GREEN TRANSITION AND AGRICULTURAL DEVELOPMENT: A COUPLED AGRICULTURAL ENERGY EFFICIENCY AND AGRICULTURAL GREEN SUSTAINABLE DEVELOPMENT COORDINATION ANALYSIS OF AGRICULTURAL AGGLOMERATIONS IN CHINA

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Abstracts. This study explores the coupling relationship between AEE (Agricultural Energy Efficiency) and AGSD (Agricultural Green Sustainable Development) in China's agricultural agglomeration areas from 2011 to 2021. A carbon emission model and the super-efficiency DEA-SBM-ML (Date Envelopment Analysis – Slacks Based Measure – Malumquist-Luenberger) method are used to measure AEE, while an AGSD system is built with hybrid weighting. A coupling coordination model was used to analyze the AEE-AGSD coordination. The research conclusions are as follows: (1) AEE in China's agricultural agglomeration areas shows a stable improvement; however, Gansu and Yunnan lagged. (2) The comprehensive AGSD scores exhibit a significant upward trend, although provinces like Xinjiang and Heilongjiang remain at relatively low levels. (3) Both the AEE and AGSD coupling coordination scores show an average increase of 8.11%. The coupling coordination score in the southern areas exceeds that of the northern areas by 4.98%. There is a substantial variation in the coupling coordination degrees, with most provinces achieving a good level; while Gansu stayed at barely level, urging agricultural model optimization. This study expands cross-disciplinary research on energy and ecosystems, providing theoretical support for coordinated agricultural modernization and green sustainability in China, as well as empirical insights for other regions worldwide.
Keywords: *AEE, AGSD, coupling coordination degree, DEA-SBM-ML, agricultural agglomeration areas*

Abbreviations: AAFA, Average Annual Feeding Amount; ACEP, Agricultural Carbon Emission Performance; AEE, Agricultural Energy Efficiency; AGSD, Agricultural Green Sustainable Development; DEA, Date Envelopment Analysis; DSFP, Dual-side Stochastic Fractional Planning; EBM, Epsilon-based Measure; EC, Efficiency Change; EE, Energy Efficiency; EF, Emission Factors; GWP, Global Warming Potential; LQ, Location Quotient; ML, Malumquist-Luenberger; SBM, Slacks Based Measure; TC, Technological Change; TFEPC, Total Factor Energy Productivity Change; TFP, Total Factor Productivity; WAEN, Water-Agriculture-Energy Nexus

Introduction

In China, agriculture plays a crucial role in the nation's overall economic development while simultaneously impacting human health and ecosystem integrity (Ofosu-Ampong et al., 2025; Vinod Chandra et al., 2024). As a unique ecosystem, the productivity of agricultural systems is determined by the quantity, structure, and type of external energy inputs, especially those derived from industrial sources. Since the twentieth century, agriculture has shifted from relying on traditional natural labor and biomass to modern fossil-based energy inputs such as diesel and coal, significantly boosting productivity (Majeed et al., 2023; Kabir and Ekici, 2024; Peng et al., 2024; Chatterjee, 2024; Wang et al., 2025). Notably, since China's reform and opening-up, the rapid advancement of agriculture has been closely linked to the extensive use of energy (Li et al., 2021a; Evans et al., 2022). China's agricultural development model is gradually shifting from yield-centered growth to a more ecologically sustainable approach. According to the *Opinions*

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of the People's Republic of China on Comprehensively and Accurately Implementing the New Development Concept and Achieving Dual Carbon Peak and Carbon Neutrality, it is essential to accelerate green agricultural development and pursue a path of green, ecological, and efficient modernization in agriculture. The input-output data for AEE (Agricultural Energy Efficiency), primarily derived from the *China Statistical Yearbook of Agriculture*, serves as the foundation for agricultural modernization. This process aims to optimize production factors, increase yields, and ultimately facilitate high-quality development in agriculture and rural areas (Xiong et al., 2022). Reducing energy consumption lowers greenhouse gas emissions, helping to mitigate agriculture's contribution to the greenhouse effect (Luan et al., 2024). Moreover, promoting energy-efficient technologies can significantly reduce input costs, thereby enhancing the economic sustainability of agricultural practices (Luan et al., 2024). In the near term, China faces an inherent tension between rapid agricultural modernization and the need for ecological protection (Li et al., 2021a). Therefore, the relationship between AEE and AGSD (Agricultural Green Sustainable Development) is pivotal to the success of the green, low-carbon transition and presents a significant challenge to sustainable development (Wu et al., 2024).

Currently, scholars have primarily focused on the calculation methods for AEE (Unakitan et al., 2010; Hamedani et al., 2011; Kazemi et al., 2015; Luan et al., 2024) and the factors influencing AEE (Li et al., 2021a; Wang et al., 2024; Soltani et al., 2023). A survey and economic analysis on input usage was conducted among canola farmers in the Trakya region of Turkey, with data collected from 100 farmers through face-to-face interviews. It shows that energy was used more efficiently on larger farms (Unakitan et al., 2010). Energy consumption in potato production and the relationship between energy inputs and yield were analyzed in the Kaboud Rahang area of Hamadan State in Iran, identifying seed energy as the most significant factor influencing yield based on parameter estimation. This research also highlighted that chemicals, diesel, and machinery were other critical inputs contributing substantially to yield (Hamedani et al., 2011). Energy use patterns in rice production were compared across Golestan, Mazandaran, and Gilan provinces in northern Iran, noting significant differences in input energy during agronomic practices, such as crop rotation, transplanting dates, and land preparation (Kazemi et al., 2015). Variations in EE (Energy Efficiency), TGR (Technological Gap Ratio), and TFEPC (Total Factor Energy Productivity Change) were investigated across 30 provinces and three distinct regions in China, revealing significant discrepancies (Luan et al., 2024). Based on panel data from 28 provinces from 1995 to 2018, agricultural energy input in China was calculated by categorizing it into direct and indirect energy (Li et al., 2021a). Subsequently, the EBM (Epsilon-based Measure) mixed distance function model was employed to assess energy efficiency in Chinese agriculture. The nuclear density function and spatial autocorrelation were applied to analyze the dynamic evolution of agricultural energy efficiency, while a dynamic panel model was utilized to examine its influencing factors (Li et al., 2021a). Impacts of climate change on energy inputs and outputs were investigated in the agricultural sector of the Hamadan-Bahar plain in western Iran, with physiological, meteorological, hydrological, and economic dimensions considered under different time scales and climatic scenarios. This research demonstrates that energy is used more efficiently in large farms (Soltani et al., 2023). Additionally, Trade-offs between addressing water scarcity and maintaining energy efficiency within current agricultural practices were explored (Hamedani et al., 2011).

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Research on AGSD has mainly concentrated on its philosophy (Bindraban et al., 2000; Steinborn and Svirezhev, 2000), indicators (Kanter et al., 2018; Quintero-Angel and González-Acevedo, 2018) and comprehensive evaluation system (Matraeva et al., 2019; Wang et al., 2024). Comprehensive indicators to assess agricultural production capacity and its temporal changes were developed, aimed at promoting sustainable land management and resource use (Bindraban et al., 2000). An indicator of agroecosystem sustainability based on entropy overproduction was proposed at the Kiel Ecology Centre, analyzing agricultural energy inputs and outputs in 1988 and 1987 to illustrate variations in entropy with land management practices (Steinborn and Svirezhev, 2000). The field of agricultural trade-off analysis was reviewed, which emerged to enhance understanding of interactions across scales, from fields to farms and regions to continents. This analysis outlined four stages: defining the decision context and relevant indicators, selecting methods for generating indicator values, evaluating trade-off options with stakeholders, and promoting the uptake of outcomes by decision-makers (Kanter et al., 2018). Aligning food production with sustainability principles and utilizing evaluation methods that support decision-making while accounting for social metabolism were emphasized. This perspective concluded that a holistic sustainability assessment should integrate social, economic, and ecological dimensions, moving beyond traditional linear methods (Quintero-Angel and González-Acevedo, 2018). A comprehensive evaluation index for agricultural green development was constructed, covering the entire life cycle from input to output. This system includes three subsystems (green input, green production, and green product) and 19 indicators, with a simulated annealing algorithm used for projection pursuit optimization. Application of this model evaluated agricultural green development across 31 provinces in China during 2013-2020, analyzing regional differences among eastern, central, and western areas (Wang et al., 2024).

Although research on AEE and AGSD had reached a relatively mature state within their respective fields, studies examining the relationship between the two remained scarce. Most of the previous studies are based on theories or models, and in-depth studies based on actual cases and practical experience are still somewhat lacking. A multi-objective non-linear optimization method for sustainable agricultural management was developed based on the WEFNI (Water-Energy-Food Nexus Index) and CO_2 emissions. The model demonstrated significant effects on water conservation and agricultural CO_2 emission reduction, being crucial for promoting sustainable agricultural development (Feng et al., 2024). A DSFP (Dual-side Stochastic Fractional Planning) method was proposed to identify optimal water allocation schemes for WAEN (Water-Agriculture-Energy Nexus) systems, accounting for climate change impacts. This approach addresses water scarcity issues while promoting future sustainability. To gain nuanced understanding of how environmental contexts impact AEE and AGSD in practice, further field investigations and case analyses are required to provide targeted recommendations (Zhang et al., 2024).

Agricultural agglomeration area is an important carrier of agricultural modernization (Wang et al., 2023) and agricultural industry agglomeration refers to the high concentration of agricultural production and factors in a certain area due to natural endowment, government promotion or market factors (Liu et al., 2022a). Agricultural production in China has obvious agglomeration characteristics. It takes a compact spatial organizational form in the process of agglomeration will produce a variety of spillover or economies of scale and other agglomeration effects. The importance of economies of scale formed by the agglomeration of agricultural production was emphasized. This mechanism exhibits a threshold effect on promoting farm household income, where

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income increases only when a certain agglomeration level is achieved (Richards, 2018). Agricultural production agglomeration can also reduce the cost of transportation and improve labor productivity (Ciccone, 2002). Therefore, in the context of the continuous agglomeration of the agricultural industry, what are the directions and mechanisms of influence of agro-industrial agglomeration on the AEE as well as on the AGSD?

