Article

Industrial Agglomeration, Land Consolidation, and Agricultural Energy Inefficiency in China: An Analysis Using By-Production Technology and Simultaneous Equations Model

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Abstract: Improving agricultural energy inefficiency is essential for achieving sustainable agricultural development and promoting major agricultural countries to achieve carbon peak and carbon neutrality goals. This paper analyzes agricultural energy inefficiency in China, using panel data from 30 provinces between 2000 and 2021. The by-production technology model is employed to measure and decompose inefficiency, and the simultaneous equations model and moderating effect model are utilized to study the impact mechanism of industrial agglomeration, land consolidation, and agricultural energy inefficiency. The findings reveal several key points: First, the average inefficiency of agricultural energy in China increased from 0.370 to 0.514, with economic inefficiency rising at a faster rate than environmental inefficiency. Second, agricultural industrial agglomeration serves to inhibit both agricultural energy economic inefficiency and environmental inefficiency, which, in turn, hampers the development of industrial agglomeration. This relationship shows heterogeneity across the eastern, central, and western regions, as well as between major and non-major grain production areas. Third, land consolidation—both nationally and specifically in the central, major grain-producing, and non-major grain-producing areas—effectively mitigates the deterioration of agricultural energy inefficiency caused by industrial agglomeration. In the eastern region, land consolidation can enhance the inhibitory effect of industrial agglomeration on energy inefficiency. This paper highlights the interconnections between industrial agglomeration, land consolidation, and agricultural energy inefficiency, providing valuable policy references for the development of sustainable agriculture and the proactive and steady advancement of carbon peak and carbon neutrality goals.

Keywords: industrial agglomeration; land consolidation; agricultural energy inefficiency; by-production technology; simultaneous equations model

1. Introduction

China's energy consumption remains the highest among global consumers. However, the country has committed to achieving carbon peak and carbon neutrality by 2030, which places significant pressure on China—both as the world's largest developing country and a major agricultural nation—to reduce carbon emissions. Agriculture is increasingly recognized as a crucial sector for countries aiming to combat, mitigate, and adapt to climate change. Given this context, China's agricultural sector is seen as having substantial potential for emission reduction. However, since China's reform and opening up in 1978, the main development goal of increasing agricultural product output has led to the input of large amounts of high-carbon production materials like pesticides, fertilizers, and agricultural machinery, driving a steady rise in the energy consumption and the deterioration of the environment within the agricultural sector. This growth model, which prioritizes resource exploitation and environmental degradation, has come under scrutiny [1]. To safeguard the interests and well-being of future generations, it is essential to transition to a

development model that ensures long-term environmental protection alongside economic growth. After 2000, China's agricultural sector gradually entered a period of adjustment and transformation, placing equal emphasis on both "quantity" and "quality" [2]. The introduction of green and low-carbon policies marks a significant shift toward achieving a sustainable rural economy [3]. While China's agricultural energy consumption has been continuously rising to significant levels, this issue has not yet received sufficient attention. As agricultural mechanization levels improve, agricultural energy inputs are expected to continue increasing, thereby increasing carbon emissions [4]. With the rise in China's demand for food, particularly livestock products [5], the country's agriculture faces significant challenges and pressures in balancing energy consumption management with ensuring food security [6], and it is urgent to find a balance between agricultural economic growth and sustainability [3].

From the perspective of agricultural energy inputs, energy consumption plays a dual role: it is both a significant source of carbon emissions and a crucial driver of economic growth and social development [7]. Consequently, it is essential to examine the relationship between energy inputs, agricultural economic growth, and carbon emissions. Energy efficiency refers to producing the same amount of services or useful outputs with less energy [8]. The main methods of evaluation include parametric and non-parametric analyses. Rahman and Hasan (2014) utilized the stochastic production frontier method to estimate the productivity and energy efficiency of wheat cultivation in Bangladesh [9]. Houshyar et al. (2015) analyzed the energy efficiency of maize production using the Cobb–Douglas production model [10]. Considering undesirable outputs, the non-parametric Data Envelopment Analysis (DEA) method is regarded as an appropriate technique for determining the ratio of target input to actual input. Yang et al. (2018) employed the DEA approach to assess the total factor energy efficiency of Chinese agriculture, finding that agricultural energy efficiency has been continuously improving but with significant regional differences [11]. Fei and Lin (2016) and Li et al. (2017) used DEA and the Malmquist index to measure the energy efficiency of Chinese agriculture, revealing that the overall agricultural energy efficiency in China is relatively low, with significant regional disparities [12,13].

However, the aforementioned methods primarily employ single-frontier and weakly disposable production technology models when dealing with the relationship between desirable and undesirable outputs. This not only violates the law of conservation of matter but also fails to separately examine the relationship between polluting inputs and undesirable outputs, making it impossible to distinguish the contributions of economic or environmental factors to energy efficiency. Achieving energy sustainability goals necessitates the estimation of potential inefficiencies. With the current constraints on land and freshwater resources, ongoing energy inefficiency will escalate energy consumption, leading to higher energy expenditures and reduced access to energy services [14]. Improving energy efficiency in the medium and long term is crucial for maintaining and strengthening the relationship between energy and both economic and environmental indicators [15]. Conversely, failure to address energy inefficiencies could jeopardize the Sustainable Development Goals (SDGs) [14].

Murty et al. (2012) introduced the by-production technology (BP technology) model, a piece of environmental production technology built on the DEA framework that meets the material balance principle [16]. It can decompose inefficiency values into economic and environmental dimensions and has been widely applied in the energy and environmental performance literature [17–19]. Therefore, using the by-production technology model to measure agricultural energy inefficiency and decompose it into economic and environmental dimensions can provide new evidence-based guidelines for assessing China's agricultural energy efficiency.

Therefore, unlike other pieces of literature that focus solely on improving agricultural energy efficiency [20], the failure to implement stringent policy measures to reduce energy inefficiency will also compromise environmental performance. To address this issue, we employ the BP technology model to measure and decompose the value of agricultural

energy inefficiency, allowing for an exploration of the factors affecting energy utilization inefficiency from both economic and environmental perspectives. Eliminating energy utilization inefficiencies means that less energy can be used to produce the same level of agricultural output, resulting in lower carbon emissions. This approach can significantly contribute to accelerating the achievement of carbon peak and carbon neutrality goals.

In exploring agricultural energy efficiency, many pieces of literature have pointed out that factors such as economic development, technological progress, management practices, and resource endowment can significantly impact agricultural energy efficiency [21]. The global trend of agricultural production agglomeration and its effects on agricultural energy efficiency have also attracted considerable attention [22,23]. Theoretically, economic spatial agglomeration can reduce carbon emissions through scale effects, technological spillover effects, and competition effects [24]. Barkley et al. (1999) indicated that the development of industrial clusters is the key driver of agricultural economic growth [25]. However, excessive industrial agglomeration can lead to congestion effects [26] and diminishing scale effects [27], which are detrimental to sustainable agricultural development.

