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Coupling Coordination between Agricultural Eco-Efficiency and Urbanization in China Considering Food Security

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Abstract: When studying the coupling coordination relationship between agricultural eco-efficiency and urbanization, it is crucial to consider food security, especially in a populous country like China. This paper focuses on 31 provinces in China as the research units, covering the time period from 2000 to 2020. Based on the concept of agricultural eco-efficiency, an evaluation index system was developed to include undesirable outputs (carbon emissions), and agricultural eco-efficiency scores were calculated using the SBM–DEA model. An urbanization evaluation index system, covering six dimensions and twelve indexes, was constructed. A comprehensive index of urbanization is measured using the entropy method. On this basis, a coupling coordination model was applied to quantify the relationship between agricultural eco-efficiency and urbanization at the provincial scale in China. The results showed that the agricultural eco-efficiency of all provincial units in China exhibited an overall trend of improvement. Average efficiency followed a spatial pattern of majority grain-consuming areas > grain production–consumption balance areas > majority grain-producing areas. The level of coupling between agricultural eco-efficiency and urbanization is generally low. Currently, no regions have reached the stage of synergy or high-level coupling. Most regions are currently in an antagonistic stage with a coupling degree of $0.3 < C \leq 0.5$. The classification of coupling coordination levels changed from four levels of "severe imbalance", "moderate imbalance", "mild imbalance", and "primary coordination" to "moderate imbalance", "mild imbalance", "primary coordination", and "intermediate coordination". The level of "severe imbalance" disappeared, the level of "intermediate coordination" appeared, and the level of "mild imbalance" became the largest scale level. From the perspective of food security, the proportion of grain production in the categories of "primary coordination" and "intermediate coordination" was less than 10%, and these provinces never achieved self-sufficiency in food production. The proportion of grain production at the "mild imbalance" level reached 62.4%, while the per capita grain production at the "moderate imbalance" level reached 846.7 kg. Provinces with lower levels of coupling coordination have stronger food security capabilities. It can be observed that the weaker the coupling coordination between agricultural eco-efficiency and urbanization, the higher the food self-sufficiency. Based on the research results above, we discussed strategies to enhance agricultural eco-efficiency in majority grain-producing regions by focusing on technological progress and technical efficiency. Additionally, we analyzed approaches to achieve grain self-sufficiency in regions characterized by a high level of coordination between agricultural eco-efficiency and urbanization, considering both production and trade dimensions.

Keywords: agricultural eco-efficiency; urbanization; coupling coordination; food security; China

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1. Introduction

Agricultural eco-efficiency is the extension and application of the concept of ecological efficiency to the field of agriculture. It emphasizes the efficient utilization of resources and the reduction of environmental pollution in agricultural production, aiming to achieve a balance between economic and ecological benefits [1]. Among existing achievements, research from an ecological perspective still accounts for a large proportion, for example, evaluating the risk resistance and efficiency improvement path of major crops, input and utilization efficiency of fertilizers and pesticides, ecological efficiency of tropical fruit production systems, etc. [2–4]. These research results aim to reduce the negative impact of agricultural production processes on the environment and promote sustainable agricultural development. Currently, China's agricultural growth has not yet transitioned from the production mode of "high input, high output, and high emissions". Problems such as soil fertility destruction, agricultural non-point source pollution, resource overconsumption, and low environmental efficiency have not been completely resolved. Therefore, research on and methods for agricultural eco-efficiency in China's academic community are becoming increasingly widespread. Research primarily focuses on national, basin, and provincial levels, with the Bohai Sea [5], Chagan Lake [6], Yellow River basin [7–10], majority grain-producing areas [11–13], Dongting Lake plain [14,15], and the Yangtze River economic belt [16,17] being regions with more research findings. Among them, research on the impact of a specific element on agricultural eco-efficiency is more abundant. Topics such as specialization of cultivation, smart agriculture, integration of agriculture and tourism, agglomeration of agricultural industries, agricultural insurance, financial investment, technological progress, labor force transfer, intensity of agricultural resource utilization, scale of agricultural land management, environmental regulations, and agricultural policies are currently popular research areas [18–22]. In recent years, there has been an increasing amount of research on "agricultural eco-efficiency". Existing research has examined the coupling relationship between agricultural eco-efficiency and urbanization, agricultural modernization, and agricultural mechanization, using major grain-producing areas in East China and Northeast China as examples [23,24]. Within the research findings on the integration of agricultural eco-efficiency and urbanization, it is commonly believed that regions where agricultural eco-efficiency is closely linked and harmonized with urbanization are primarily majority grain-producing areas with high levels of urbanization or economic development. Common measurement methods mainly include the index system method, ecological footprint method, stochastic frontier analysis (SFA), and data envelopment analysis (DEA) [1,25]. In the analysis of influencing factors, commonly used methods include multiple linear models, Tobit models, geographic detectors, etc. In practice, a combination of two or more methods is often utilized [26–28].