Overall, current research still lacks sufficient interdisciplinary integration. A fundamental limitation lies in the long-standing disconnect between AEE and AGSD studies. Existing research on AEE often centers on improving energy input-output efficiency, while overlooking ecological outcomes such as water depletion and soil degradation. Conversely, AGSD studies typically emphasize environmental performance but seldom incorporate critical factors related to agricultural energy transitions. This disciplinary divide hinders a comprehensive understanding of the synergy between energy conservation and ecological sustainability in agriculture.

To address the long-standing lack of systematic integration between AEE and AGSD research, this study will establish a two-stage research framework of "cluster identification-focused analysis." First, agricultural agglomeration levels across 31 Chinese provinces will be measured over a defined time period to identify typical agricultural clusters. Based on these results, provinces with high agglomeration levels will be selected as key sample regions. An integrated evaluation framework combining an entropy-weighted DEA-SBM-ML (Date Envelopment Analysis-Slacks Based Measure-Malumquist Luenberger) model with an AGSD assessment system will then be constructed to analyze the coupling coordination between AEE and AGSD. This research framework will overcome existing limitations in spatial coverage and analytical depth, unify energy efficiency and green development performance metrics, and reveal the dynamic coupling and evolutionary characteristics between them. Ultimately, the study will provide theoretical support and empirical evidence for the transformation toward sustainable and green agricultural development in China.

Research methodology and data sources

This study will integrate the geographical characteristics of agricultural agglomerations with relevant research insights and national policies to construct a carbon emission measurement model. The DEA-SBM-ML model will be used to measure AEE, and the hierarchical analysis and entropy value methods will be applied, combining subjective and objective weighting approaches to determine indicator weights. Indicator data will then be processed using range normalization, establishing a comprehensive AGSD indicator system. Finally, a coupling coordination model will be constructed to analyze and explore the coordination relationships within the two systems. The overall methodological framework is illustrated in *Figure 1*.

Area of study

Definition of agricultural agglomeration areas

This study defines provincial-level agricultural agglomeration areas as regions meeting two criteria:

1. Agglomeration intensity: *LQ* (Location Quotient) > 1.15.
2. Sustainability: Maintained top 9 national ranking in agricultural agglomeration during 2011-2021.

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Demarcation methodology

Geographic boundaries directly correspond to provincial administrative divisions, justified by:

1. China's National Bureau of Statistics' institutional design specifies that the agricultural statistical system operates at the provincial level.
2. Provincial units constitute integrated agricultural policy implementation zones.

Quantification approach

In this study, the location entropy index is selected to measure the level of agricultural industry agglomeration, which is calculated by the next formula:

$$LQ_{ij} = \left(\frac{y_{ij}}{y_i}\right) / \left(\frac{y_j}{y}\right) \quad \text{(Eq.1)}$$

In the above formula, y_{ij} and y_i represent the provincial gross agricultural output and gross regional product, respectively; y_j and y represent the national agricultural output and national GDP, respectively; LQ_{ij} represents the location entropy of the agricultural industry, and the increase in its value reflects the strengthening of the spatial aggregation of the agricultural industry.

Data sources

The data used in this study are compiled from multiple authoritative national and provincial sources to ensure reliability and comparability across regions and time. Specifically:

1. Provincial agricultural energy consumption data were obtained from the *China Energy Statistical Yearbook* (2010-2021) and the *China Agricultural Yearbook*.
2. Socioeconomic and environmental indicators come from the *China Statistical Yearbook*, Provincial Statistical Yearbooks, and the National Bureau of Statistics database.
3. Agricultural agglomeration data were extracted from the *China Rural Statistical Yearbook*, with administrative boundaries derived from the National Geomatics Center's 1:4 million geographic database.
4. Carbon emission factors follow the *Climate Change 2022: Mitigation of Climate Change.*

All indicator data undergo range normalization for standardization. Linear interpolation is applied to address missing values, ensuring temporal continuity in the dataset.

Research methodology

Calculation methods for agricultural carbon emissions

Based on data availability and the rationality of calculation methods, this study combines the factor input method and the planting and breeding department addition method to establish an agricultural carbon emission model from three aspects: carbon emissions from agricultural production activities, rice cultivation, and livestock farming. The calculation methods are as follows:

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$$C = \sum C_i = \sum E_i \theta_i \quad \text{(Eq.2)}$$

In the above formula, C represents the total amount of agricultural carbon emissions, million tons per year; C_i represents carbon emissions from various agricultural carbon sources, million tons per year; E_i is the quantity of each carbon source; ϑ_i represents the carbon emission factor of each carbon source. The specific calculations for carbon emissions from agricultural production activities, rice cultivation, and livestock farming are provided below.

(1) Carbon emissions from agricultural production activities

Carbon emissions from agricultural production activities originate from three principal sources. Firstly, emissions stem from inputs of agricultural production factors, encompassing both direct and indirect carbon generation during the manufacturing and application of chemical fertilizers, pesticides, and agricultural films. Secondly, energy consumption contributes significantly through the combustion of diesel fuel in field operation machinery, particularly plowing, tillage, and harvesting equipment. Harvesting machinery plays a distinct role due to fuel expenditure during crop reaping, threshing, and grain transport operations. Thirdly, greenhouse gas emissions arise from productive agricultural practices: These encompass organic carbon loss through topsoil disruption during tillage operations, energy-intensive post-harvest processes such as electricity- or liquid fuel-dependent grain drying, short-haul agricultural transport activities, along with fossil energy consumption primarily from irrigation water pumping systems. For comprehensive quantification, the enhanced carbon emission model integrates these pathways in the following formula (Chen et al., 2018; He et al., 2018; Liu and Yang, 2021):

$$C_{prod} = \sum (IP \times EF) + \beta D_{total-field} + \gamma E_{irrig} \quad \text{(Eq.3)}$$

In the above formula, C_{prod} represents the total carbon emissions from agricultural production activities, IP represents quantities of fertilizers, pesticides, agricultural films, EF represents corresponding emission factors, E_{irrig} represents energy consumption for irrigation systems, $\beta = 0.5927$ kg(C)/kg, γ represents corresponding emission factor for irrigation, specific data are shown in *Table 1*.

Table 1. *Carbon emission factors of agricultural production activities*

Input elements	Carbon emission factor	Reference sources
Fertilizer	0.8956 kg(C)/kg	Oak Ridge National Laboratory (Liu and Yang, 2021)
Pesticide	4.93414 kg(C)/kg	(Li et al., 2011; Zhi and Gao, 2009)
Agricultural film	5.185 kg(C)/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University (Liu and Yang, 2021)
Diesel	0.5927 kg(C)/kg	(Change, 2007)
Ploughing	312.6 kg(C)/km^2	College of Biology and Technology, China Agricultural University (Liu and Yang, 2021)
Irrigation	266.48 kg(C)/hm^2	(Duan et al., 2011)

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(2) Carbon emissions from rice cultivation

The CO_2 produced by rice accounts for about 95 percent of the emissions from all food crops. Therefore, most scholars consider only the CO_2 produced by rice production when measuring CO_2 emissions from the plantation industry. The formula for calculating carbon emissions from rice plantations is shown in *Equation 4*.

$$C_{rice} = \sum E_{i_{rice}} \theta_{i_{rice}} \quad \text{(Eq.4)}$$

In the above formula, C_{rice} represents the total carbon emissions from rice cultivation, million tons; $E_{i_{rice}}$ represents the activity data for province and city i, i.e., the area of rice cultivation in each province and city, m^2; $\theta_{i_{rice}}$ represents the carbon emission factor for province and city.

In the process of rice cultivation, there are also emissions of CH_4, which is a greenhouse gas. The greenhouse effect of CH_4 is considerably more potent than that of CO_2. In this study, the GWP (Global Warming Potential) index is used to convert CH_4 emissions into CO_2-equivalent amounts for statistical calculations. GWP is an indicator that measures the contribution of different greenhouse gases to global climate warming, with the GWP value of CO_2 defined as 1. According to international climate agreements, such as the Kyoto Protocol, and assessment reports from the IPCC (Intergovernmental Panel on Climate Change), the GWP value of CH_4 can vary across different time horizons, as shown in *Table 2*. Therefore, in this study, the GWP value for methane is taken as 28.

The CH_4 emission rate from rice cultivation varies across different regions of China due to climate and temperature changes. This study references the emission factors calculated by Min and Hu (2012) for the rice growth cycle in various regions of China, with specific data presented in *Table 3*.

(3) Carbon emissions from livestock farming

Livestock farming activities, particularly ruminant farming, represent a significant source of carbon emissions from the agricultural sector. These emissions can be attributed to two primary sources: methane emissions resulting from the fermentation of livestock manure, and nitrous oxide and methane emissions associated with the handling and storage of livestock excreta. The formula utilized to quantify carbon emissions from livestock farming is illustrated in *Equation 5*.

$$C_{livestock} = \sum E_{i_{livestock}} \theta_{i_{livestock}} \quad \text{(Eq.5)}$$

In the above formula, $C_{livestock}$ represents the total carbon emission from livestock farming, million tons per year; $E_{i_{livestock}}$ represents the average annual feeding quantity of various livestock and poultry; $\theta_{i_{livestock}}$ represents the carbon emission factor of livestock and poultry. The greenhouse gas emissions from livestock and poultry mainly consist of CH_4 and N_2O. In calculations, it is necessary to convert CH_4 and N_2O emissions into CO_2-equivalent emissions using the GWP index, as shown in *Table 2*. The GWP value for CH_4 is taken as 28, for N_2O is taken as 298. Due to the differences in the rearing cycle of

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livestock and poultry, it is necessary to re-arrange their annual average rearing quantity. This study draws on the calculation method (Min and Hu, 2012), adjusting the number of head reared according to the slaughter rate.

