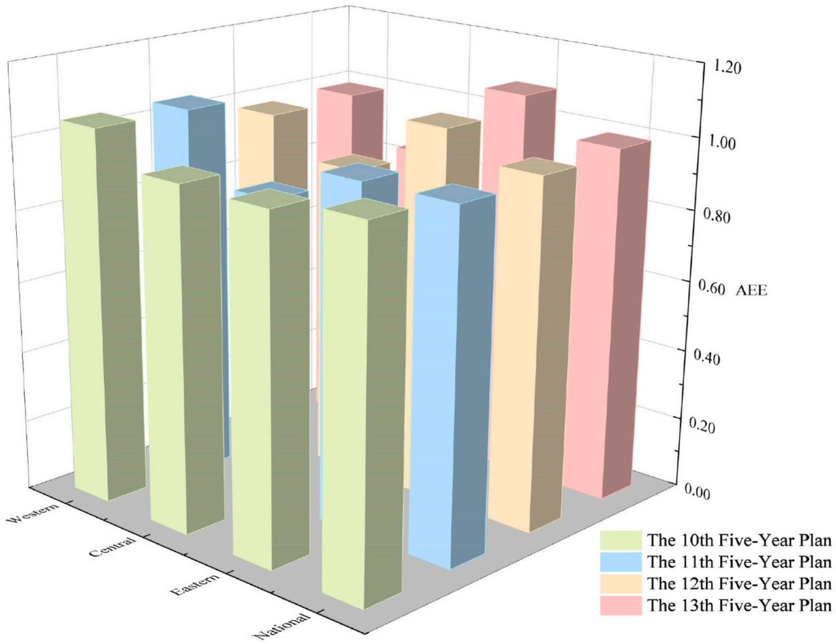

Fig. 5. Trends in AEE at the national and regional (east, central and west) levels during the 10th–13th Five-Year Plan period. (10th to 13th Five-Year Plans: 2001–2005; 2006–2010; 2011–2015; 2016–2020).

ranking was Eastern > Western > Central. From different periods, the AEE of the western region decreased during the 10th until the 13th Five-Year Plan but remained stable, above the national average and reached the effective state.

Such finding can be explained as follows. The western region's economic growth was less advanced than that of the east and central regions; most of its areas were located in the food balance zone, which on the one hand had a slightly lower intensity of agricultural production activities compared with the east and central regions. This condition resulted in relatively less agricultural carbon emissions and surface pollution and on the other hand benefited from the Western Development Strategy, which has been continuously promoted since 1999 and enabled the western region to attain agricultural economic development. In addition, the ecological and environmental conditions have reached a new level. The eastern region was the only one of the three regions to show an overall increase in AEE, with the lowest AEE value in the Tenth Five-Year Plan period being close to 1. Thus, the eastern region has been successful in balancing agricultural economic growth and environmental protection, which is closely related to its in-depth implementation of strategies for building an ecological civilisation and developing the agricultural economy and its recycling, which promoted energy saving, emission reduction and income generation.

The central region displayed a "central collapse" and had the lowest AEE year-round, with the lowest point observed in the 11th Five-Year Plan. The national, eastern and western regions show a large gap that gradually widened over time. This result was probably due to most of the central regions being located in functional food production areas, where agricultural production activities are relatively more intensive and require more manpower, fertilisers, pesticides and machinery, which led to more agricultural carbon emissions and surface pollution and weakened the carbon sink effect of agro-ecosystems.

4.3. Dynamic evolutionary trends of AEE

Kernel density estimates can be applied to analyse the dynamic evolution of the AEE distribution at the national and regional levels, and the overall pattern of the horizontal distribution of AEE can be portrayed. By comparing different periods, the dynamic characteristics of the AEE distribution can be captured, see Fig. 6(a–d).