Currently, China's agricultural production is characterized by significant agglomeration, with numerous major agricultural production areas emerging. This has led to a transition from scarcity to abundance in the supply of agricultural products, with the production of key agricultural commodities ranking among the highest in the world. China's rural land consolidation has evolved through a development process, beginning with the transformation of medium- and low-yield farmland, progressing to the construction of high-standard farmland, and ultimately leading to the transformation and upgrading of existing high-standard farmland. The existing literature indicates that both industrial agglomeration and land consolidation can contribute to reducing carbon emissions. However, the intensive production mode in these major agricultural production areas implies higher agricultural energy consumption, and carbon emissions tend to increase [12,28]. Meanwhile, if different agglomeration patterns and associated internal and external forces obstruct the transmission channels of these reduction effects, it will not only fail to suppress energy inefficiency but also hinder the enhancement of industrial agglomeration [29]. Particularly, as China rapidly transitions from a traditional self-sufficient agricultural model to an intensive modern one, it faces growing challenges in managing energy consumption while ensuring food security [6]. Therefore, a more comprehensive understanding of the interaction between agricultural energy inputs, energy consumption, and economic growth is essential [30,31]. However, the existing literature primarily focuses on the relationship between industrial agglomeration or land consolidation and agricultural energy efficiency. Few studies analyze the internal relationships among industrial agglomeration, land, and energy inefficiency, and many overlook the interactions between these variables. Whether industrial agglomeration can reduce energy inefficiency is closely related to the effectiveness of the industrial agglomeration impact mechanism.

So, this study aims to achieve the following goals: (1) Based on the literature review, clarify the relationship between industrial agglomeration, land consolidation, and agricultural energy inefficiency to provide valuable insights for enriching subsequent research in this area; (2) analyze the development trends and regional differences in China's agricultural energy inefficiency; and (3) explore the influencing factors of agricultural energy inefficiency with a particular focus on the impact of industrial agglomeration and land consolidation. This study uses statistical data from 30 provinces in mainland China and employs BP technology to assess the inefficiency values of agricultural energy in the country from both economic and environmental dimensions. The results indicate that China's agricultural energy inefficiency is increasing and exhibits regional disparities. There is a significant interactive effect between industrial agglomeration, agricultural energy economic inefficiency, and environmental inefficiency, which also varies by region. Additionally, the study reveals that the moderating effect of land consolidation on the relationship between industrial agglomeration and energy efficiency differs across regions with varying levels of economic development and agricultural function positioning. This study enriches the

research on agricultural energy inefficiency and holds significant theoretical and practical implications for optimizing the spatial organization of China's agriculture and improving supporting policies to promote sustainable agricultural development and achieve agricultural carbon emission reduction.

The remainder of this article is organized as follows: Section 2 presents a literature review and hypotheses regarding the relationship between industrial agglomeration, land consolidation, and agricultural energy inefficiency. Section 3 outlines the research methods and data sources used in the study. Section 4 discusses the empirical results related to agricultural energy inefficiency. Finally, Section 5 provides the conclusions and policy implications derived from the findings.

2. The Literature Review and Hypotheses

2.1. Industrial Agglomeration and Agricultural Energy Inefficiency

As industrial agglomeration theory continues to evolve, scholars have increasingly focused on studying the impact of industrial agglomeration on agricultural energy efficiency. The improvement of agricultural industrial agglomeration can bring about economies of scale, allowing for the concentrated construction, use, and management of infrastructure related to agricultural production, such as drainage and irrigation systems, pollution control, and road transportation. This can lead to reduced production costs and lower energy consumption, resulting in better output and environmental benefits [32,33]. Furthermore, agricultural industrial agglomeration can strengthen the connections between agricultural enterprises, promoting learning, exchange, and cooperation among them. This is beneficial for improving production techniques, enhancing production efficiency, and improving product quality. Some scholars argue that the knowledge and technology spillovers resulting from industrial agglomeration can enhance energy efficiency. Based on provincial data from China spanning from 1991 to 2019, it found that industrial agglomeration can reduce agricultural carbon emissions by advancing green agricultural technology and enhancing human capital, thereby improving agricultural energy efficiency [34]. Lu et al. (2024) discovered that the agglomeration of grain production influences the environmental efficiency by influencing farmland scale management and facilitating agricultural technology spillovers, as revealed by their analysis of provincial data in China from 1990 to 2019 using a super-efficient DEA model [35]. Industrial agglomeration can enhance the resilience of the agricultural economy by improving productive services and increasing production efficiency [36], which in turn helps to reduce energy inefficiency.

However, some pieces of literature suggest that while industrial agglomeration significantly increases production, it also leads to the accumulation of agricultural chemical pollutants and straw waste, exacerbating agricultural non-point source pollution and leading to ecological damage and environmental degradation [37–39]. This puts farmers under immense pressure to increase yields while simultaneously minimizing environmental impacts [40]. Some scholars synthesize these viewpoints, suggesting that the impact of industrial agglomeration on agricultural energy efficiency is nonlinear. As agglomeration intensifies, energy efficiency initially improves, but beyond a certain threshold, further agglomeration results decrease in energy efficiency. Conversely, Lu et al. (2024) proposed a "U-shaped" relationship between industrial agglomeration and agricultural environmental efficiency [35]. To the left of the critical point, labor shortages and outdated production methods constrain modern agricultural production, leading to low factor utilization and reduced energy efficiency. On the right side, rational division of labor and modern production practices enable intensive factor input and scientific management, thereby improving energy efficiency.

When factoring in production activities, energy inefficiency can have a negative impact on industrial agglomeration. The intensification of environmental pollution may drive people to migrate to areas with better environmental conditions [25], leading to a labor shortage in affected regions and hindering industrial agglomeration. Additionally, environmental degradation increases production costs for enterprises, resulting in decreased

operational efficiency [41,42]. Companies that are unable to benefit from trade may have to cease production and exit the market, further diminishing industrial agglomeration [43]. Furthermore, environmental deterioration can lead to increased government regulation, heightened barriers to entry for businesses, and higher expenditures on environmental protection, all of which inhibit economic activities [44] and contribute to a reduction in industrial agglomeration. More broadly, environmental pollution poses a direct threat to the achievement of SDGs [45].

Currently, scholars not only focus on measuring overall energy efficiency and decompose it into environmental and economic dimensions [46], but also emphasize the importance of investigating energy inefficiency for selecting optimal energy policies [47,48]. At the same time, few pieces of literature focus on agricultural energy inefficiency. In view of this, the following research hypothesis is proposed:

H1. *There is an interaction among agricultural industrial agglomeration, energy economic inefficiency, and energy environmental inefficiency; however, the specific directions of their influence on one another remain unclear.*

2.2. Moderating Effect of Land Consolidation

Land consolidation is an effective policy tool to improve agricultural production and foster sustainable agricultural development [49,50]. It has been successfully implemented in many countries [51,52]. Land consolidation is beneficial for improving agricultural energy efficiency in several ways. Firstly, land consolidation can enhance the efficiency of intermediate input allocation. For example, it reduces land fragmentation [53], facilitates contiguous farming, reduces fertilizer usage [54] and energy consumption [55], and improves the recycling rate of agricultural film [56], thereby improving the efficiency of intermediate input allocation. Secondly, land consolidation optimizes the quality of input factors. Contiguous farming accelerates the substitution of modern input factors, such as agricultural machinery [57] and irrigation systems [58], for agricultural labor [59], facilitating water-saving irrigation, straw return utilization, and other emission reduction and carbon sequestration measures. This has, to a certain extent, both enhanced the comprehensive agricultural production capacity [49,60] and reduced agricultural energy carbon emissions [61,62].

The impact of industrial agglomeration on agricultural energy efficiency is influenced by regional land consolidation. Generally, the evolution of agricultural industrial agglomeration is contingent upon land distribution. When existing labor, production inputs, and technology in a region are reorganized due to changes in land quality and operational scale, agricultural industrial agglomeration can alter factor allocation and technological input. This continuous development along the current path affects agricultural energy and environmental efficiency. In such cases, industrial agglomeration and land consolidation can produce synergistic effects, collaboratively enhancing agricultural energy efficiency.