Table 2. *Global warming potential (GWP) values relative to CO_2*

Chemical formula	GWP values for 100-year time horizon		
	Second Assessment Report (SAR)	**Fourth Assessment Report (AR4)**	**Fifth Assessment Report (AR5)**
CO_2	1	1	1
CH_4	21	25	28
N_2O	310	298	298

Table 3. *CH_4 emission factors for the rice cultivation ($g/m^2 \cdot year$)*

	Early rice	Late rice	Middle-season rice
Hainan	13.43	49.4	52.29
Guangxi	12.41	49.1	47.78
Yunnan	2.38	7.6	7.25
Xinjiang	-	-	10.5
Heilongjiang	-	-	8.31
Guizhou	5.1	21	22.05
Gansu	-	-	6.83
Sichuan	6.55	18.5	25.73
Henan	-	-	17.85

In China, livestock with an annual slaughter rate greater than or equal to 1 include pigs, rabbits, and poultry, which correspond to an average production cycle of 200 d, 105 d, and 55 d, respectively, and the formula for the *AAFA* (Average Annual Feeding Amount) is the follows:

$$AAFA = \frac{A_i L_i}{365} \quad \text{(Eq.6)}$$

In the above formula, $AAFA$ represents the average annual feeding amount; A_i represents the average production period of livestock and poultry; L_i represents the livestock and poultry slaughter rate.

If the annual slaughter rate is less than 1, the formula for the *AAFA* is the follows:

$$AAFA = \frac{t + (t-1)}{365} \quad \text{(Eq.7)}$$

In the above formula, t represents the amount of livestock in t year-end; t-1 represents the amount of livestock in t-1 year-end.

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The main livestock species that produce Greenhouse gases emissions in the livestock sector are cattle, camels, donkeys, horses, mules, pigs, sheep, rabbits, poultry, with corresponding carbon emission factors as shown in *Table 4*.

Table 4. *Greenhouse gases emission factors for the livestock farming (kg/head·year)*

Variety	Enteric fermentation CH_4 emission factor	Emissions of feces		Source
		CH_4 emission factor	N_2O emission factor	
Milk Cow	68	16	1	IPCC
Buffalo	55	2	1.34	IPCC
OX	47	1	1.39	IPCC
Camel	46	1.92	1.39	IPCC
Horse	18	1.64	1.39	IPCC
Donkey	10	0.9	1.39	IPCC
Mule	10	0.9	1.39	IPCC
Goat	5	0.17	033	IPCC
Sheep	5	0.15	0.33	IPCC
Pig	1	3.5	0.53	IPCC
Rabbit	0.254	0.08	0.02	IPCC
Poultry	0	0.02	0.02	IPCC

Calculation of energy efficiency

(1) Super-efficiency slacks based measure model with undesirable output

The super-efficiency SBM model, developed by Tone (2002), enables simultaneous energy efficiency analysis in both input and output dimensions, addressing the limitations of radial DEA models that lack slack variables. Unlike radial models, the super-efficiency SBM model accommodates slack, allowing for a nuanced differentiation among efficient DMUs. Given that undesired outputs frequently accompany energy consumption processes, Tone's model incorporates these adverse outputs, thus enhancing the accuracy of efficiency assessments.

Assume that there are *n* decision-making units, each comprising three components: input *m*, desired output r_1, and undesirable output r_2. The vector are expressed as: $x \in R_m$, $y^g \in R_{r1}$, $y^b \in R_{r2}$, X, Y^g, Y^b represent the matrix, and are greater than or equal to 0, $X = [x_1, x_2 ... x_n] \in R^{m \times n}$, $Y^g = [y_1^g, y_2^g ... y_n^g] \in R^{r_1 \times n}$, $Y^b = [y_1^u, y_2^u ... y_n^u] \in R^{r_2 \times n}$, the model is formulated as follows (Ball et al., 2005; Chen et al., 2021):

$$P_{min} = \frac{1 - \frac{\sum_{i=1}^{m} \frac{s_i^-}{x_{ik}}}{m}}{1 + \frac{1}{(r_1 + r_2)} \left(\sum_{s=1}^{r_1} \frac{s_p^g}{y_{pk}^g} + \sum_{q=1}^{r_2} \frac{s_q^b}{y_{qk}^b} \right)} \quad \text{(Eq.8)}$$

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$$\begin{cases} x_{ik} = X\lambda_j + S_i, i = 1,2,\ldots,m; \\ y_{pk}^g = Y^g\lambda_j + S_p^g, s = 1,2,\ldots,r_1; \\ y_{qk}^b = Y^b\lambda_j + S_q^b, q = 1,2,\ldots,r_2; \\ \lambda_j \geq 0, j = 1,2,\ldots,n, j \neq 0; \\ s_p^g \geq 0, p = 1,2,\ldots,r_1; \\ s_q^b \geq 0, q = 1,2,\ldots,r_2. \end{cases} \quad \text{(Eq.9)}$$

In the above formula, P represents the efficiency value; m, r_1, r_2 represent the three elements of input, desired output and undesirable output. Category, s^-, s^g, s^b are the slack vector of input, desired output and undesirable output respectively. When $s^-, s^b > 0$, this indicates an overuse of inputs, insufficient desired output, and increased undesirable output. When $s^g > 0$, it indicates a shortfall in the desired output. λ represents weight vector, and P is the objective function. When $P = 1$, this shows that the decision-making unit is feasible and efficient, indicating optimal emissions. Conversely, when $P < 1$, it suggests that the decision-making unit may experience partial losses and is inefficient. In such cases, adjustments to input and output are required to achieve the optimal state of the decision-making unit, thereby promoting improvements in agricultural carbon emission efficiency.

(2) Malmquist-Luenberger index

The SBM model is a static analytical model. Due to the different production frontiers referenced in different years, it is not possible to judge the efficiency change of the same decision unit in different periods by simple numerical comparisons. Therefore, this study will further compute the TFP (Total Factor Productivity) index constructed (Ball et al., 2005; Meng and Qu, 2022), which measures the change in TFP from period t to period $t + 1$. ML index as specified below:

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \times \left(\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)}\right) / 2 \quad \text{(Eq.10)}$$

In the above formula, $D^t\left(x^{t+1}, y^{t+1}\right)$, $D^t\left(x^t, y^t\right)$ represent the distance function of the decision unit in period $t + 1$ period and t period, respectively, using the production frontier in period t as a reference; $D^{t+1}\left(x^{t+1}, y^{t+1}\right)$, $D^{t+1}\left(x^t, y^t\right)$ represent the distance function of the decision unit in period t and period $t + 1$, respectively, using the production frontier in period t as a reference; The ML index is greater than 1, which indicates that the total factor productivity grows from period t to period $t + 1$. The ML index can be decomposed into two parts, i.e., the index of EC (Efficiency Change) and TC (Technological Change), respectively, which are decomposed as follows:

$$EC = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \quad \text{(Eq.11)}$$

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$$TC = \left(\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}\left(x^t, y^t\right)} \right) / 2 \quad \text{(Eq.12)}$$

Construction of agricultural green sustainable development index system

To accurately evaluate the spatial and temporal dynamics of sustainable agricultural development in China major agricultural agglomerations during 2010-2021 and to analyze the score of coordination, this study employs the theory of sustainable agricultural development and the entropy method proposed by Zhao et al. (2018). This model is developed based on data availability and the fundamental principles of the sustainable development capacity evaluation index system. It consists of five primary indicators: demographic system sustainability, social system sustainability, economic system sustainability, resource system sustainability, and environmental system sustainability. Each primary indicator includes several secondary indicators, resulting in a total of 21 secondary indicators, as shown in *Table 5*.

Table 5. *Evaluation indicators and weights for sustainable agricultural development systems*

Primary indicators	Secondary indicators	Unit	Attributes
Population system	Proportion of rural population with education	%	Forward
	Natural population growth rate	%	Reverse
	Regional population density	%	Reverse
Social systems	Rural per capita electricity consumption	kW·h/person	Forward
	The per capita housing area of villagers	m^2/person	Forward
	Engel coefficient of rural residents	%	Reverse
Economic systems	Gross agricultural product per capita	yuan/person	Forward
	Per capita net income of rural residents	yuan/person	Forward
	Investment in agricultural fixed assets	yuan×10^9	Forward
	Agricultural output per unit sown area	yuan/hm^2	Forward
Resource systems	Per capita cultivated land area	hm^2/person	Forward
	Agricultural land productivity	kg/hm^2	Forward
	Total mechanical power per unit of arable land area	kW/hm^2	Forward
	Agricultural water consumption	billion m^3	Forward
	Effective irrigation rate	%	Forward
Environmental systems	Intensity of fertilization	kg/hm^2	Reverse
	Pesticide Intensity	kg/hm^2	Reverse
	Intensity of film use	kg/hm^2	Reverse
	Soil erosion control area	10^3 hm^2	Forward
	Forest cover	%	Forward
	Agricultural disaster rate	%	Reverse

The entropy value method is first applied to determine the dynamic weights of each secondary index for each year (Cheng et al., 2016; Li et al., 2021b). This method, which assesses the degree of dispersion among evaluation indexes, is favored for its objectivity, comprehensiveness, and reduced complexity. A higher degree of dispersion indicates a greater impact on the comprehensive index evaluation score. By utilizing the entropy

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value method, the analysis minimizes subjective factors in measuring the comprehensive index score of sustainable agricultural development. Next, based on the dynamic weights established by the entropy value method, the secondary indexes for each year are weighted and calculated to derive the primary indexes. Ultimately, this process enables the calculation of the comprehensive score for sustainable agricultural development across various regions in China during 2010-2021. This operation is repeated for each subsequent year.

The specific calculation steps are as follows (Cheng et al., 2016; Li et al., 2021b):

1. The raw indicators are standardized. Indicators a_{ij} is made dimensionless and homogenized by the method of polar deviation. So that the numerical magnitude is normalized between (0, 10), a linear dimensionless method is used, which is shown in the follows:

Positive indicators:

$$x_{ij} = \frac{a_{ij} - a_{ij,\min}}{a_{ij,\max} - a_{ij,\min}} \quad \text{(Eq.13)}$$

Negative indicators:

$$x_{ij} = \frac{a_{ij,\max} - a_{ij}}{a_{ij,\max} - a_{ij,\min}} \quad \text{(Eq.14)}$$

In the above formula, a_{ij} represents the raw value of the indicator for region j of item i; x_{ij} represents the standardized value of the indicator in the area of the first item.

2. The methodology for calculating the share of x_{ij} in the sum of the standard values for each is as follows:

$$P_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij} \quad \text{(Eq.15)}$$

3. Calculate the information entropy of the j indicator:

$$E_j = -\frac{\sum_{i=1}^{m} P_{ij} \ln P_{ij}}{\ln m} (j = 1, 2, \ldots, n) \quad \text{(Eq.16)}$$

In the above formula, m represents the number of districts.