In terms of wave peaks, the AEE kernel densities in the national and western regions showed a multi-peaked state, increasing in a zigzag manner, and the AEE exhibited multipolar differentiation. In the eastern region, the AEE kernel density curve changed to a 'multi-peak-bimodal' state, which indicates that the AEE was multipolar or bipolar. The wave crests in the central region presented 'multi-peak-bimodal-multi-peak' variations and a tendency to weaken and then deepening of the bipolar or multipolar differentiation. The two peaks of the central region's nuclear density curve gradually decreased in height and increased in distance, which indicates that the polarisation of the AEE in this region gradually weakened. Overall, a widespread polarisation of AEE occurred across the country and the three regions and the balanced development of agro-ecological governance in the provinces within each region needs to be strengthened in the future.

In terms of the locations, the curve centre of the national nuclear density shows minimal changes, with an overall leftward shift. The overall AEE of the country declined as a whole between 2001 and 2020. For the eastern region, the nuclear density curve shifted to the left and then to the right, which thereby reflects a decreasing and increasing development trend of the regional AEE. The nuclear

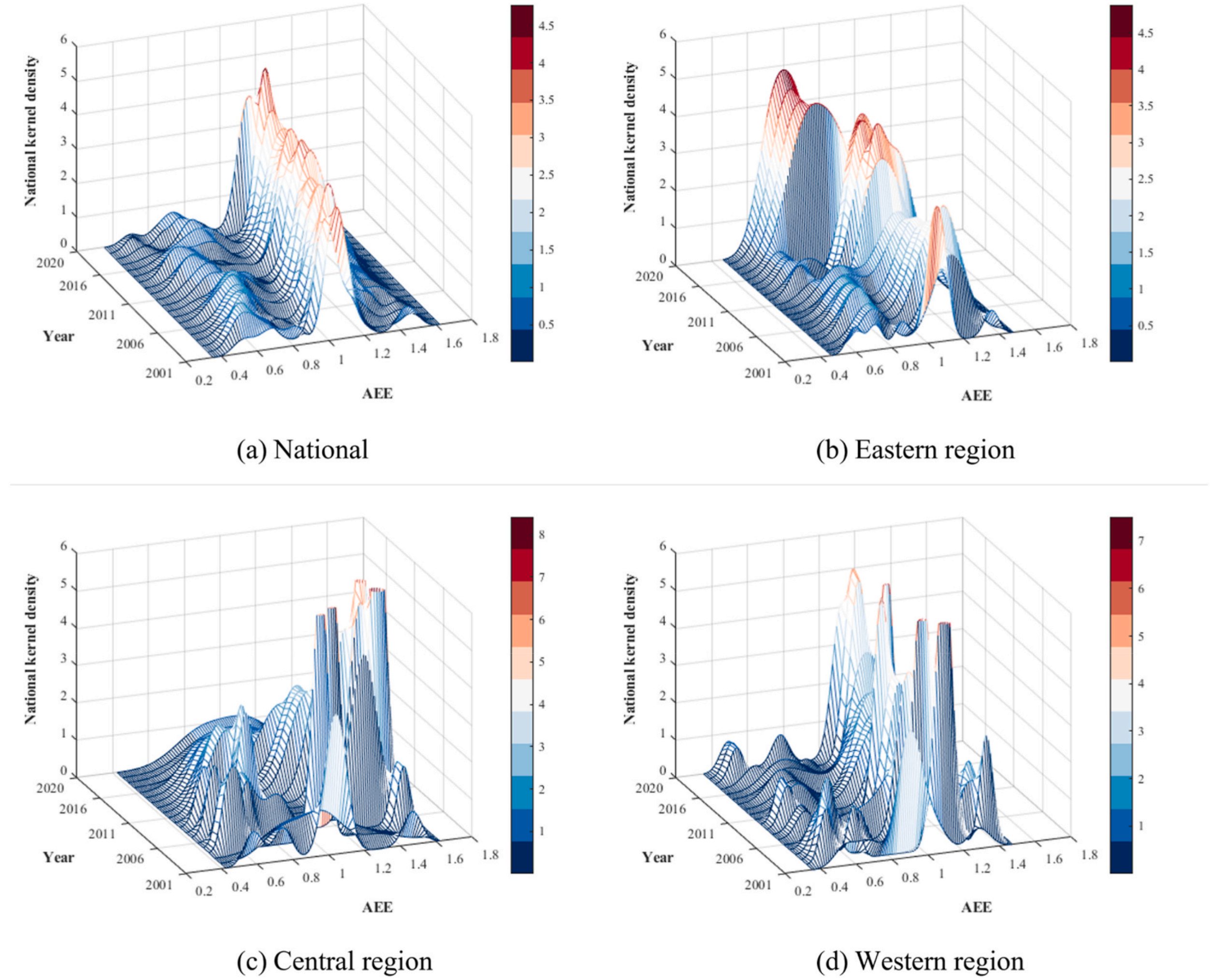

Fig. 6. Dynamic AEE evolution at national and regional (east, central and west) levels.

density curve for the central region showed a left-right-left shift, which implies that the AEE had a ‘decreasing-rising-decreasing’ trend over time. For the western region, the nuclear density curve shifted to the left, which reflects a decrease in AEE during the study period. Therefore, enhancing the development of AEE in the central and western regions will require focus in the future.