Land consolidation promotes the deepening of horizontal and vertical divisions of labor in industrial agglomeration, providing a transmission channel for the spillover effects of industrial agglomeration and enhancing its promotion of agricultural energy efficiency. On the one hand, land consolidation optimizes land use spatial layouts, forming a pattern of multi-regional, multi-centralized agricultural specialization. Horizontal division of labor can effectively save transaction costs, improve transaction efficiency, facilitate agricultural production through shared technologies and infrastructure, and accelerate technological innovation [63], thereby decreasing pollution emissions in both agricultural production and exchange processes. More importantly, the clustering of horizontal division of labor contributes to the accumulation and spillover effects of human capital and promotes information dissemination, technological imitation, and innovation among producers, making entities with any skill level more productive in environments rich in human capital. On the other hand, land consolidation has optimized the operating environment for agricultural machinery and enhanced overall land productivity through initiatives

such as field road construction, land consolidation, and mechanization transformation. These improvements can, in turn, foster the development of the service market within the agricultural production chain, ultimately strengthening the vertical division of labor. Improving agricultural energy efficiency relies not only on technological advancements but also on the adoption of energy-saving technologies by microeconomic agents. Classical economic growth theory considers agricultural technological progress as an exogenous variable and views farmers as passive adopters of new technologies. Under conditions of factor marketization, once farmers engage in the vertical division of labor in agriculture, the progress of energy-saving agricultural technologies becomes endogenous. Furthermore, the development of vertical division of labor in agriculture implies a requirement for horizontal division of labor, whereby farmers need to engage in contiguous cultivation to establish a sufficient scale of service market capacity. As the scale of the service market gradually increases, service entities further promote agricultural energy reduction technology.

Based on this, the following hypothesis is proposed:

H2. *Land consolidation serves as a moderating factor in the relationship between industrial agglomeration and agricultural energy and environmental inefficiency.*

3. Methodology and Data

3.1. Methodology

3.1.1. Measurement Methods of Agricultural Energy Inefficiency

The inefficiency calculated in this paper can be divided into economic inefficiency and environmental inefficiency. The decomposition method is based on the modeling of the by-production model, where all inputs can produce desired outputs, but all inputs except labor can generate undesirable outputs. The by-product model used in this paper is based on Balezentis et al. (2021) [64], and specific models can be referred to in this paper.

3.1.2. Simultaneous Equations Model

Building on the theoretical analysis provided above, there is a mutual dependence between industrial agglomeration and energy inefficiency, aligning with the assumptions of the simultaneous equations model. Additionally, considering the potential endogeneity issues arising from simultaneous bias or variable omission, employing the simultaneous equations model to estimate the relationship between industrial agglomeration and energy inefficiency is more appropriate. In addition, the panel simultaneous equations model may have over-identification problem; therefore, the Three-Stage Least Squares (3SLS) method is chosen for identification and estimation. This study constructs a system of simultaneous equations for industrial agglomeration, economic inefficiency, and environmental inefficiency, as follows:

$$ia_{it} = \alpha_1 + \beta_1 en_{it} + \beta_2 ec_{it} + \Lambda\Gamma_{it} + \nu_{it} \tag{1}$$

$$ec_{it} = \alpha_2 + \beta_3 ia_{it} + \beta_4 en_{it} + \Phi Z_{it} + \varepsilon_{it} \tag{2}$$

$$en_{it} = \alpha_3 + \beta_5 ia_{it} + \beta_6 ec_{it} + \Psi Q_{it} + \mu_{it} \tag{3}$$

where i and t denote the province and year, respectively; ia_{it} represents the degree of industrial agglomeration; ec_{it} represents the level of economic inefficiency; en_{it} represents the level of environmental inefficiency; α is the constant term; and β indicates the influence coefficients of industrial agglomeration, economic inefficiency, and environmental inefficiency on each set of equations. Γ, Z, and Q are the sets of control variables for the economic inefficiency equation and the environmental inefficiency equation, respectively; Λ, Φ, and Ψ are the respective estimated parameter matrices; and ε and μ are the random disturbance terms.

Γ is the set of control variables for the industrial agglomeration equation, including labor endowment, capital endowment, land endowment, and agricultural irrigation rate.

Z is the set of control variables for the economic inefficiency equation, including agricultural labor transfer, industrial structure, number of agricultural patents, farmers' education levels, and agricultural planting structure.

Q is the set of control variables for the environmental inefficiency equation, including labor transfer, industrial structure, agricultural patents, environmental regulation, urban–rural income disparity, urbanization level, and agricultural disaster rate.

Taking into account the potential impact of the interaction effect between industrial agglomeration and land consolidation on agricultural energy inefficiency, and to avoid the obvious positive correlation between land resources and land consolidation, we further include land consolidation, the interaction term of industrial agglomeration and land consolidation in models (2) and (3). By testing the significance of the coefficient associated with this interaction term, we examine the moderating effect of land consolidation on agricultural energy economic inefficiency and environmental inefficiency. The extended simultaneous equations model is established as follows:

$$ec_{it} = \alpha_2 + \beta_3 ai_{it} + \beta_4 en_{it} + \phi_1 lc_{it} + \phi_2 ia_{it} \times lc_{it} + \Phi Z_{it} + \varepsilon_{it} \tag{4}$$

$$en_{it} = \alpha_3 + \beta_5 ia_{it} + \beta_6 ec_{it} + \phi_3 lc_{it} + \phi_4 ia_{it} \times lc_{it} + \Psi Q_{it} + \mu_{it} \tag{5}$$

where *lc* represents land consolidation, and ϕ is the estimated coefficient for the interaction term between industrial agglomeration and land consolidation. The other variables have the same meaning as previously mentioned.

3.2. Data

3.2.1. Variable Selection

Agricultural industrial agglomeration: Drawing on the study by Glaeser et al. (1992), we employ the location quotient to assess the extent of agricultural industrial agglomeration [65]. This is represented by the ratio of the added value of the primary industry in a specific region to the national added value of the primary industry, divided by the ratio of the region's GDP of the region to the national GDP. The formula is as follows:

$$ia_i = \frac{Q_i / \sum Q_i}{G_i / \sum G_i} \tag{6}$$

where ia_i is the agricultural industrial location quotient, Q_i is the added value of the primary industry in a specific region, and G_i is the GDP of the specific region.

Agricultural energy efficiency: Using the aforementioned method, agricultural energy inefficiency is calculated and decomposed into economic inefficiency and environmental inefficiency.

In the equation for calculating agricultural energy efficiency, the input variables include agricultural capital stock, labor, land, and energy. For agricultural capital, the perpetual inventory method is employed to measure the capital stock of the primary industry as the capital input indicator (unit: billion CNY), with an asset depreciation rate set at 5.42%. Labor input: The number of people employed in the primary industry in each province of China is used as the indicator for labor input (unit: ten thousand people). Land input: The total sown area of crops in each province of China is selected as the arable land input indicator (unit: thousand hectares, khm^2). Energy input indicator: The consumption of energy inputs such as raw coal, gasoline, diesel, electricity, and agricultural chemicals including pesticides, fertilizers, and agricultural films is uniformly converted to ten thousand tons of standard coal equivalent (unit: ten thousand tce). The energy conversion values of each input are based on findings from He et al. (2017) and Yuan and Peng (2017) [66,67].