4. Calculate the dynamic weights of the indicators:

$$W_j = -\frac{1 - E_j}{n - \sum_{j=1}^{n} E_j} \quad \text{(Eq.17)}$$

In the above formula, n represents the number of indicators, using the entropy value method to calculate the weight of each indicator, the essence of which is to use the value

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coefficient of the indicator information to calculate, and the higher the value coefficient, the greater the impact on the comprehensive evaluation of sustainable agricultural development.

5. Calculate the sustainability of each subsystem. The weights of the indicators included in each subsystem are normalized by the formula:

$$W_{kj} = W_j / \sum_{j=1}^{r} W_j \quad \text{(Eq.18)}$$

The formula for the sustainability of systems:

$$S_{ki} = \sum_{j=1}^{r} W_{kJ}^{*} X_{ij} \quad \text{(Eq.19)}$$

When $k = 1, 2, ..., 5$, S_{ki} represents the sustainable capacity of population system, social system, economic system, resource system and environment system in the region respectively; r is the number of indicators included in each subsystem.

Calculate the weight of each subsystem sustainability in the comprehensive evaluation score of sustainable agricultural development as follows:

$$W_k = \sum_{J=1}^{r} W_J \quad \text{(Eq.20)}$$

Sustainability composite evaluation score:

$$S_i = \sum_{j=1}^{r} W_k S_{ki} \quad \text{(Eq.21)}$$

In the above formula, S_i represents sustainability composite evaluation score.

Coupled agricultural energy efficiency - agricultural green sustainable development coordination model

The coupled coordination model is usually used to characterize the relationship between two or more systems or elements that interact and coordinate with each other (Wang et al., 2021). In this study, the coupled coordination model consists of two sub-models, the AEE model and the AGSD evaluation model. The coupled coordination model measures the coupled coordinated development and interaction level between the two sub-models, as shown in the following formula (Qin et al., 2024; Tao et al., 2023):

$$C = \mathrm{n} \times \left[\frac{U_1 \times U_2}{(U_1 + U_2)^{\mathrm{n}}} \right]^{\frac{1}{2}} \quad \text{(Eq.22)}$$

C is the coupling score that measures the magnitude of the synergy of the system, C closer to 1 means better coupling, and the score of C is between (0, 1); U_1 and U_2 represent the

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scale index of AEE and AGSD; n is the adjustment coefficient, which is between (-2, 5). In order to better explore the state of development and score of synergy of the coupling coordination between agricultural AEE and AGSD, the coupling coordination model is further introduced into the study, and the model expression is as follows:

$$P = \alpha U_1 + \beta U_2 \quad \text{(Eq.23)}$$

$$D = \sqrt{C \times P} \quad \text{(Eq.24)}$$

P is the integrated development index of two or more systems, and D is the coupling coordination score that represents the level of coordinated development of the whole system (Liu et al., 2022b; Tao et al., 2023) D represents the coupling coordination score between AEE and AGSD, and its value ranges between (0, 1); P represents the comprehensive coordination score of AEE and AGSD, where α and β are the specific coefficients of the sub-models. This study emphasizes the equal importance of AEE and AGSD, setting $\alpha = \beta = 0.5$ (Liao et al., 2020). The coupling coordination score is classified into 10 degrees, with specific degree classifications detailed in *Table 6*.

Table 6. *Coupling coordination degree of AEE and AGSD*

Coupling coordination score	Coordination degree	Coupling coordination degree	$f(x) > g(x)$	$f(x) < g(x)$
(0, 0.1]	1	Extreme disarray	Lagging AEE	Lagging AGSD
(0.1, 0.2]	2	Severe disarray	Lagging AEE	Lagging AGSD
(0.2, 0.3]	3	Mild disarray	Lagging AEE	Lagging AGSD
(0.4, 0.5]	5	On the verge of disarray	Lagging AEE	Lagging AGSD
(0.5, 0.6]	6	Barely (coordinated)	Lagging AEE	Lagging AGSD
(0.6, 0.7]	7	Elementary (coordination)	Lagging AEE	Lagging AGSD
(0.7, 0.8]	8	Intermediate (coordination)	Lagging AEE	Lagging AGSD
(0.8, 0.9]	9	Good (coordination)	Lagging AEE	Lagging AGSD
(0.9, 1.0]	10	High (coordination)	Lagging AEE	Lagging AGSD

Model structure

Figure 1 presents the conceptual framework and methodological roadmap of this study. It delineates the logical sequence from the identification of agricultural agglomeration areas, data processing, and index system construction specifically targeting AEE and AGSD, to the application of the DEA-SBM-ML model and coupling coordination analysis, culminating in spatial-temporal interpretation and policy-oriented discussion.

Results and discussion

2010-2021 spatial pattern and core agglomeration zones of provincial agriculture

During the 2010-2021 period, China's provincial agricultural agglomeration LQ values demonstrate a distinct phased evolutionary pattern as depicted in *Figure 2*; nationally maintaining relative stability before 2014, a decisive surge occurs in 2015 where approximately 92% of provinces register LQ increases exceeding 70%: Heilongjiang

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surges by 184.7% and Hebei by 88.8%, establishing a tripartite temporal framework with 2015 as the nodal point: a period of stability spanning 2010-2014, a surge phase in 2015, and a period of sustained high-level fluctuations during 2016 to 2021. This structural shift closely relates to the 2015 reform of the agricultural machinery purchase subsidy policy, which significantly enhances central fiscal support, optimizes subsidy mechanisms, promotes the widespread adoption of large and medium-sized agricultural machinery, and thereby strengthens agricultural specialization within scaled farming zones. Agricultural agglomeration intensity follows *Equation 1* in the Section "Quantification approach".

The results of the measurement of the average agricultural agglomeration score in each province of China are illustrated in *Figure 3*. The agglomeration of agricultural concentration across different provinces demonstrates significant spatial imbalances. Heilongjiang, Xinjiang, and Gansu exhibit the highest agricultural agglomeration levels. Provinces such as Hainan, Guizhou, Guangxi, Yunnan, Henan, and Sichuan show relatively high agricultural concentration, while eastern regions including Beijing, Shanghai, Tianjin, Zhejiang, Guangdong, and Jiangsu, as well as coastal areas, demonstrate lower agglomeration scores. Regions with elevated agglomeration levels are characterized by advanced agricultural development, encompassing superior production bases, larger production scales, and higher concentration indices. For future AEE-AGSD coupling research, regions with high agricultural agglomeration should be selected. Accordingly, this study selects the 9 provinces with the highest agglomeration scores: Heilongjiang, Xinjiang, Gansu, Hainan, Guizhou, Guangxi, Yunnan, Henan, and Sichuan. Provincial agricultural agglomeration core agglomeration follows *Equation 1* in the Section "Quantification approach".

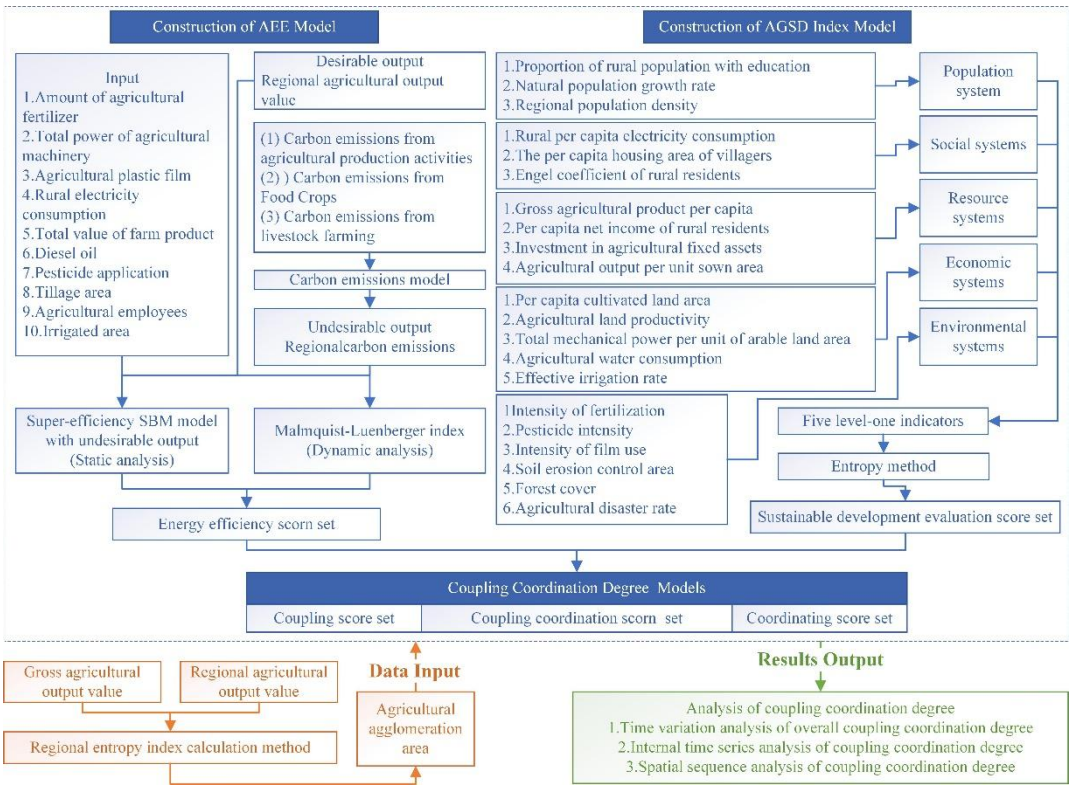

Figure 1. *Structure of the coupled AEE-AGSD coordination model*

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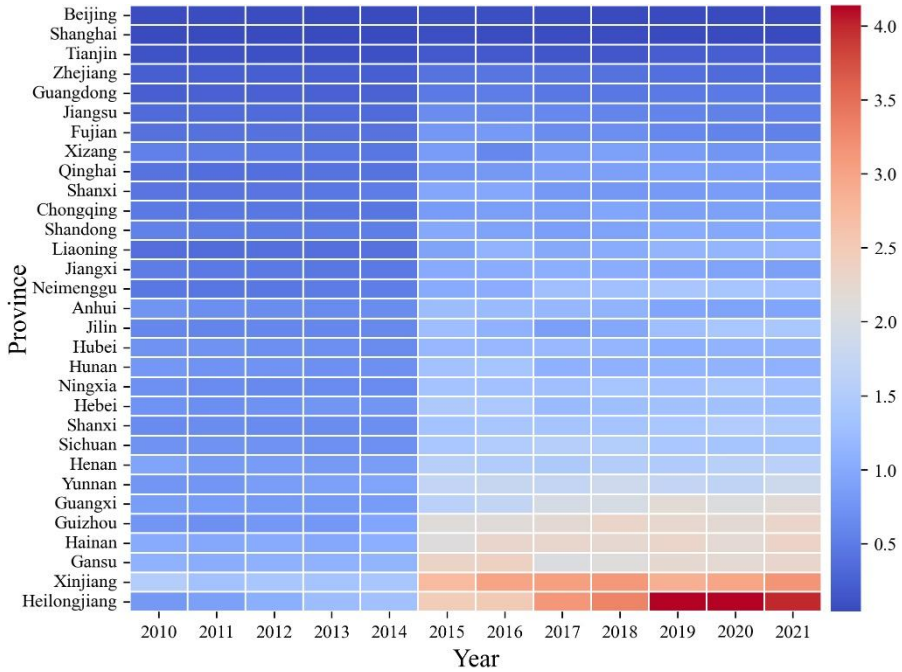