In terms of distribution extensibility, a certain amount of left trailing was observed in all study areas, which means that several provinces had substantially lower AEE than others. The AEE kernel density curves for the national and western regions showed an overall trend of ‘convergence’; that is, the likelihood of extreme values of AEE decreased. For the eastern and central regions, the kernel density curves exhibited a widening trend, with the spatial gap between the two regions gradually widening. In the future, more attention can be paid to narrowing the spatial gap between different provinces within the region.

In terms of distribution patterns, the kernel density curves for the national, eastern and western regions were relatively similar, with the wave height showing an upward trend from 2001 to 2020 while the wave width narrowed. This result indicates the decreased absolute difference in AEE among the national, eastern and western regions. The evolution of the kernel density curve for the central region can be broadly divided into two phases; the wave height mainly increased and the width of the single peak narrowed from 2001 to 2011 and vice versa from 2012 to 2020. This finding indicates a decreasing and then the increasing trend of AEE differences in the central region. Therefore, further reduction of the absolute inter- and intra-regional AEE differences is an important part of enhancing the regional AEE rate.

4.4. Provincial variation analysis of AEE

Further comparisons were made for the periods 2001–2020 and 2001–2005 (10th Five-Year Plan), 2006–2010 (11th Five-Year Plan), 2011–2015 (12th Five-Year Plan) and 2016–2020 (13th Five-Year Plan) (Table 3). The top 10 provinces in terms of average AEE value from 2001 to 2020 were Guizhou, Guangxi, Shaanxi, Jilin, Xinjiang, Guangdong, Hainan, Jiangsu, Beijing and Shanghai, all

Table 3
Top 30 provincial AEE averages and their rankings.