Scholars have made numerous attempts at and explorations in studying the coupling of agricultural eco-efficiency and urbanization, leading to significant achievements [11,23,29]. However, there are still two aspects that have not received sufficient attention. Firstly, the lack of a close connection with food security issues is evident. Secondly, there is a lack of flexibility in selecting research scales. In response to the above issues, we believe that it is necessary to first enhance agricultural eco-efficiency within the context of food security. This is an urgent need in the "post-pandemic era" to ensure global food security, especially for populous countries like China, where the pursuit of ecological benefits, economic advantages, and food security must be synchronized. Agricultural eco-efficiency does not imply neglecting food production and solely focusing on ecological protection. The urbanization process must also consider the crucial role of food security as populations and land become concentrated in urban areas. Existing research on the coordination of agricultural eco-efficiency and urbanization primarily focuses on defining the concept of agricultural eco-efficiency, constructing indicator systems, selecting research methods, and delineating coordination levels with urbanization. Consensus has been reached on these aspects [30–32]. Some discussions related to food security are limited to studying provinces with high grain production or majority grain-producing areas as case studies. However, there has been no classification, analysis, and evaluation of food security issues based on research on the coordination of agricultural eco-efficiency and urbanization. Secondly, studies that solely focus on food security concerns conduct screening only when selecting case study areas, for example, using some grain-producing provinces or majority grain-producing areas as case studies. This approach allows for an understanding of the level of coupling coordination between agricultural eco-efficiency and urbanization within these areas. However, it does not reveal the position of these areas on a larger scale, variations compared to other regions, and the underlying reasons for these differences. In conclusion, this article will conduct multi-scale coupling coordination evaluations based on the background of food security, providing a beneficial supplement to existing research on the coordination of agricultural eco-efficiency and urbanization.

Exploring the coupling coordination of China's agricultural eco-efficiency and urbanization against the backdrop of food security is of practical significance. The main grain-producing areas are crucial strategic regions for ensuring China's food security. From 2000 to 2020, the proportion of grain production in China increased from 70.6% to 78.6%, demonstrating strong stability and growth trends. However, most of these major grain-producing regions also experience severe agricultural pollution, encounter significant resource and environmental pressures, and are constrained by the migration of agricultural labor. Additionally, in many rapidly urbanizing areas of China, economic and social development is progressing swiftly, but there is a gradual disconnection from agricultural production. Urban development exerts varying degrees of pressure on agricultural production factors. Improving agricultural eco-efficiency and coordinating it with urbanization development is an important and challenging issue in the process of urban–rural and industrial development in China. Therefore, the focus will be on researching the coupling coordination between China's agricultural eco-efficiency and urbanization, while also considering food security. Food security will be assessed using indicators such as grain production and per capita grain production. Specifically, calculations and evaluations will be conducted on various levels of coupling coordination between grain production and per capita grain production. The research scale will mainly focus on the provincial level, while also conducting a multi-scale comprehensive evaluation of majority grain-producing areas, majority grain-consuming areas, and grain production–consumption balance areas. Efforts will be made to complement existing research on the coupling of agricultural eco-efficiency and urbanization. At the operational level, this study establishes an evaluation index system for agricultural eco-efficiency based on inputs, expected outputs, and unexpected outputs. It also establishes an evaluation index system for urbanization based on population, economy, infrastructure, social services, resource environment, and innovation in research and development. The SBM–DEA model, entropy method, and coupling coordination model are utilized to assess agricultural eco-efficiency, urbanization composite index, and the degree of their coupling coordination. This includes results for provincial units, as well as classification results for majority grain-producing areas, majority grain-consuming areas, and grain production–consumption balance areas. Furthermore, the study examines the relationships between levels of coupling coordination and grain production, as well as per capita grain production. It also proposes relevant policy recommendations.