Figure 2. *Spatiotemporal evolution of agricultural agglomeration intensity across Chinese provinces*

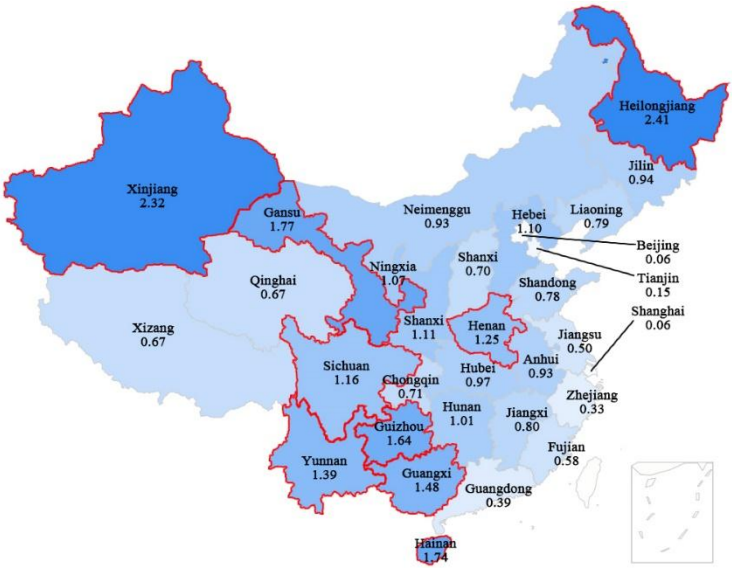

Figure 3. *2010-2021 Spatial distribution of provincial agricultural agglomeration core agglomeration zones: top 9 provinces with LQ > 1.15*

Changes in the intensity of agricultural carbon emissions

As *Figure 4* illustrates, the total agricultural carbon emissions of the 9 provinces during 2010-2021 demonstrate that during 2013-2014, China's agricultural carbon emissions exhibit an overall upward trajectory. Additionally, regions including Xinjiang and Guizhou exhibit notable emission increases. This phenomenon results from expanded agricultural production in these areas and inadequate implementation of mitigation

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measures. Consequently, a fundamental contradiction exists between agricultural carbon reduction and activity expansion. Regarding the overall trend, a gradual emission decline occurs across most regions starting in 2015. While regional variations persist—some regions show pronounced decreases while others maintain relative stability—the dominant downward trajectory remains evident. This outcome attributes itself to the effective implementation of emission-reduction measures by both government entities and farmers. Strategies including fertilizer use reduction, efficient irrigation promotion, on-farm carbon sink management, and accelerated agricultural modernization gain widespread adoption and application. Carbon emissions follows *Equations 2-7* in the Section "Calculation methods for agricultural carbon emissions".

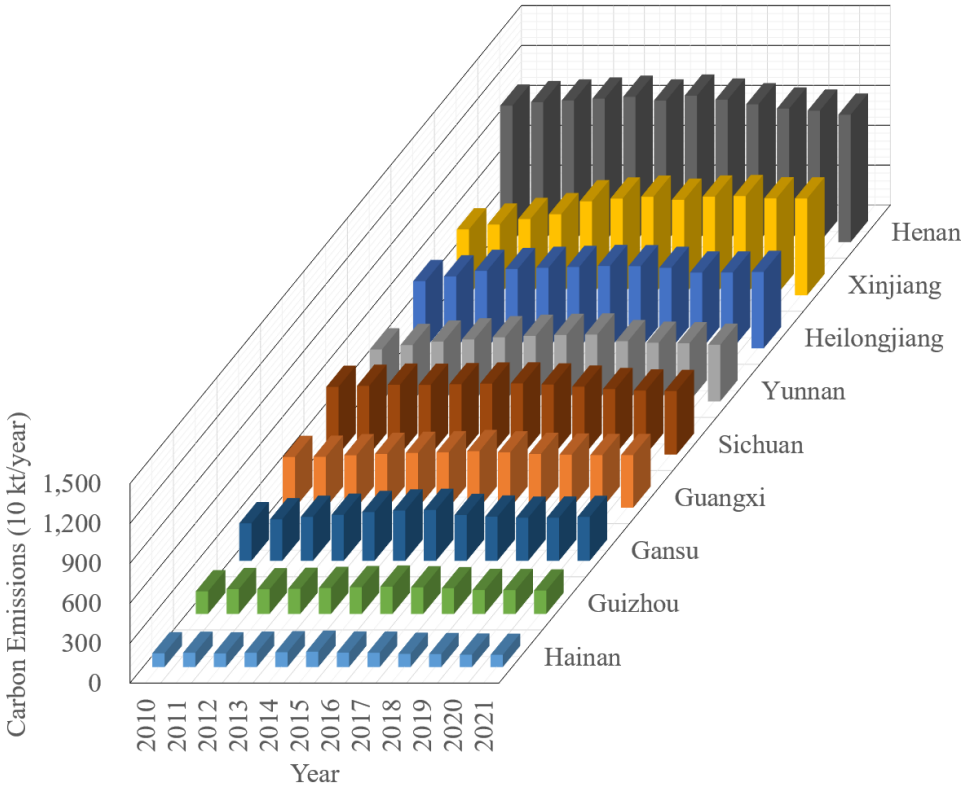

Figure 4. *2010-2021 Spatiotemporal dynamics of agricultural carbon emissions in China's nine core agricultural agglomeration provinces*

Spatial and temporal patterns of total factor productivity in agricultural energy

Evaluation and analysis of super-efficiency slacks based measure models from a static perspective in 9 provinces

The AEE levels of the 9 provinces are assessed using the super-efficiency SBM model with non-desired outputs, as *Figure 5* illustrates. The results indicate that during 2011-2021, most provinces maintain high AEE levels around 1.0, except Gansu and Yunnan. The low AEE levels in these two provinces result from uncoordinated allocation of agricultural resources and inputs, leading to excessive undesired outputs. In 2019, AEE levels in Guizhou, Heilongjiang, and Guangxi experience a notable decline followed by recovery to higher levels. This transient fluctuation stems primarily from climatic disasters including droughts and floods.

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The figure data indicate strong stability in China's agricultural production system, reflecting government strategic initiatives to adjust the agricultural energy structure. These initiatives focus on promoting renewable energy, strengthening technological innovation, and facilitating energy-saving agricultural machinery application. For example, the government develops energy-efficient agricultural greenhouses, advances farm building renovations for energy efficiency, and constructs green farm buildings. Additionally, measures implement agricultural surface pollution control, enhance pesticide-fertilizer efficiency, promote straw utilization, and accelerate recycling of agricultural film and pesticide packaging waste. Energy productivity index follows *Equations 8-9* in the Section "Calculation of energy efficiency".

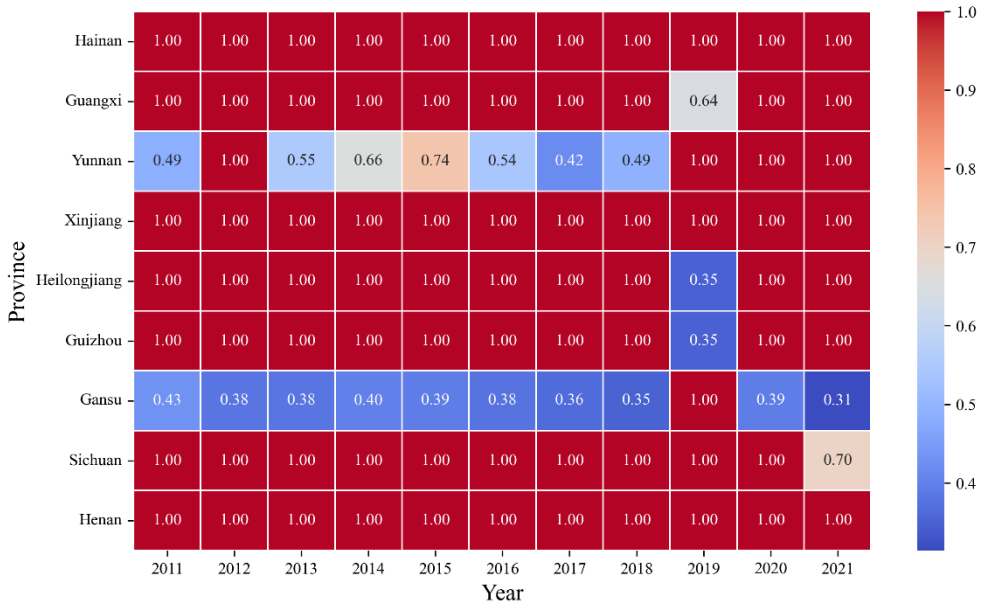

Figure 5. *2011-2021 Interannual dynamics of energy productivity index in nine key agricultural agglomeration provinces*

Analysis of the Malmquist-Luenberger index evaluation from a dynamic perspective

To clarify dynamic changes in agricultural production efficiency across the 9 provinces and assess technical efficiency impacts, this study employs ML index decomposition of AEE during 2011-2021. As *Figure 6* shows, the ML index for each province remains relatively stable during 2011-2017, with most values exceeding 1. This indicates that agricultural production factors and technological productivity positively influence energy utilization efficiency during this phase. However, during 2018-2020, ML index disparities among provinces increase, with most exhibiting downward trends—particularly Guizhou, Gansu, and Yunnan experiencing significant fluctuations. Notably, Guizhou agricultural productivity fluctuates most dramatically, rising from 0.3217 to 2.8454 between 2018 and 2019. This outcome primarily arises from inadequacies in investment, technology, and policy implementation during agricultural development transitions, leading to AEE fluctuations between > 1 and < 1 thresholds. This variation underscores the necessity of enhancing technological innovation and resource optimization to improve overall efficiency. ML Index calculation follows *Equations 10-12* in the Section "Calculation of energy efficiency".