Region	DMU	2001–2020		2001–2005 The 10th Five-Year Plan		2006–2010 The 11th Five-Year Plan		2011–2015 The 12th Five-Year Plan		2016–2020 The 13th Five-Year Plan	
		Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank	Efficiency	Rank
Eastern	Shanghai	1.096	10	1.131	6	1.103	9	1.088	10	1.061	13
	Shandong	0.808	24	0.610	26	0.642	24	0.960	23	1.015	22
	Tianjin	1.083	11	1.060	13	1.012	20	1.034	18	1.218	1
	Beijing	1.138	9	1.155	5	1.146	4	1.147	6	1.103	11
	Jiangsu	1.158	8	1.042	17	1.142	7	1.243	1	1.202	2
	Hebei	0.811	23	0.564	29	0.627	26	1.020	20	1.031	21
	Hainan	1.168	7	1.256	3	1.143	5	1.127	8	1.142	7
	Zhejiang	1.025	20	1.023	21	1.016	19	1.016	22	1.042	15
	Fujian	0.692	26	0.487	30	0.634	25	0.712	25	0.917	23
	Guangdong	1.122	6	1.121	8	1.113	8	1.116	9	1.139	8
	Liaoning	1.036	18	1.023	21	1.008	21	1.044	13	1.069	12
Central	Shanxi	0.528	30	0.578	28	0.465	30	0.506	28	0.559	29
	Jilin	1.209	4	1.481	1	1.070	10	1.134	7	1.144	6
	Anhui	0.649	27	0.814	23	0.568	28	0.583	27	0.615	28
	Jiangxi	1.037	17	1.042	17	1.028	17	1.037	16	1.039	17
	Henan	1.047	14	1.038	19	1.043	12	1.055	12	1.050	14
	Hubei	0.609	29	0.608	27	0.592	27	0.586	26	0.647	27
	Hunan	0.972	21	1.060	13	1.031	16	1.036	17	0.750	26
	Heilongjiang	1.075	12	1.029	20	1.052	11	1.087	11	1.130	9
Western	Yunnan	0.876	22	0.748	24	0.945	23	0.932	24	0.862	24
	Sichuan	1.048	13	1.073	11	1.034	14	1.044	13	1.040	16
	Gansu	0.630	28	0.641	25	0.538	29	0.498	29	0.828	25
	Ningxia	1.038	16	1.050	16	1.034	14	1.032	19	1.036	19
	Qinghai	0.733	25	1.055	15	1.027	18	0.450	30	0.399	30
	Chongqing	1.029	19	1.066	12	0.967	22	1.043	15	1.038	18
	Xinjiang	1.173	5	1.122	7	1.181	3	1.190	3	1.197	3
	Inner Mongolia	1.045	15	1.080	10	1.043	12	1.020	20	1.036	19
	Guangxi	1.234	2	1.254	4	1.275	2	1.241	2	1.165	5
	Guizhou	1.254	1	1.327	2	1.311	1	1.187	4	1.185	4
	Shaanxi	1.125	3	1.084	9	1.143	5	1.158	5	1.113	10
National		1.017	/	0.987	/	0.964	/	0.978	/	0.992	/

of which had an average AEE value of over 1 and played the role of ‘leader’. A total of 50 % of these provinces are located in the eastern region, and 40 % are in the western region. Hunan, Yunnan, Hebei, Shandong, Qinghai, Fujian, Anhui, Gansu, Hubei and Shanxi are in the bottom 10, with average AEE values not reaching the efficiency frontier and ‘catching up’ and with a more even regional distribution.

Comparing the average AEE ranking of provinces between the 10th and the 13th Five-Year Plans, we discovered that about 35% of the provinces have increased in ranking mainly due to the following reasons. The large area under crop cultivation, a large variety of farm-related inputs and relatively intensive production methods, although also accompanied by high carbon emissions output, have played a significant role in carbon sinks, such as Liaoning and Heilongjiang. Agricultural production conditions, crop cultivation methods and waste treatment processes have also been increasingly improved owing to increased policy support and technological backwardness [54], thus effectively improving AEE, such as in Jiangsu and Zhejiang.

About 40% of the provinces have dropped in rankings possibly because of their relatively fragile ecological environment, severe soil erosion and a development model that is more dependent on resources and the environment, which led to increased polluting emissions from agricultural production, such as Qinghai and Guizhou. Such a condition may also be due to the limited focus of development on cultivation in these regions and little incentive to explore low-carbon agricultural technologies, such as in Shanghai and Beijing. The remaining provinces, on the other hand, showed less variation in ranking. This finding corresponds to the small decline in the overall AEE national trend in Fig. 3. Altogether, several provinces in China still have to reconcile low-carbon and high-

Table 4
Tobit model regression results.