In the equation for calculating agricultural energy efficiency, the output variables include desirable output variables and undesirable output variables. Desirable output variables: The added value of the primary industry in each province of China is selected as the expected output variable (unit: billion CNY). Undesirable output variables: Agricultural

carbon emissions are selected as the non-expected output, measured from four aspects: agricultural cultivation, agricultural inputs, rice growth, and livestock farming. The carbon emissions from agriculture are uniformly converted to carbon equivalents (unit: ten thousand tons). The conversion coefficients for agricultural carbon emissions are referenced from the research of IPCC, West and Marland (2002), and Gao et al. (2022) [68,69]. Other influencing variables are defined and described in Table 1.

Table 1. Definitions and descriptive statistics of the variables.

Variable	Symbol	Variable Definition	Max	Min	Mean	SD
Industrial agglomeration	ia	Agglomeration of agricultural industries	3.270	0.032	1.190	0.608
Economic inefficiency	eci	Economic inefficiency of agricultural energy	1.038	0.000	0.190	0.239
Environmental inefficiency	eni	Environmental inefficiency of agricultural energy	0.451	0.000	0.241	0.135
Labor endowment	labe	Proportion of employment in the primary industry to total employment	0.739	0.018	0.381	0.158
Capital endowment	cape	Per capita agricultural labor to capital stock in the primary industry	38.025	0.002	1.983	3.299
Land endowment	lane	Ratio of crop planting area to employment in the primary industry	2.920	0.008	0.654	0.344
Agricultural irrigation rate	irr	Proportion of effective irrigated area to total crop planting area	1.000	0.060	0.388	0.173
Industrial structure	instr	Non-agricultural value added to regional gross domestic product	0.379	0.002	0.118	0.065
Labor mobility	labtr	Ratio of non-agricultural employment to total rural employment	0.982	0.182	0.618	0.162
Agricultural patents	tech	Number of invention patents, logarithmically transformed	9.554	0.000	5.982	1.738
Education level	edu	Average years of education for population aged 6 and above in rural areas with junior high school education or above	9.732	4.344	7.379	0.771
Agricultural planting structure	plstr	Proportion of grain crop planting area to total crop planting area	0.971	0.328	0.652	0.131
Agricultural disaster rate	disr	Proportion of disaster-affected area to total crop planting area	0.936	0.000	0.222	0.161
Environmental regulation	enreg	Investment in environmental pollution control converted by proportion of output value of primary industry to gross domestic product	22.487	0.918	5.607	3.722
Urban–rural income disparity	inc	Per capita disposable income of urban residents to net income per capita of rural residents	4.759	1.842	2.807	0.561
Level of urbanization	urb	Urban population to total population	0.896	0.217	0.522	0.151
Land consolidation	lc	Proportion of improved and high-standard farmland to total cultivated land as representing land remediation policy	1.000	0.002	0.266	0.244

3.2.2. Data Source

This paper utilizes panel data from 30 provinces in China spanning from the year 2000 to 2021 to examine the impact of industrial agglomeration on agricultural energy inefficiency. Due to limitations in data availability, the research does not include Tibet.

The data in this paper mainly come from the "China Statistical Yearbook", "China Rural Statistical Yearbook", and "China Financial Yearbook", as well as the Chinese patent database from CNKI. Among them, agricultural patent searches are limited to the IPC code A01 category; data on high-standard farmland construction from 2018 to 2021 are sourced from the website of Chinese Ministry of Agriculture and Rural Affairs. To mitigate the impact of price fluctuations, price data are adjusted to constant price data using the GDP deflator index, with 2000 set as the base year. Descriptive statistical results for the relevant variables are detailed in Table 1.

4. Results

4.1. The Spatiotemporal Variation in Agricultural Energy Inefficiency

By observing the development trend of agricultural energy inefficiency in China from 2000 to 2021 (Figure 1), it is found that, firstly, the mean value of agricultural energy inefficiency in China demonstrates an increasing trend, rising from 0.370 to 0.514, with an annual growth rate of 0.90%. Secondly, the mean annual growth rate of economic inefficiency was 0.0089, accounting for a proportion of agricultural energy inefficiency mean value that has risen from 31.64% to 50.80%. Thirdly, the mean annual growth rate of environmental inefficiency is 0.0001, with its proportion of agricultural energy inefficiency mean value decreasing from 69.36% to 49.20%. This conclusion aligns with the findings of Jiang et al. (2020), which indicate that China's agricultural energy and environmental performance values are on a downward trend [20]. The deterioration is primarily attributed to a decline in technical efficiency [12].
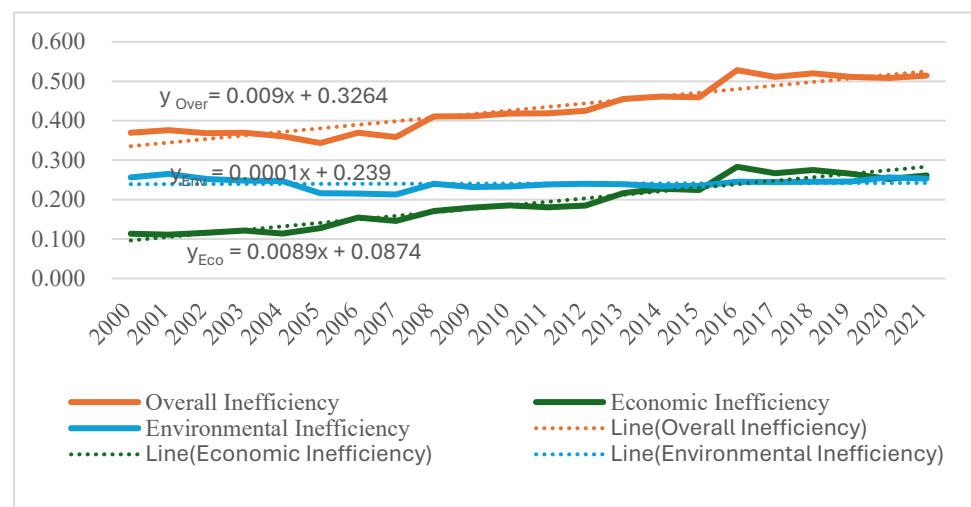
Figure 1. Average agricultural energy inefficiency in China and decomposition of economic and environmental dimensions.

To further analyze the regional disparities in agricultural energy inefficiency, the 30 provinces in the entire sample are categorized into eastern, central, and western regions, as well as major grain production areas and non-major grain production areas, based on two dimensions: differences in the level of economic and social development and differences in the positof grain production levels. Figure 2 illustrates that the energy inefficiency of agriculture in the eastern regions is significantly lower than that in the central and western regions. Energy inefficiency reflects the potential for energy savings, indicating that the energy-saving potential in eastern agriculture is less than that in the central and western regions [12,13]. Additionally, the energy inefficiency of agriculture in major grain production areas is lower than that in non-major grain production areas. Although Shen et al. (2024) note that ecological efficiency decreases from major grain sale areas to major grain production areas and then to grain balance areas [70], it is important to highlight that the non-major grain production areas included in this study encompass both major grain