2. Mechanism and Indicators

2.1. Coupling Mechanism

"Coupling" is a concept derived from physics, used to describe the phenomenon of interactive effects between two or more independent yet interrelated systems [11,23]. The mutual influence and interaction between agricultural eco-efficiency and urbanization can be seen in Figure 1.

Improving agricultural eco-efficiency can provide a fundamental guarantee for the development of urbanization. Firstly, the improvement of agricultural eco-efficiency is a process that involves the efficient utilization of agricultural resources and the comprehensive reduction of environmental pollution. By promoting improvements in the ecological environment, reducing agricultural non-point source pollution, and enhancing green supply levels, we can effectively meet the ecological and environmental protection requirements of urbanization development. Secondly, agricultural eco-efficiency encompasses both economic and ecological benefits. The improvement of agricultural eco-efficiency not only signifies environmental enhancement but also includes a comprehensive improvement in agricultural output and benefits. It usually directly promotes an increase in grain yield per unit of area, which can ensure the quantity and quality of agricultural products for urban development. Lastly, to some extent, improving agricultural eco-efficiency will inevitably promote the mechanization and intensification of agricultural production processes, resulting in an increase in mechanized operations in agriculture and a decrease in the agricultural labor force. This will promote the transition of primary industry workers to secondary and tertiary industries, accelerating urban population growth and comprehensively advancing the process of urbanization.

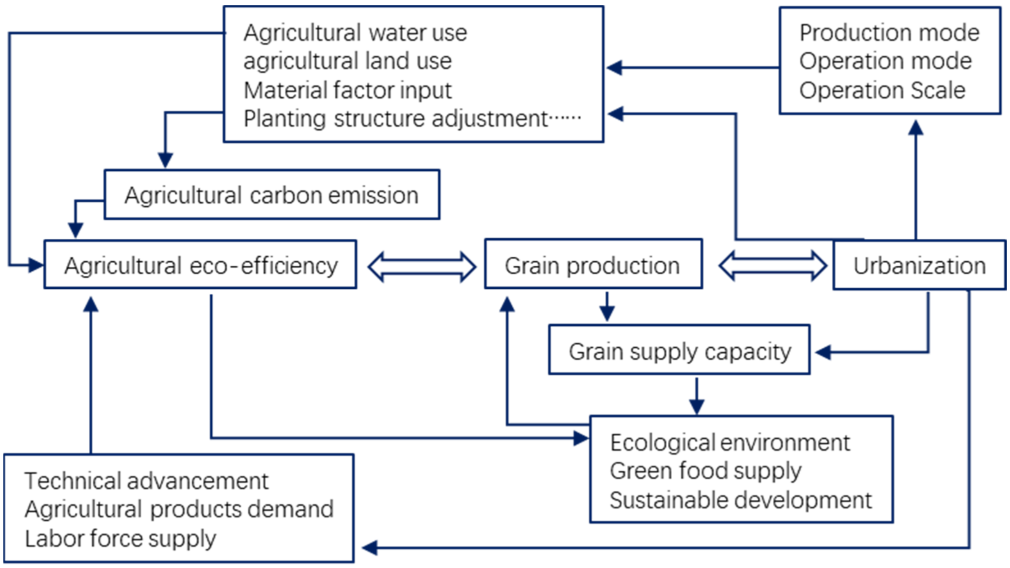

Figure 1. Coupling relationship between agricultural eco-efficiency and urbanization under the framework of food security.