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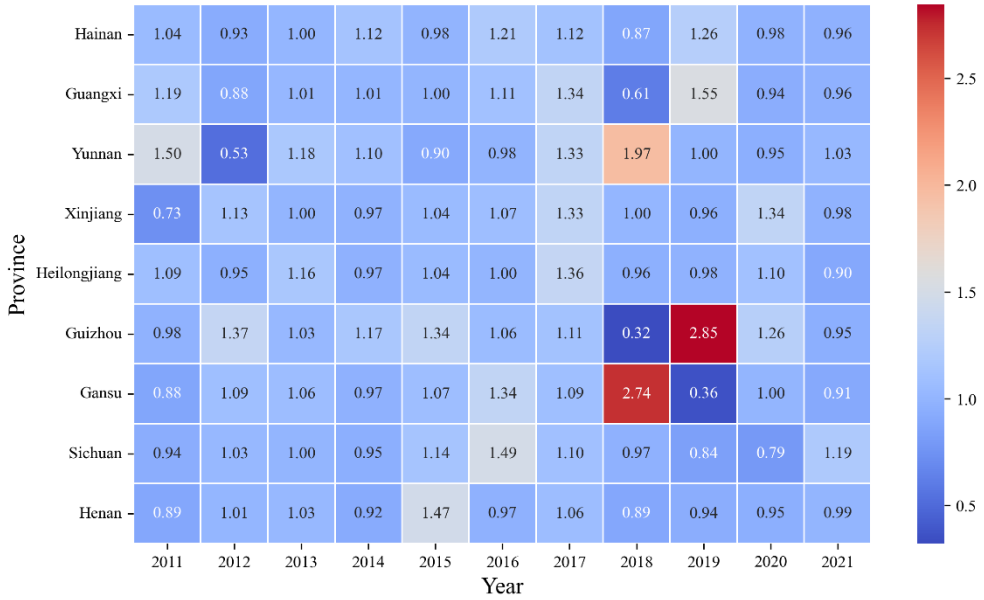

Figure 6. *2011-2021 Spatiotemporal dynamics of total factor productivity in China's agricultural agglomeration zones: a Malmquist-Luenberger index approach*

Spatio-temporal pattern of agricultural green sustainable development in agricultural aggregation area

As illustrated in *Figures 7* and *8*, the comprehensive AGSD scores for agricultural agglomeration areas in China demonstrate a significant upward trajectory during 2010-2021. In 2010, the average score for these areas registers at 0.2916, rising to 0.4139 by 2021, marking an increase of 0.1223. *Figure 9* reveals differences in AGSD scores among the 9 provinces. Provinces such as Hainan, Guizhou, and Sichuan show a continuous and stable increase in AGSD scores, reflecting substantial progress in promoting sustainable agriculture. In contrast, provinces like Xinjiang and Heilongjiang have experienced score improvements but remain at relatively low levels. To achieve comprehensive sustainable agricultural development, the government, as the primary advocate for agricultural environmental protection, must actively enhance public awareness and education regarding agricultural environmental protection. This includes implementing integrated measures to curb the excessive use of pesticides and fertilizers, improving the efficient utilization of agricultural waste, refining agricultural environmental protection policies, and intensifying environment conservation efforts to promote environmentally friendly and sustainable agricultural production. Comprehensive score of AGSD calculation follows *Equations 13-21* in the Section "Construction of agricultural green sustainable development index system".

Spatiotemporal evolution and regional disparities of coupling coordination between agricultural energy efficiency and green sustainable development

Figure 10 illustrates the temporal evolution of indicators, showing during 2011-2021 the coupling score (C) of agricultural agglomeration areas in China increases cumulatively by 91%, while the coordination index (P) rises by 16.54% over the same period. Critically, the coupling coordination index (D) exhibits an overall growth of 8.11% across the decade-long study period, deriving from direct endpoint comparison.

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These figures collectively indicate a substantial long-term growth trend. This progress reflects increasingly synchronized development between AEE and AGSD in major agricultural agglomeration areas, demonstrating their strong systemic interrelationship.

Figure 11 illustrates the coupled AEE-AGSD coordination scores across regions. In this figure, southern areas comprise Hainan, Guangxi, Yunnan, Guizhou, and Sichuan, while northern areas encompass Xinjiang, Heilongjiang, Gansu, and Henan. As depicted, the coordination score in southern areas exhibits gradual enhancement over time with a 10.34% growth rate. In contrast, the northern coordination score demonstrates continuous improvement, though its average development speed remains 4.98% lower than southern areas at 5.36% growth. However, northern areas exhibit higher development speeds than southern areas in 2011 and 2019. This pattern indicates progressively strengthening intrinsic AEE-AGSD coordination in both regions. Consequently, China's strategies for maintaining productivity while protecting agricultural ecological environments prove effective and suitable, with more pronounced impacts in southern areas. Calculation follows *Equations 21-24* in the Section "Coupled agricultural energy efficiency – agricultural green sustainable development coordination model".

Figure 7. *2010 Comprehensive score of AGSD in nine major agricultural agglomeration provinces of China*

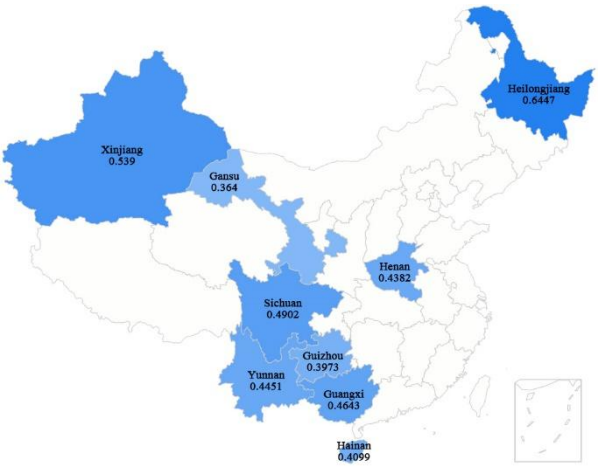

Figure 8. *2021 Comprehensive score of AGSD in nine major agricultural agglomeration provinces of China*

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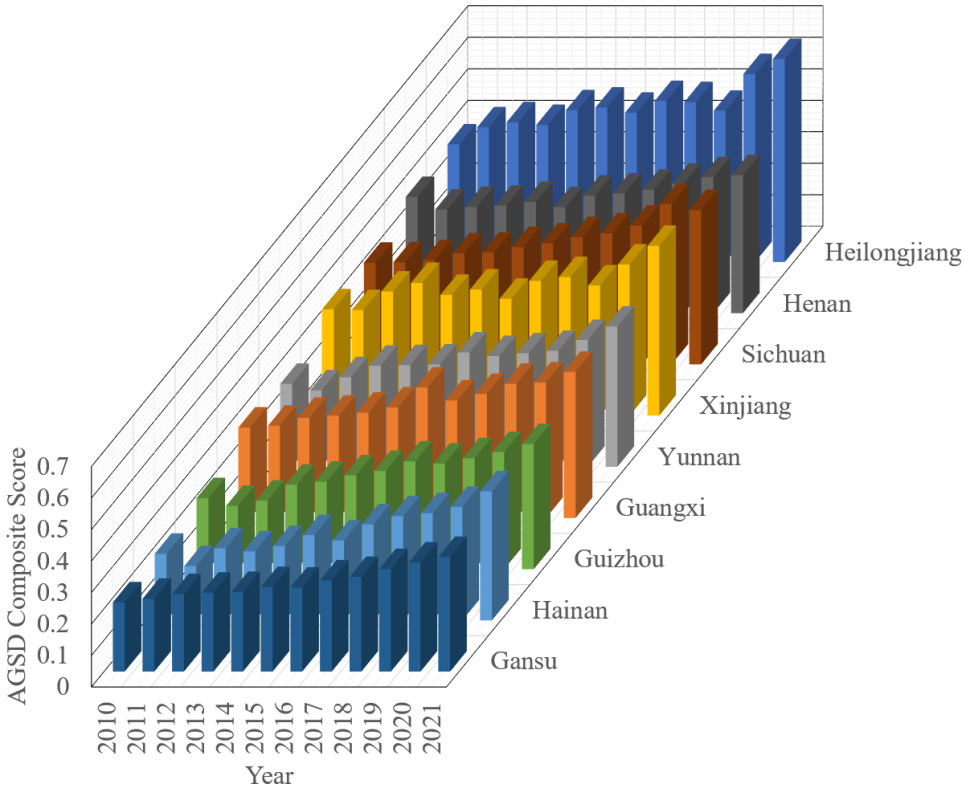

Figure 9. *2010-2021 Spatiotemporal evolution of AGSD performance in China's core agricultural agglomeration zones*

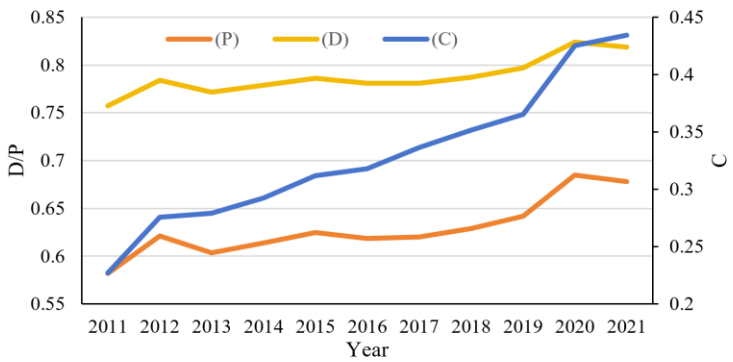

Figure 10. *2011-2021 Dynamics of coupling coordination indicators in China's core agricultural agglomeration provinces: evolving patterns of C, P, and D values*

Figure 11. *2011-2021 Spatiotemporal dynamics of AEE-AGSD coordination degree across regional stratifications: northern, southern, and aggregate performance*

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Figure 12 illustrates the coupled AEE-AGSD coordination score across different provinces. As illustrated in the figure, there are significant differences in the coupling coordination score among the provinces. Provinces with average values between 0.8 and 0.9 include Hainan, Guangxi, Xinjiang, Heilongjiang, Sichuan, and Henan. Provinces with average values ranging from 0.7 to 0.8 are Yunnan and Guizhou, while Gansu has an average value between 0.5 and 0.6. Provinces with average values below 0.7 indicate unsatisfactory coordination score in the coupling process of AEE and AGSD. It is evident that Gansu coordination score requires further improvement. Provinces that experience an increase greater than 7% include Hainan, Xinjiang, Heilongjiang, and Guizhou, while the remaining regions show increases below 7%, with Sichuan experiencing the largest decline of 5.28%. Calculation follows *Equations 21-24* in the Section "Coupled agricultural energy efficiency – agricultural green sustainable development coordination model".