sale areas and grain balance areas. Consequently, the energy inefficiency of major grain production areas does not differ significantly from that of non-major grain production areas.
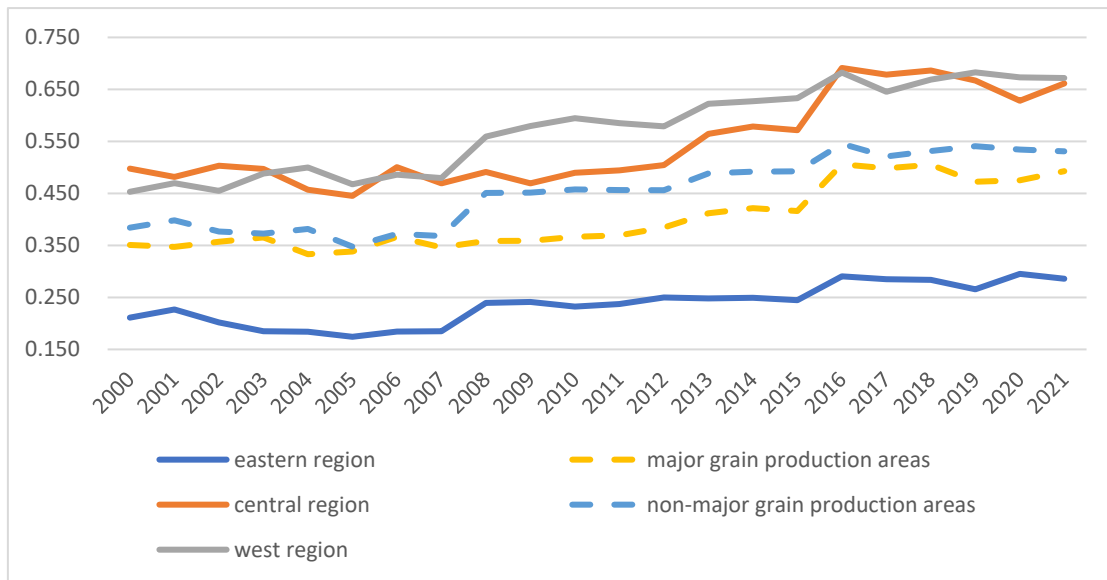
Figure 2. Regional differences in average agricultural energy inefficiency in China.

Further analysis of the regional disparities in agricultural energy economic inefficiency and environmental inefficiency is based on the above two dimensions. Figure 3 indicates that the mean values of economic inefficiency increase sequentially in the eastern, central, and western regions, with the gap between the mean values of economic inefficiency in the eastern and central regions greater than that between the central and western regions. The mean value of economic inefficiency in grain-producing areas is lower than that in non-grain-producing areas and its annual growth rate is lower than that in non-grain-producing areas.
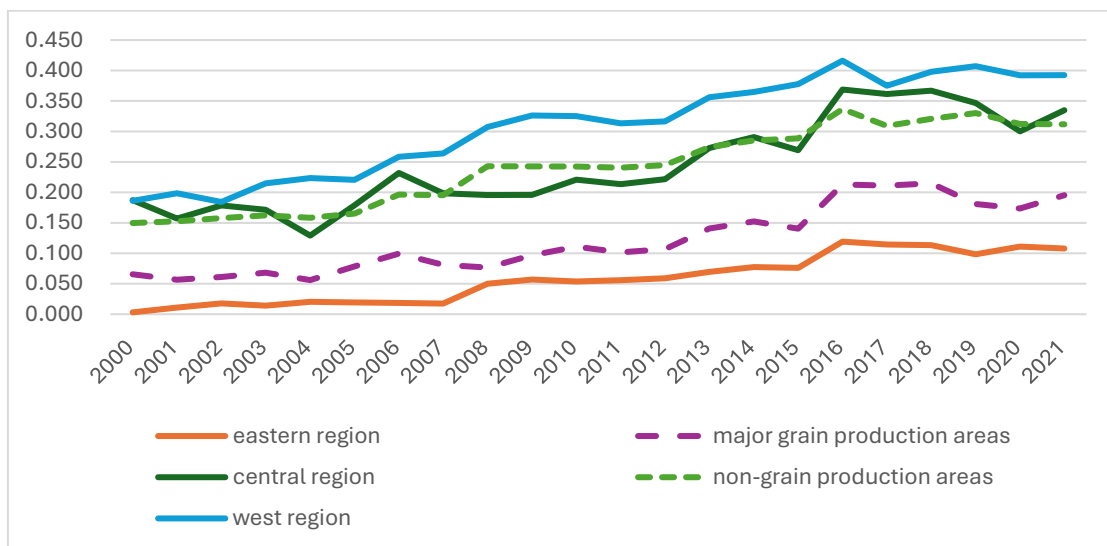
Figure 3. Regional differences in average economic inefficiency of agricultural energy in China.

Figure 4 illustrates that the mean values of environmental inefficiency increase sequentially in the eastern, western, and central regions, with the gap between the mean values of environmental inefficiency in the eastern and western regions greater than that

between the western and central regions. The mean value of environmental inefficiency in non-grain-producing areas is lower than that in grain-producing areas, and its annual growth rate shows a downward trend. Benefiting from resource endowments and favorable policies, the agricultural economic benefits in major grain production areas are more secure compared to those in non-major grain production areas, resulting in lower economic inefficiency in the former. Conversely, the lower agricultural economic benefits in non-major grain production areas lead farmers to increase their use of fertilizers and pesticides to boost agricultural economic growth. This over-reliance on chemical inputs further exacerbates economic inefficiency [71].
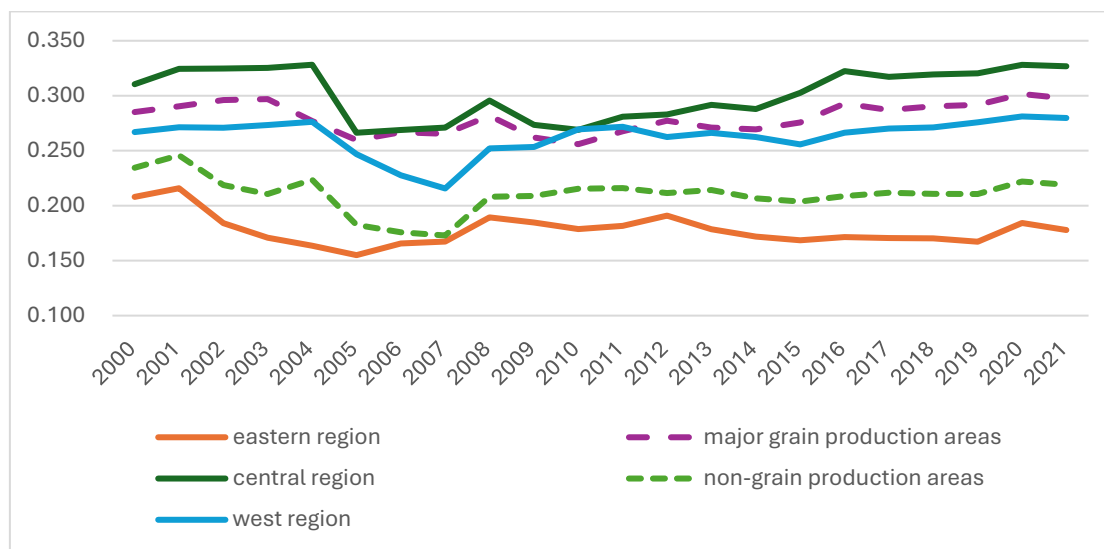
Figure 4. Regional differences in average environmental inefficiency of agricultural energy in China.

4.2. The Estimation Results of the Simultaneous Equations Model

4.2.1. Baseline Regression Results

According to the identification conditions of the simultaneous equations, it is known that the simultaneous equations constructed in this study constitute an over-identified model, suitable for estimation using 3SLS. For comparison and robustness testing, the lagged one period of industrial agglomeration, economic inefficiency, and environmental inefficiency are again used as explanatory variables and estimated using 3SLS (columns five to seven in Table 2). It is evident that there are no notable differences in the signs and significance of the coefficient estimates for all variables in the model. That is, Hypothesis 1 has been verified. The following analysis mainly focuses on the results of columns two to four in Table 2.