Variable	Coefficient			
	National	Eastern	Central	Western
UR	1.389**(0.622)	2.718***(0.506)	−2.154***(0.557)	0.853(1.779)
ADR	−0.183(0.155)	0.170(0.195)	−0.200(0.128)	−0.270(0.321)
ACOR	0.528***(0.105)	0.603***(0.114)	0.482***(0.111)	0.857**(0.272)
AIS	−1.540**(0.589)	−0.892(0.751)	−0.941(0.591)	−4.456**(1.410)
EDLA	−0.195**(0.098)	0.042(0.084)	0.186**(0.082)	−0.165(0.253)
cons	2.871***(0.679)	−0.379 (0.617)	0.888(0.626)	4.892**(1.637)

Note: Standard error is in parentheses; ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

efficiency agricultural activities due to their resource endowment, production environment and own development orientation and the need to further adjust their cultivation structure and optimise their production methods.

5. Analysis of factors influencing AEE

5.1. Regression results and analysis

The three areas of Eastern, Central, and Western China differ significantly in terms of the extent of agriculture industry development and the impact of indicators, which in turn may have different influences on the AEE of each region. To propose targeted measures to improve AEE, this study carried out an empirical analysis using a panel Tobit model at the national and regional levels. Table 4 shows the specific effects of each variable.

UR passed the 5%, 1% and 1% significance tests for the national, eastern and central regions, respectively. For the first two, positive regression coefficients of 1.389 and 2.718 were observed, respectively. The regression coefficient for the central region was −2.154. Thus, UR had a positive influence on national and eastern regional AEE and a negative one on central regional AEE. Conversely, in the western region, UR revealed a positive but insignificant effect on AEE. This is intimately tied to the question of this region's quantity and quality of human capital. For the national and eastern regions, increased UR implied a large concentration of population in the cities and a large proportion of non-farm population, which is environmentally conscious and has a great potential to consume agricultural products. This condition provides an impetus for agricultural economic development and thus contributes to the AEE development. However, if the population size exceeds the environmental or carrying capacity, environmental pressures increase, and a shortage of agricultural employment occurs. Thus, the driving force of UR for AEE will not only gradually diminish but turn into a disincentive, as occurred in the central region.

The effect of the ADR on AEE was insignificant nationally at the national and regional levels. Agriculture, as the industry most closely integrated with nature, is inherently characterised by its natural vulnerability to natural hazards. If agricultural products are affected, then the desired output will be reduced, which may reduce the AEE by increasing the undesired output while causing a loss of factor inputs. However, with the continuous innovation of agricultural science and technology, especially after the 'dual carbon' target, the number of new technologies and products is increasing, disaster prevention and control mechanism in each region are further optimized, and the capability to cope with natural disasters is strengthened. Thus, the impact of ADR on AEE becomes insignificant.

ACOR showed a positive effect on national, eastern and central AEE at the 1% significance level, with regression coefficients of 0.528, 0.603 and 0.482, respectively. ACOR also presented a positive effect on AEE in the west at the 5% significance level, with a regression coefficient of 0.857. These results suggest that an increase in the ACOR will increase the AEE across China in the eastern, central and western regions. In a certain sense, ACOR reflects the process of 'carbon peaking' and 'carbon neutralization' in agriculture. The higher the ACOR, the better the carbon sequestration effect of agriculture and the better the net carbon sink effect. Therefore, although several regions have a large crop cultivation area, a large variety of farm-related inputs and relatively intensive production methods, although accompanied by high carbon emissions output, play a significant carbon sink role and thus support the advancement of AEE.

AIS showed a significant negative effect on AEE for the national and western regions at the 5% significance level with respective coefficients of −1.540 and −4.456. However, AIS exhibited no significant impact on AEE for the other two regions. AIS presented a negative influence on the national and western AEE, i.e. the larger the share of agricultural value added in the agriculture, forestry, animal husbandry and fishery in the narrow sense, the lower the national and western AEE. This finding is attributed to increased dependence of agriculture on agricultural inputs compared with those of forestry, fisheries and animal husbandry, which generates more agricultural surface pollution. In addition, the special properties of agriculture led to more GHG emissions and an imbalance between economic development and ecological management in agriculture, which resulted in a lower AEE. However, in the other two regions, this effect is inconsequential.