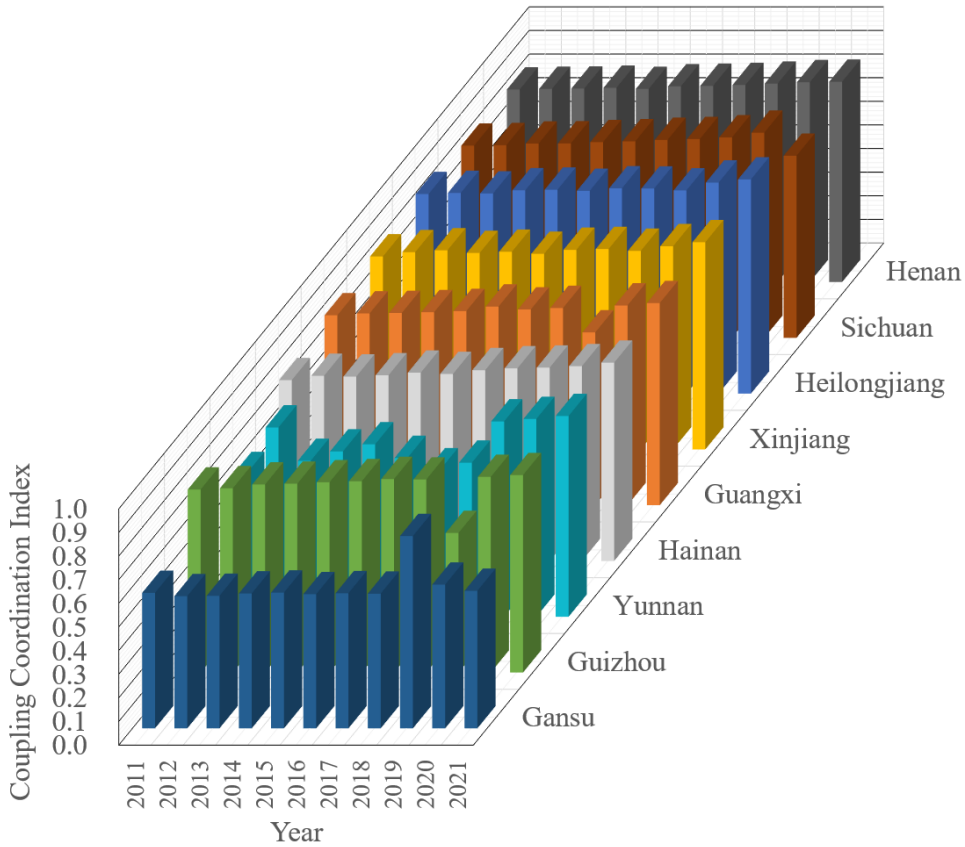

Figure 12. *2011-2021 Interprovincial dynamics of AEE-AGSD coordination degree in China's nine core agricultural agglomeration provinces*

Figure 13 illustrates the coupled AEE-AGSD coordination degree. As illustrated, the overall coupling coordination degree for the 9 provinces is relatively high. Notably, Hainan and Guizhou show improvements in their coupling coordination degree from Intermediate to Good between 2011 and 2021, indicating significant progress in the assessment of AEE and AGSD, as well as continuous enhancement in coupling coordination. Except for Guangxi, Sichuan, Henan, and Heilongjiang, which maintain a stable degree of development, all other provinces exhibit an upward trend over the eleven-

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year period, with the number of provinces in the Good coordination degree increasing to 8. Among these, Yunnan demonstrates particularly notable growth, advancing from Elementary to Good, thus spanning two degrees. Only Gansu remains in the Barely degree for most of the period 2011-2021. These changes in degrees reflect the efforts and achievements of various provinces in optimizing agricultural development models under the support of national policies and local implementation. Through the promotion of agricultural technological innovation, adjustment of industrial structures, and improvement of agricultural production efficiency, a coordinated development of economic benefits and ecological environments in the agricultural sector has been realized. It is recommended to further enhance the monitoring system for agricultural energy efficiency and sustainable development indicators, conduct regular assessments of the coupling coordination degree, and timely adjust relevant policies. Calculation follows *Equation 21-24* in the Section "Coupled agricultural energy efficiency – agricultural green sustainable development coordination model".

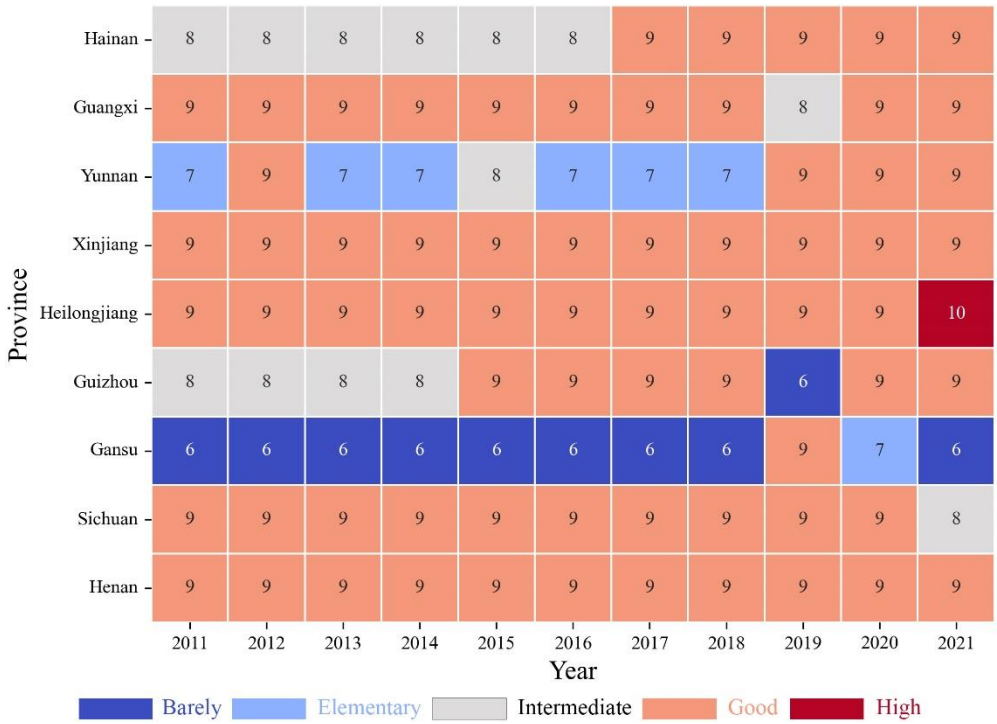

Figure 13. *2011-2021 Spatiotemporal trajectories of AEE-AGSD coordination degree across China's nine key agricultural agglomeration provinces*

Conclusion

This study constructs a coupling coordination model based on AEE and AGSD, in which the AEE sub-model regards carbon emissions as undesirable outputs and incorporates a static-dynamic dual perspective analysis. The dynamic dual analysis aims to enhance the scientific rigor of the regional agricultural energy utilization efficiency evaluation system. The regional agricultural AGSD sub-model is developed from five perspectives: population, society, economy, resources, and environment. Utilizing this model, an in-depth analysis of China agricultural agglomeration areas is conducted, leading to the following conclusions:

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1. Overall, the AEE in China agricultural agglomeration areas shows a stable improvement; however, Gansu and Yunnan maintain relatively low AEE levels. The fluctuations in the ML index from 2018 to 2020 highlight the importance of enhancing technological innovation and resource optimization for overall efficiency during the agricultural development transition.

2. The comprehensive AGSD scores in China agricultural agglomeration areas exhibit a significant upward trend, although provinces like Xinjiang and Heilongjiang remain at relatively low levels. To achieve comprehensive sustainable agricultural development, local governments need to strengthen environmental protection efforts to promote environmentally friendly and sustainable agricultural production.

3. Both the AEE and AGSD coupling coordination scores in China agricultural agglomeration areas show a growth trend, with an average increase of 8.11%. The coupling coordination score in the southern areas exceeds that of the northern areas by 4.98%. There is a substantial variation in the coupling coordination degrees, with most provinces achieving a good level; over half of the provinces have seen an increase of one level. Notably, Gansu remains in the Barely degree for most of the period from 2011 to 2021, indicating a need for further optimization of agricultural development models.

This study expands cross-disciplinary research on energy and ecosystems, providing theoretical support for coordinated agricultural modernization and green sustainability in China, as well as empirical insights for other regions worldwide.

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REFERENCES

[1] Ball, E., Färe, R., Grosskopf, S., Zaim, O. (2005): Accounting for externalities in the measurement of productivity growth: the Malmquist cost productivity measure. – Structural Change and Economic Dynamics 16(3): 374-394.

[2] Bindraban, P. S., Stoorvogel, J. J., Jansen, D. M., Vlaming, J., Groot, J. J. R. (2000): Land quality indicators for sustainable land management: proposed method for yield gap and soil nutrient balance. – Agriculture, Ecosystems & Environment 81(2): 103-112.

[3] Chatterjee, R. (2024): How state governance can offer a new paradigm to energy transition in Indian agriculture? – Energy Policy 185: 113965.