In the industrial agglomeration equation, the estimated coefficient of economic inefficiency is −0.296, and it passes the significance test at the 1% confidence level. This suggests that economic inefficiency hinders the development of industrial agglomeration. The increased production costs associated with economic inefficiency lead to lower profits, which may prompt agricultural enterprises to relocate to other regions [42], ultimately reducing the level of industrial agglomeration. The estimated coefficient of environmental inefficiency is 5.768, achieving significance at the 1% level, indicating a neglect of agricultural energy environmental inefficiency in the development process of industrial agglomeration. Despite China's shift in focus toward increasing the output of grain and other agricultural products since 2000, smallholders exhibit a low level of agricultural specialization. They continue to rely heavily on energy-intensive inputs such as fertilizers, pesticides, and machinery, often overlooking the carbon emissions resulting from increased agricultural energy consumption. This suggests that an increase in energy consumption can still contribute to a certain degree of enhanced industrial agglomeration. This is largely

attributable to the incomplete infrastructure in China's rural areas, which results in a low level of production specialization among farmers. Consequently, farmers are compelled to develop agriculture at the expense of environmental sustainability.

Table 2. Results of simultaneous equations estimation.

Variable	3SLS			Explaining Variables Lagged One Period		
	ia	eci	eni	ia	ec	en
ia		1.251 ***	0.158 ***		0.317 ***	0.090 ***
		(0.133)	(0.037)		(0.038)	(0.019)
eci	−0.296 ***		0.026 **	−0.243 ***		0.008 **
	(0.085)		(0.012)	(0.075)		(0.004)
eni	5.951 ***	−1.274 ***		2.158 ***	−0.037 ***	
	(0.353)	(0.271)		(0.137)	(0.008)	
labe	0.283 *			2.142 ***		
	(0.145)			(0.144)		
cape	0.007 **			0.007		
	(0.003)			(0.006)		
lane	0.016 **			0.220 ***		
	(0.007)			(0.050)		
irr	0.348 ***			0.294**		
	(0.126)			(0.119)		
instr		1.541 ***	0.061		1.804 ***	0.026
		(1.164)	(0.045)		(0.413)	(0.024)
labtr		−0.613 ***	−0.045 ***		−0.971 ***	−0.150 *
		(0.141)	(0.016)		(0.102)	(0.084)
tech		−0.130 ***	0.002 **		−0.045 ***	0.021 ***
		(0.017)	(0.001)		(0.008)	(0.004)
edu		0.028 **			0.039 **	
		(0.012)			(0.016)	
plstr		0.736 ***			0.512 ***	
		(0.087)			(0.063)	
disr		0.069			0.079	
		(0.075)			(0.064)	
enreg			−0.002 **			−0.006 ***
			(0.001)			(0.001)
inc			0.002			0.007
			(0.006)			(0.012)
urb			−0.162 ***			−0.263 ***
			(0.040)			(0.069)
_cons	−0.405 ***	0.826 ***	0.038	−0.360 ***	0.178	−0.133
	(0.112)	(0.166)	(0.058)	(0.090)	(0.114)	(0.085)
N		660			629	
R^2	0.354	0.571	0.418	0.352	0.574	0.445

Note: ***, **, * indicate that the statistical value is significant at the significance level of 1%, 5%, and 10%.

Regarding the control variables, agricultural labor, capital, and land management scale can effectively promote the advancement of agricultural industrial agglomeration. Additionally, infrastructure improvements represented by agricultural irrigation can also enhance industrial agglomeration.

In the economic inefficiency equation, the estimated coefficient of industrial agglomeration is 1.251, and it passes the significance test at the 1% level. This indicates that industrial agglomeration exacerbates agricultural energy economic inefficiency. The development of agricultural industrial agglomeration in China is still in its early stages, characterized by insufficient infrastructure and supporting facilities. This inadequacy results in "over-crowded" industrial agglomeration areas, leading to "lock-in" and "crowding" effects that diminish the utilization efficiency of agricultural resources. As noted by Kanter et al. (2018), excessive agglomeration due to inadequate supporting facilities can hinder sustainable agricultural development and may negatively impact technological innovation [40] and the upgrading of industrial structures [72]. Additionally, although industrial agglomeration increases agricultural output, it exacerbates economic inefficiency by exacerbating the phenomenon of "cheap grain hurting farmers." The estimated coefficient of environmental inefficiency is −1.274, and it also passes the significance test at the 1% level, indicating that environmental inefficiency plays a role in enhancing economic efficiency. Under the pursuit of agricultural output growth, the extensive use of fertilizers and pesticides helps increase agricultural output, which in turn weakens economic inefficiency by increasing agricultural energy consumption.

Regarding the control variables, the industrial structure indicated by the proportion of the primary industry and the proportion of grain planting significantly exacerbate economic inefficiency. This is due to the inherent weakness of agriculture. A higher proportion of agricultural output and a greater amount of labor engaged in agriculture result in lower value agricultural products, thereby exacerbating agricultural energy economic inefficiency. Labor transfer, agricultural technology level, and farmer education level help suppress economic inefficiency. Obviously, labor transfer will accelerate the transfer of agricultural land and then increase the scale of farmer land management. This process helps achieve economies of scale, which in turn reduces economic inefficiency. The more agricultural patents, the more developed agricultural technology, and the improvement in farmer education levels help accelerate the application of technology implied by patent information, thereby helping to suppress economic inefficiency. The coefficient of natural conditions represented by the proportion of disaster-affected areas is positive but not significant. However, as environmental awareness among the public increases, not only do some individuals migrate [73], but the growing demand for healthy agricultural products also compels farmers to prioritize the adoption of green technologies [74].

In the environmental inefficiency equation, the estimated coefficient of industrial agglomeration is 0.158, and it is statistically significant at the 1% level, indicating that industrial agglomeration exacerbates environmental inefficiency. As mentioned above, the goal of farmers pursuing output growth requires extensive use of fertilizers and pesticides, and the "lock-in" and "crowding-out" effects in Chinese agricultural agglomeration areas reduce factor allocation efficiency. Redundant agricultural energy consumption increases carbon emissions [4], thereby exacerbating agricultural energy environmental inefficiency. The estimated coefficient of economic inefficiency is 0.026, passing the significance test at the 5% level, indicating that economic inefficiency also exacerbates environmental inefficiency. Due to Chinese farmers' preference for increasing fertilizer and pesticide inputs to boost agricultural output, excessive use of fertilizers and pesticides not only raises carbon emissions caused by energy consumption but also damages soil habitat, thereby reducing agricultural energy environmental efficiency.

Regarding the control variables, labor transfer, environmental regulation, and urbanization help suppress agricultural energy environmental inefficiency. The increase in urbanization level further absorbs surplus labor transfer and promotes the improvement of land management scale while improving labor factor allocation efficiency, thereby

suppressing agricultural energy environmental inefficiency. Additionally, the increase in urbanization level enhances people's environmental awareness, prompting agricultural producers to implement agricultural environmental regulations more willingly, thereby suppressing environmental inefficiency. Agricultural patents exacerbate agricultural energy environmental inefficiency, stemming from China's agricultural goal orientation toward increasing agricultural output, with patents tending to increase production while not only increasing agricultural energy consumption but also overlooking the carbon emissions caused by excessive energy consumption. Finally, the estimated coefficients of the proportion of the primary industry and the ratio of farmer to urban income are positive but not significant.

4.2.2. Heterogeneity Analysis

In China, there are notable variations in geographical features and economic development stages among different regions. Moreover, the varying importance of safeguarding national food security positions may lead to differentiated effects on agricultural energy inefficiency during the process of agricultural industrial agglomeration. Therefore, this study conducts further refined analysis from two dimensions: differences in economic and social development levels as well as variations in the positioning of grain production levels.