EDLA showed a negative effect on the national and regional AEE with a regression coefficient of −0.195 but manifested a significant positive effect in the central region with a coefficient of 0.186, both passing at the 5% significance level. Although EDLA had a positive and negative effect on AEE in the eastern and western regions, respectively, neither passed the significance level test. According to the environmental Kuznets curve, an uncertain relationship is observed between the different stages of economic development and environmental quality. When the EDLA is relatively low, the pursuit of output becomes more urgent. Excessive pursuit of output will make people more inclined to adopt a crude development model, and agricultural economic development will not be able to keep up with the needs for ecological environmental protection. As a result, the AEE decreases, as in the case of China's overall agricultural development status. When the agricultural economy has reached a certain level of development, on the one hand, the economic support becomes stronger, and on the other hand, the negative effect of crude development on agro-ecology becomes increasingly evident, all of which drive people to work towards ecological development, which in turn promotes higher AEE, such as in the central region. However, this condition has not played a significant role in the other two regions.

5.2. Robustness tests

Robustness tests were carried out to further verify the above empirical results. Given the characteristics of the range of values of explanatory variables in this paper, instead of adopting a permutation measure for the test, the substitution variable method was applied for the robustness test. Drawing from the work of [23] on the use of food crop sown area/total crop sown area to characterise the AIS, this paper used this indicator to replace the original AIS indicator, with other variables remaining unchanged and re-tests being conducted at the national and regional levels. Table 5 presents the Tobit regression results.

At the national level, UR, ACOR and EDLA passed the significance level test at 5%, 10% and 5%, respectively. For the regression coefficients of these factors, their direction did not change, except for AIS, but their magnitude changed slightly, which is consistent with the main regression results. At the regional level, the eastern and central regions show variations in the direction and significance of the regression coefficients for certain variables, but the main findings were generally consistent with those in the previous section. Meanwhile, the western region showed no changes in direction and significance of the regression coefficients. Altogether, the results of this robust regression did not deviate systematically from those of the benchmark model regression, and the overall results were not significantly different. Thus, the empirical results were robust.

6. Conclusion and policy implications

6.1. Conclusions and discussion

This study combined the strategic requirements of China's 'dual carbon' target with the current status of AEE research and reconstructed an AEE evaluation index system that is consistent with the country's national conditions. AEE was re-measured for 30 Chinese provinces from 2001 to 2020 by using the super-efficiency SBM-DEA model, which considers undesirable outputs. The dynamic distribution patterns and evolutionary trends of AEE were also explored at three levels: national as a whole, three major regions and provincial perspectives. Aside from that, the influencing factors of AEE were examined by combining the kernel density estimation and Tobit model approaches. Through this study, we have drawn several remarkable conclusions.

(1) The AEE, which takes into account the multiple characteristics of agriculture in terms of carbon reduction, carbon sink and pollution reduction, is more in line with the current reality in China than the AEE under the traditional model. According to the results of the remeasurement, from 2001 to 2020, China's AEE declined slightly but with several inter-year fluctuations, and the overall curve was 'V' shaped. The curve evolution can be broadly categorized into two stages: a fluctuating decline and a fluctuating rise. China's AEE during the period of the 13th Five-Year Plan was significantly better than that of the 10th to 12th Five-Year Plans. AEE has gradually 'rebounded' since 2006. This finding indicates that China's efforts to build 'two types of agriculture' and reduce agricultural surface pollution in the 12th Five-Year Plan period and the zero growth of fertiliser and pesticide use during the 13th Five-Year Plan period have contributed to the low carbon cycle development in agriculture. The measures that support the transition of agriculture to low-carbon recycling have been beneficial. However, the national AEE did not reach the efficiency frontier for a number of years, which indicates that China's overall AEE has greater potential to increase when considering the ecological concepts of 'carbon peaking' and 'carbon neutrality'.