[4] Chen, L., Zhang, J., He, K. (2018): Different spatial impact of agricultural industrial agglomerations on carbon efficiency: mechanism, spatial effects and groups differences. – Journal of China Agricultural University 23(9): 218-230.

[5] Chen, Y., Miao, J., Zhu, Z. (2021): Measuring green total factor productivity of China's agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO2 emissions. – Journal of Cleaner Production 318: 128543.

[6] Cheng, J., Dai, S., Ye, X. (2016): Spatiotemporal heterogeneity of industrial pollution in China. – China Economic Review 40: 179-191.

[7] Ciccone, A. (2002): Agglomeration effects in Europe. – European Economic Review 46(2): 213-227.

[8] Duan, H., Zhang, R., Zhao, J. (2011): Carbon footprint analysis of farmland ecosystem in China. – Journal of Soil and Water Conservation 25(5): 203-208.

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DOI: http://dx.doi.org/10.15666/aeer/2304_81778203
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[9] Evans, D. L., Falagán, N., Hardman, C. A., Kourmpetli, S., Liu, L., Mead, B. R., Davies, J. a. C. (2022): Ecosystem service delivery by urban agriculture and green infrastructure—a systematic review. – Ecosystem Services 54: 101405.
[10] Feng, M., Chen, Y., Li, Z., Duan, W., Zhu, Z., Liu, Y., Zhou, Y. (2024): Optimisation model for sustainable agricultural development based on water-energy-food nexus and CO2 emissions: a case study in Tarim River basin. – Energy Conversion and Management 303: 118174.
[11] Hamedani, S. R., Shabani, Z., Rafiee, S. (2011): Energy inputs and crop yield relationship in potato production in Hamadan province of Iran. – Energy 36(5): 2367-2371.
[12] He, Y., Chen, R., Wu, H. (2018): Spatial dynamics of agricultural carbon emissions in China and the related driving factors. – Chinese Journal of Eco-Agriculture 29(9): 1269-1282.
[13] Intergovernmental Panel on Climate Change (2007): Climate Change 2007: Synthesis Report. – Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva.
[14] Kabir, M., Ekici, S. (2024): Energy-agriculture nexus: exploring the future of artificial intelligence applications. – Energy Nexus 13: 100263.
[15] Kanter, D. R., Musumba, M., Wood, S. L. R., Palm, C., Antle, J., Balvanera, P., Dale, V. H., Havlik, P., Kline, K. L., Scholes, R. J., Thornton, P., Tittonell, P., Andelman, S. (2018): Evaluating agricultural trade-offs in the age of sustainable development. – Agricultural Systems 163: 73-88.
[16] Kazemi, H., Kamkar, B., Lakzaei, S., Badsar, M., Shahbyki, M. (2015): Energy flow analysis for rice production in different geographical regions of Iran. – Energy 84: 390-396.
[17] Li, B., Zhang, J., Li, H. (2011): Research on spatial-temporal characteristics and affecting factors decomposition of agricultural carbon emission in China. – China Popul. Resour. Environ. 21(8): 80-86.
[18] Li, H., Luo, L., Zhang, X., Zhang, J. (2021a): Dynamic change of agricultural energy efficiency and its influencing factors in China. – Chinese Journal of Population, Resources and Environment 19(4): 311-320.
[19] Li, W., Wang, Y., Xie, S., Cheng, X. (2021b): Coupling coordination analysis and spatiotemporal heterogeneity between urbanization and ecosystem health in Chongqing municipality, China. – Science of The Total Environment 791: 148311.
[20] Liao, S., Wu, Y., Wong, S. W., Shen, L. (2020): Provincial perspective analysis on the coordination between urbanization growth and resource environment carrying capacity (RECC) in China. – Science of The Total Environment 730: 138964.
[21] Liu, D., Bai, L., Li, X., Zhang, Y., Qiao, Q., Lu, Z., Liu, J. (2022a): Spatial characteristics and driving forces of anthropogenic phosphorus emissions in the Yangtze River Economic Belt, China. – Resources, Conservation and Recycling 176: 105937.
[22] Liu, M., Yang, L. (2021): Spatial pattern of China's agricultural carbon emission performance. – Ecological Indicators 133: 108345.
[23] Liu, S., Ma, L., Yao, Y., Cui, X. (2022b): Man-land relationship based on the spatial coupling of population and residential land—a case study of Yuzhong County in Longzhong Loess Hilly Region, China. – Land Use Policy 116: 106059.
[24] Luan, X., Yasmeen, R., Hassan Shah, W. U. (2024): Assessing energy efficiency, regional disparities in production technology, and factors influencing total factor energy productivity change in the agricultural sector of China. – Heliyon 10(15): e35043.
[25] Majeed, Y., Khan, M. U., Waseem, M., Zahid, U., Mahmood, F., Majeed, F., Sultan, M., Raza, A. (2023): Renewable energy as an alternative source for energy management in agriculture. – Energy Reports 10: 344-359.
[26] Matraeva, L., Solodukha, P., Erokhin, S., Babenko, M. (2019): Improvement of Russian energy efficiency strategy within the framework of "green economy" concept (based on the analysis of experience of foreign countries). – Energy Policy 125: 478-486.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81778203
© 2025, ALÖKI Kft., Budapest, Hungary

[27] Meng, M., Qu, D. (2022): Understanding the green energy efficiencies of provinces in China: a Super-SBM and GML analysis. – Energy 239: 121912.
[28] Min, J., Hu, H. (2012): Measurement of greenhouse gas emissions from agricultural production in China. – China Population Resources and Environment 22(7): 7.
[29] Ofosu-Ampong, K., Abera, W., Müller, A., Adjei-Nsiah, S., Boateng, R., Acheampong, B. (2025): Framing behaviour change for sustainable agriculture: themes, approaches, and future directions. – Farming System 3(1): 100123.
[30] Peng, B., Streimikiene, D., Agnusdei, G. P., Balezentis, T. (2024): Is sustainable energy development ensured in the EU agriculture? Structural shifts and the energy-related greenhouse gas emission intensity. – Journal of Cleaner Production 445: 141325.
[31] Qin, J., Ou, D., Yang, Z., Gao, X., Zhong, Y., Yang, W., Wu, J., Yang, Y., Xia, J., Liu, Y., Sun, J., Deng, O. (2024): Synergizing economic growth and carbon emission reduction in China: a path to coupling the MFLP and PLUS models for optimizing the territorial spatial functional pattern. – Science of the Total Environment 929: 171926.
[32] Quintero-Angel, M., González-Acevedo, A. (2018): Tendencies and challenges for the assessment of agricultural sustainability. – Agriculture, Ecosystems & Environment 254: 273-281.
[33] Richards, P. (2018): It's not just where you farm; it's whether your neighbor does too. How agglomeration economies are shaping new agricultural landscapes. – Journal of Economic Geography 18(1): 87-110.
[34] Soltani, S., Mosavi, S. H., Saghaian, S. H., Azhdari, S., Alamdarlo, H. N., Khalilian, S. (2023): Climate change and energy use efficiency in arid and semiarid agricultural areas: a case study of Hamadan-Bahar plain in Iran. – Energy 268: 126553.
[35] Steinborn, W., Svirezhev, Y. (2000): Entropy as an indicator of sustainability in agro-ecosystems: North Germany case study. – Ecological Modelling 133(3): 247-257.
[36] Tao, T., Ma, L., Wang, X., Wu, S., Shi, Z., Cui, X. (2023): Resilience or efficiency? Strategic options for sustainable development of agricultural systems in ecologically fragile areas of China. – Science of the Total Environment 881: 163411.
[37] Tone, K. (2002): A slacks-based measure of super-efficiency in data envelopment analysis. – European Journal of Operational Research 143(1): 32-41.
[38] Unakitan, G., Hurma, H., Yilmaz, F. (2010): An analysis of energy use efficiency of canola production in Turkey. – Energy 35(9): 3623-3627.
[39] Vinod Chandra, S. S., Anand Hareendran, S., Albaaji, G. F. (2024): Precision farming for sustainability: an agricultural intelligence model. – Computers and Electronics in Agriculture 226: 109386.
[40] Wang, C., Jiang, J., Wang, P., Kong, L., Liu, J. (2025): Exploring the potential of a novel electrostatic precipitator as an alternative to air filters in air purifiers. – Building and Environment 270: 112535.
[41] Wang, H., Liu, C., Xiong, L., Wang, F. (2023): The spatial spillover effect and impact paths of agricultural industry agglomeration on agricultural non-point source pollution: a case study in Yangtze River Delta, China. – Journal of Cleaner Production 401: 136600.
[42] Wang, J., Han, X., Liu, W., Ni, C., Wu, S. (2024): Comprehensive assessment system and spatial difference analysis on development level of green sustainable agriculture based on life cycle and SA-PP model. – Journal of Cleaner Production 434: 139724.
[43] Wang, S.-J., Kong, W., Ren, L., Zhi, D.-D., Dai, B.-T. (2021): Research on misuses and modification of coupling coordination degree model in China. – Journal of Natural Resources 36: 793.
[44] Wu, D., Zhang, Z., Liu, D., Zhang, L., Li, M., Khan, M. I., Li, T., Cui, S. (2024): Calculation and analysis of agricultural carbon emission efficiency considering water–energy–food pressure: modeling and application. – Science of the Total Environment 907: 167819.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2304_81778203
© 2025, ALÖKI Kft., Budapest, Hungary

[45] Xiong, L., Shah, F., Wu, W. (2022): Environmental and socio-economic performance of intensive farming systems with varying agricultural resource for maize production. – Science of The Total Environment 850: 158030.
[46] Zhang, Y. F., Li, Y. P., Huang, G. H., Zhai, X. B., Ma, Y. (2024): Improving efficiency and sustainability of water-agriculture-energy nexus in a transboundary river basin under climate change: a double-sided stochastic factional optimization method. – Agricultural Water Management 292: 108648.
[47] Zhao, D., Liu, C., Bao, B., Xu, B. (2018): agricultural sustainable development ability evaluation and subsystem coordination degree analysis—take the major grain-producing areas of China as an example. – Economic Geography 38(4): 157-163.
[48] Zhi, J., Gao, J. (2009): Analysis of carbon emission caused by food consumption in city and rural inhabitants in China. – Progress in Geography 28(3): 429-434.

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