(1) Comparison across regions with varying development levels. Table 3 shows that that the direction and significance of the estimated coefficients of industrial agglomeration, economic inefficiency, and environmental inefficiency in the central and western regions are relatively consistent with those of the national sample; the regression results in the eastern region show heterogeneity. In the eastern region, industrial agglomeration helps suppress agricultural energy economic inefficiency and environmental inefficiency. This is largely due to the more advanced state of agricultural industrial agglomeration in the eastern region, where land transfer and factor markets are more developed within agglomeration areas, thereby contributing to the suppression of agricultural energy inefficiency. Economic inefficiency in the eastern region reduces industrial agglomeration but also helps suppress environmental inefficiency; environmental inefficiency significantly weakens industrial agglomeration but also significantly exacerbates economic inefficiency. This is due to the higher level of economic development in the eastern region, and market competition drives agricultural energy economic inefficiency or energy inefficiency operators to change production layouts. Agricultural operators are shifting to other employment opportunities, thereby reducing the level of industrial agglomeration. However, the more developed factor markets will accelerate their land transfer to frontier producers, which will improve agricultural energy environmental inefficiency to some extent. As environmental awareness grows in developed areas, agricultural operators are not only required to optimize their production layouts but are also increasing their investments in agricultural production. This shift may negatively impact industrial agglomeration and economic efficiency in the short term. However, in the long run, agricultural producers and operators are likely to adopt green technologies in response to government incentives and public pressure, thereby reducing environmental inefficiency [74].

(2) Comparison of regions with different production focuses. Table 4 shows that regardless of whether they are in grain-producing regions, the direction and significance of the national estimates of industrial agglomeration on agricultural energy economic inefficiency and environmental inefficiency are consistent. In grain-producing regions, economic inefficiency significantly weakens industrial agglomeration and exacerbates environmental inefficiency; in non-grain-producing regions, economic inefficiency still significantly reduces industrial agglomeration but significantly suppresses environmental inefficiency. In grain-producing regions, especially, there is a particular emphasis on increasing grain production, with excessive fertilizer use playing a crucial role but also leading to increased energy consumption. This indicates that greater attention should be focused on managing agricultural energy efficiency in major grain-producing areas to ensure food security and promote sustainable development [6].

Table 3. Three-Stage Least Squares estimation results for eastern, central, and western regions.

Variable	Eastern			Central			Western		
	ia	eci	eni	ia	eci	eni	ia	eci	eni
ia		−0.267 **	−0.071 *		1.103 ***	0.063 ***		2.186 ***	0.170 ***
		(0.132)	(0.042)		(0.086)	(0.024)		(0.527)	(0.065)
eci	−1.796 ***		−0.250 *	−1.159 ***		0.408 ***	−0.567 ***		0.087 *
	(0.584)		(0.142)	(0.200)		(0.033)	(0.108)		(0.045)
eni	−4.103 ***	0.550 **		0.840	−0.873 ***		0.502 **	−3.594 ***	
	(0.632)	(0.230)		(0.474)	(0.206)		(0.232)	(0.581)	
N	162			198			198		
R²	0.589	0.468	0.404	0.446	0.690	.0625	0.366	0.364	0.557

Note: ***, **, * indicate that the statistical value is significant at the significance level of 1%, 5%, and 10%.

Table 4. Three-Stage Least Squares estimation results for major grain production areas and non-major grain production areas.

Variable	Major Grain Production Areas			Non-Major Grain Production Areas		
	ia	eci	eni	ia	eci	eni
ia		0.429 ***	0.054 **		2.413 ***	0.067 ***
		(0.100)	(0.027)		(0.352)	(0.023)
eci	−1.537 ***		0.157 **	−0.199 ***		−0.034 *
	(0.238)		(0.075)	(0.048)		(0.018)
eni	2.665 ***	−1.340 ***		4.849 ***	−4.814 ***	
	(0.305)	(0.131)		(0.339)	(0.587)	
N	286			374		
R²	0.357	0.401	0.335	0.319	0.0404	0.485

Note: ***, **, * indicate that the statistical value is significant at the significance level of 1%, 5%, and 10%.

In non-grain-producing regions, which include many economically developed areas or areas with less abundant agricultural resources, the situation may lead to the abandonment of farmland in remote areas, thereby reducing environmental inefficiency to some extent. In the major grain production areas and non-grain production areas, the sign and significance of the estimated coefficients of environmental inefficiency on industrial agglomeration and economic inefficiency align with those observed in the national sample.

4.2.3. Estimation Results of the Extended Simultaneous Equations Model

To investigate the impact of agricultural industrial agglomeration through land consolidation, the interaction term between agricultural industrial agglomeration and land consolidation was added to the simultaneous equations model, and estimation was performed using the 3SLS method. Since there is no land consolidation and its interaction term in the industrial agglomeration equation, only the estimation results of the economic inefficiency and environmental inefficiency equations are presented.

As shown in Table 5, after adjusting for land consolidation and its interaction terms, except for the western region, the estimated coefficients of industrial agglomeration, economic inefficiency, and environmental inefficiency exhibit consistency in sign and significance with the original equations without the interaction term. Moreover, the estimated coefficients of the interaction term between industrial agglomeration and land consolidation are significant for both economic inefficiency and environmental inefficiency, thereby confirming Hypothesis 2. In both national and central regions, the signs of the interaction

term between industrial agglomeration and land consolidation show positive and negative correlations with economic inefficiency and environmental inefficiency, respectively. This indicates that land consolidation can mitigate the tendency of industrial agglomeration to exacerbate agricultural energy inefficiency. In the eastern region, both the interaction term between industrial agglomeration and land consolidation and the effects of industrial agglomeration on economic and environmental inefficiency are negative, suggesting that land consolidation strengthens the inhibitory effect of industrial agglomeration on energy inefficiency. These results collectively indicate that land consolidation is beneficial in suppressing agricultural energy inefficiency.

Table 5. Regression results of the extended simultaneous equations model.

Variable	Nationwide		Eastern		Central		Western		Major Grain Production Areas		Non-Major Grain Production Areas	
	eci	eni	eci	eni	eci	eni	eci	eni	eci	eni	eci	eni
ia	0.710 ***	0.022 **	−0.119 ***	−0.382 ***	0.259 ***	0.102 **	0.461 **	0.234 *	0.136 ***	0.243 ***	0.941 ***	0.208 **
	(0.172)	(0.009)	(0.034)	(0.135)	(0.095)	(0.045)	(0.224)	(0.130)	(0.015)	(0.075)	(0.271)	(0.094)
eci		0.023 **		−0.301 ***		0.356 ***		0.109 *		0.186 *		−0.114 ***
		(0.011)		(0.098)		(0.032)		(0.056)		(0.110)		(0.024)
eni	−1.199 ***		0.463 ***		−0.990 ***		2.420 ***		−0.984 ***		−0.783 ***	
	(0.215)		(0.115)		(0.199)		(0.433)		(0.158)		(0.280)	
lc	−0.450 ***	−0.113 ***	0.299 ***	−0.249 ***	0.216 ***	0.421 ***	−0.189 ***	0.439	−0.368 ***	−0.022 **	−0.123 **	−0.186 ***
	(0.085)	(0.039)	(0.062)	(0.070)	(0.077)	(0.159)	(0.014)	(0.268)	(0.019)	(0.011)	(0.049)	(0.040)
ia*lc	−0.132 ***	−0.086 **	−0.073 **	−0.224 ***	−0.322 ***	−0.075 *	−0.093	−0.076	−0.169 ***	−0.165 **	−0.089 **	−0.052 **
	(0.013)	(0.042)	(0.039)	(0.074)	(0.099)	(0.045)	(0.147)	(0.070)	(0.031)	(0.064)	(0.037)	(0.022)
N	660		162		198		198		286		374	
R²	0.320	0.346	0.265	0.216	0.701	0.631	0.373	0.560	0.296	0.483	0.357	0.512

Note: ***, **, * indicate that the statistical value is significant at the significance level of 1%, 5%, and 10%.