(2) The national AEE showed a spatially uneven development, with significant regional differences. In 2001–2005, the western region had a better AEE than that of the eastern and central regions, which alternated in second place. In 2006–2010, the AEE showed a Western > Eastern > Central distribution. By 2011–2020, the distribution of AEE was characterised as Eastern > Western > Central. The western region had the highest initial AEE but failed to maintain its dominance and was later overtaken by the eastern region, which showed an upward trend from the 10th to the 13th Five-Year Plan period. By comparison, the central and western regions exhibited a downward trend overall. The possible explanation is that the eastern region is both a major grain-producer and grain-seller, and has continued to strengthen its strategic policy of 'focusing on grain production and the synergistic development of agriculture and animal husbandry', with more emphasis on new agricultural requirements of reducing carbon emissions and increasing sinks. Meanwhile, the central region's AEE was always below the national average and the main contributor to the rise in national AEE, which ultimately allowed China to attain green and low-carbon agricultural development. However, such growth rate was relatively slow.

(3) The dynamic evolutionary characteristics of AEE at the national and regional levels showed differences. Specifically, the national AEE revealed a multi-polar differentiation during the period under review, with a distinct overall downward trend and a reduction in inter-provincial disparities. In all three regions, AEE was multi-polar or bipolar, with inter-provincial differences widening in the eastern and central regions, which may be caused by their incoherent pace of agricultural industry restructuring and modernisation. However, the inter-provincial gap within the western region narrowed significantly, which may be

Table 5
Robustness test results.

Variable	Coefficient			
	National	Eastern	Central	Western
UR	1.446**(0.562)	3.026***(0.545)	−2.371***(0.575)	1.007(1.640)
ADR	−0.163(0.159)	0.048(0.183)	−0.232*(0.129)	−0.126(0.334)
ACOR	0.496***(0.112)	0.536***(0.113)	0.469***(0.111)	0.719**(0.278)
AIS	0.026(0.398)	0.89*(0.472)	1.128**(0.486)	−4.047**(1.815)
EDLA	−0.176**(0.087)	−0.047(0.093)	0.173**(0.082)	−0.300(0.244)
cons	1.874***(0.539)	−0.777 (0.490)	−0.156(0.496)	5.910**(2.076)

Note: Standard error is in parentheses, ***, ** and * represent significance levels of 1%, 5% and 10%, respectively.

attributed to the faster progress in harmonising agricultural production activities with the ecological environment in the provinces within the western region. All three regions need to focus on reducing the absolute differences in AEE between regions and breaking down their barriers in agricultural science and technology innovation and the flow of production factors.

(4) Significant inter-provincial differences in China's AEE were observed, and they were consistent with the current uncoordinated development of the Chinese economy. Twenty provinces showed average AEE values above 1 for the period 2001–2020, which indicates that Chinese agriculture is fully capable of achieving effective improvements in AEE under low-carbon-output conditions. The provinces with higher AEE were not limited to the developed eastern regions but also notably less developed provinces in the west, which indicates that economic base and geographical advantages do not directly determine the construction of eco-agriculture but mainly lie in their own attention and efforts. The eco-agricultural development in the central region remains bleak. Hainan, Guangdong, Jilin, Xinjiang, Guangxi, Guizhou and Shaanxi maintained their dominant position in the top 10 from the 10th to the 13th Five-Year Plan periods. Compared with the 10th Five-Year Plan, about 35 % and 40 % of provinces have increased and decreased their AEE rankings, respectively. Compared with provinces with high AEE levels, which are more mobile and less sustainable, those with low levels of AEE have a clear 'poverty trap', and it is difficult to escape the vicious cycle of bad environmental and low-carbon agriculture development.