Land consolidation enhances the concentration of resources such as land, capital, and facilities [62,75], leading to improved resource allocation efficiency and fostering technological innovation [63]. When land consolidation encompasses a wide area, it facilitates the deepening of both horizontal and vertical divisions of labor within industrial agglomeration, thereby accelerating economies of scale in agricultural operations and promoting knowledge and technology spillover effects. This, in turn, enhances technical efficiency and ultimately contributes to reductions in energy inefficiency. This effect is particularly pronounced in the eastern region, where farmland and factor markets are relatively developed, and land consolidation is implemented more comprehensively. As a result, the quality of land cultivation has significantly improved, further strengthening the inhibitory effect of industrial agglomeration on agricultural energy inefficiency. For the western region, the relatively backward level of economic development weakens the demand for land transfer, and the backward factor market not only hinders the matching of demand and supply for land transfer but also impedes technology spillover, thereby weakening the inhibitory effect of land consolidation on energy inefficiency to some extent.

In both major grain production and non-major grain production regions, the sign and significance of the estimated coefficients for industrial agglomeration, economic inefficiency, and environmental inefficiency are consistent with the national sample regression results. That is, the interaction terms in both major grain production areas and non-major grain production areas significantly suppress economic inefficiency and environmental inefficiency. Furthermore, the marginal effects of the interaction terms in major grain-producing areas are greater than those in non-major grain-producing areas. This disparity can be attributed to the superior natural endowments found in major grain production areas, which exhibit higher levels of industrial agglomeration compared to non-major grain production

areas, as well as more effective farmland scale management and technological spillover effects [35]. Moreover, grain-producing regions receive more financial investment and transfer payments, leading to higher standards and better outcomes of land consolidation, that is, land farming conditions will be better, thereby resulting in a greater regulatory effect of land consolidation.

5. Conclusions and Policy Implications

In the context of growing climate and environmental constraints, enhancing agricultural energy efficiency is an inevitable choice to meet the requirements of low-carbon and sustainable development. China's agriculture bears significant responsibility for energy conservation and efficiency improvement. Using provincial agricultural panel data from China spanning from 2000 to 2021 as an example, this study measures agricultural energy inefficiency in China, decomposing it into economic inefficiency and environmental inefficiency. Additionally, this paper examines the endogenous impact between industrial agglomeration and agricultural energy inefficiency, as well as the moderating effect of land consolidation on the relationship between industrial agglomeration and agricultural energy inefficiency. Two hypotheses in this paper have been verified, and the key findings are summarized below.

(1) The results obtained from the by-production technology model indicate that agricultural energy inefficiency is increasing, and the growth trend of economic inefficiency is greater than that of environmental inefficiency. Moreover, there exist regional disparities in both economic and environmental inefficiencies across the eastern, central, and western regions as well as between major grain-producing areas and non-major grain-producing areas.

(2) There is a significant interaction effect between industrial agglomeration and agricultural energy inefficiency in China. Industrial agglomeration exacerbates both economic and environmental inefficiencies in agricultural energy use. Conversely, economic inefficiency in agricultural energy diminishes the level of industrial agglomeration and exacerbates environmental inefficiency. Similarly, environmental inefficiency in agricultural energy promotes industrial agglomeration while exacerbating economic inefficiency.

(3) The relationship between industrial agglomeration and agricultural energy inefficiency varies by region. The eastern region exhibits greater variability, where industrial agglomeration helps to mitigate both economic and environmental inefficiencies in agricultural energy use. Economic inefficiency further suppresses environmental inefficiency, while environmental inefficiency exacerbates economic inefficiency. In non-major grain-producing areas, economic inefficiency also predicts environmental inefficiency. The estimated coefficients in other regions generally align with those found in the national sample.

(4) The moderating effects of land consolidation on the relationship between industrial agglomeration and agricultural energy inefficiency are different depending on the level of economic development and the type of agricultural functional zones. In the whole country, central regions, major grain production areas, and non-major grain production areas, land consolidation can reduce the deterioration of agricultural energy inefficiency caused by industrial agglomeration; in the eastern region, land consolidation strengthens the inhibitory effect of industrial agglomeration on energy inefficiency. At the same time, the marginal effects of the interaction terms of land consolidation in major grain production areas on economic inefficiency and environmental inefficiency are greater than those in non-major grain production areas.

Due to limitations in the perspective and data processing of this paper, several shortcomings remain, which can be addressed in future research. Firstly, the model employed can only explain the correlation between variables, without delving deeply into the role of sustainable development or establishing causal relationships. To address this, future research should integrate economic theory and sustainable development theory to analyze

the causal relationships among industrial agglomeration, land consolidation, and agricultural energy inefficiency, thereby constructing a causal chain. Secondly, the macro data utilized in this study cannot adequately explore the behavioral characteristics of farmers adopting energy-inefficient practices. While we performed heterogeneity analysis using different groupings, these groupings were based on official standards and lacked rigorous scientific derivation and validation. This insufficiently rigorous approach may introduce potential measurement errors, limiting the applicability of the conclusions to a broader context. Future research should focus on tracking farmer-level energy data to better identify the influencing factors of energy inefficiency.

In light of the research findings, the following recommendations are suggested:

Firstly, overcome the "lock-in" and "crowding-out" effects caused by low-level industrial agglomeration. Agricultural management departments should improve agricultural infrastructure to promote the development, transformation, and upgrading of agricultural industrial clusters. This ensures that industrial clusters can exert economies of scale and technological spillover effects, thereby achieving effective suppression of agricultural energy inefficiency.

Secondly, continuously monitor the characteristics of factors affecting agricultural energy. Factors influencing energy inefficiency vary over time. Agricultural countries should prioritize accelerating the absorption of surplus labor through urbanization, narrowing the urban–rural income gap, and enhancing farmers' human capital alongside the implementation of environmental regulations. Additionally, there is a need to expedite the promotion and application of green and low-carbon technologies. This includes the introduction of advanced agricultural machinery, improved agronomic practices, enhanced livestock and poultry breeding management, and the adoption of climate-smart agriculture. Focusing on these initiatives can foster sustainable agricultural development. By improving technical efficiency, agricultural countries can better leverage the economic and environmental benefits of existing technologies [76]. To achieve this, it is essential to strengthen research and development efforts in green technologies, refine agricultural energy measures, and align them with existing policies to enhance technical efficiency and reduce energy inefficiency.

Lastly, implement differentiated land remediation policies tailored to local conditions. In provinces with lower levels of economic development, efforts should focus on improving the quality of industrial agglomeration development while accelerating urbanization and labor force transition. Additionally, promoting the scale management of agricultural land will help realize the inhibitory effects of land remediation on energy inefficiency. For non-major grain production areas, efforts should emphasize enhancing the quality of land remediation construction. Simultaneously, proactive measures such as promoting straw returning, organic and green manure application, and soil testing and formula fertilization should be implemented to enhance the role of land reclamation in promoting the sustainable development of agriculture.

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