(5) The relationship between each impact factor and AEE showed inconsistent significance and different coefficients in the direction of correlation, and locational differences have been detected. UR and ACOR contributed significantly to the improvement of national AEE, with UR showing dominance. The level of agriculture hindered the improvement of national AEE. At the regional level, UR showed a limited role in driving AEE in the west but can greatly hinder AEE improvement in the centre while significantly aiding it in the east. ACOR had a significant positive effect on AEE in all three study regions. Thus, the strategic requirements of 'peak carbon' and 'carbon neutral' can significantly promote the green and low-carbon agricultural development in China. AIS only inhibited the AEE improvement in the western region. Meanwhile, the EDLA showed a positive contribution to AEE in the central region, with no significant effect on the other two regions. The different influencing factors exhibited different performances on AEE across the country and the three regions, and evident regional differences were observed. This finding indicates the need to adjust the imbalance between the regional supply and demand of different resources by means of proper allocation.

6.2. Policy implications

According to the results, a comprehensive and balanced promotion of AEE from point to point and from part to the whole can be achieved in the following ways. Under the spatial unevenness in AEE, the win-win cooperation mechanism between regions can be continuously improved. Thus, each region can fully utilise its own advantages in agricultural production resources and avoid 'factor congestion'. While ensuring that the eastern and central regions have their own advantages in green and low-carbon agricultural development, they should also consider the AEE development in the central region. It should also take into consideration its own development conditions to build a green and low-carbon agricultural industry chain and seek a balanced and coordinated development between agricultural economic growth, resource conservation and environmental protection.

Secondly, based on actual situation, we should implement a region-specific management model for green and low-carbon agricultural development on the premise of ensuring agricultural production, and regions with high AEE, such as Guizhou and Guangdong, should play a model role in radiation and establish an agricultural information and data sharing platform in this era of big data. For provinces with low AEE, such as Shanxi and Hebei, the use of chemical resources such as pesticides and fertilisers needs control, and the scale of production and specialisation of labour should be improved, which is an effective way to achieve 'overtaking' in the green and low-carbon agricultural development. Provinces such as Jilin and Inner Mongolia, where AEE can still be increased, need to focus on increasing the 'green content' to improve the 'gold content' and can continue to innovate new technologies for resource conservation and efficient resource use, develop high-tech agriculture and rely on technological changes to increase the sustainability of green and low-carbon agricultural production.

Thirdly, we intend to implement multiple measures to promote green and low-carbon agricultural development to achieve carbon peaking and neutrality. The 'visible hand' and 'invisible hand' should be actively used to promote AEE improvement. We need to create channels for the inter-provincial flow of green and low-carbon agricultural production factors through reasonable policy design. On the other hand, we should actively adjust and optimise the AIS, reduce the cultivation of crops with high resource consumption and chemical inputs and increase the cultivation of high-yielding and resistant crops to increase the net carbon effect of agriculture while reducing emissions of surface pollution. We will continue the following endeavours: improve the quality of UR; raise the disposable income of residents by stabilizing employment, lowering the tax burden, widening their investment channels and strengthening social security; enhance the concept of ecological civilization; and promote agriculture quality and efficiency.

6.3. Outlook

The research in this paper makes a useful addition to the established literature, but still has some limitations that can be added to and extended in the future. Specifically, given data availability, this paper does not focus its research perspective on agriculture in the broad sense, but rather on agriculture in the narrow sense, i.e., cultivation. In the future, we may be able to obtain more data by conducting extensive research or applying for data disclosure. In addition, the time interval of the study can be extended in future studies to incorporate machine learning methods for forecasting in order to comprehensively analyse the dynamics of AEE in China by 2030 or 2060.

Funding statement

This work was supported by Ministry of Education Humanities and Social Sciences Research Planning Fund Project (22YJA790075).

Data availability statement

Data will be made available on request.

Ethics approval and consent to participate

This paper is original research that has not been published elsewhere, and is not under consideration for publication elsewhere. Ethical approval and informed consent do not apply to this study.

Consent for publication

Not applicable.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Li Yang: Writing – review & editing, Writing – original draft, Visualization, Data curation, Conceptualization. **Zhenyu Guan:** Software, Methodology, Investigation, Data curation. **Shiying Chen:** Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis. **Zhenhua He:** Validation, Supervision, Data curation.

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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