The improvement of urbanization levels can enhance the efficiency of agricultural ecology. Firstly, urbanization development will attract some of the agricultural labor force from rural areas to enter cities, transitioning from agriculture to secondary and tertiary industries. These farmers typically engage in multiple jobs, commuting between urban and rural areas and different industries. Their departure from rural areas could accelerate land transfer and large-scale farming, while their return could promote changes in agricultural production methods and management practices, potentially enhancing the efficiency of agricultural ecology. Secondly, urbanization development changes the dietary structure of urban and rural residents, increasing the demand for higher-quality food. This will, to some extent, drive agricultural production towards greener and more refined practices, guiding producers and operators to actively reform production technologies and management concepts. This, in turn, could promote the enhancement of agricultural eco-efficiency. Lastly, the development of urbanization will inevitably lead to competition or pressure between urbanization and agricultural production in terms of water usage, land usage, and the input of material resources. Both systems need to explore ways to achieve maximum output benefits with minimal resource consumption and environmental pollution through ongoing competitive cooperation.

This article explores the interconnected relationship between agricultural eco-efficiency and urbanization, considering food security. Agricultural eco-efficiency aims to enhance agricultural production or value, and rapid urbanization leads to increased demand for agricultural products. As two independent yet interrelated systems, agricultural eco-efficiency and urbanization, in addition to the complementary and supportive roles mentioned above, also have common conflicts and contradictions with respect to production factors, with grain production being a significant manifestation of these conflicts and contradictions.

Stably increasing total grain production and promoting the coordinated development of agricultural eco-efficiency and urbanization must go hand in hand. Neglecting to discuss the coordination relationship between the two without considering food security is contradictory to actual needs. This aspect serves as the starting point and overarching logic of this study.

2.2. Agricultural Eco-Efficiency Evaluation Index System

Based on the connotations of agricultural eco-efficiency and referring to existing research results, an evaluation index system for agricultural eco-efficiency was constructed. The system comprises three aspects: input indicators, expected output indicators, and non-expected output indicators. As shown in Table 1, input indicators include land, labor, and agricultural material inputs. Specifically, these indicators include number of primary industry employees, crop planting area, effective irrigation area, fertilizer application amount, total power of agricultural machinery, rural electricity consumption, pesticide usage, agricultural film usage, and diesel fuel usage. The expected output indicator is the total agricultural output value, while the non-expected output indicator is agricultural carbon emissions. Agricultural carbon emissions refer to the carbon emissions generated from agricultural land use and rice cultivation. Nine carbon source factors, including fertilizers, pesticides, agricultural film, diesel fuel, agricultural irrigation, land cultivation, early rice, medium rice, and late rice, were chosen for calculating carbon emissions. During the calculation process, carbon emissions from fertilizers, pesticides, diesel fuel, and agricultural irrigation were determined by multiplying their total amounts applied by their corresponding carbon emission coefficients. Similarly, carbon emissions from land cultivation were calculated by multiplying the effective irrigation area and crop planting area by their respective carbon emission coefficients. The carbon emissions from early, medium, and late rice were calculated by multiplying the distinct carbon emission coefficients of each type, as suggested by Min Jisheng, with the corresponding planting areas of early, medium, and late rice in various provinces. The carbon source factors and their carbon emission coefficients are listed in Table 2, demonstrating a range of carbon emission coefficients for early, medium, and late rice. The agricultural carbon emissions for each province each year are the sum of the carbon emissions from the aforementioned sources.

Table 1. Agricultural eco-efficiency evaluation index system.

Target Layer	System Layer Index	Evaluation Index
Agricultural eco-efficiency	Input	Crop sown area
		Number of employees in primary industry
		Effective irrigated area
		Fertilizer application rate
		Total power of agricultural machinery
		Rural electricity consumption
		Pesticide use
		Agricultural film usage
		Agricultural diesel use
	Expected output	Gross agricultural output value
	Undesirable output	Carbon emissions

Table 2. Carbon source factors and carbon emission coefficients of agricultural carbon emissions. Note: The carbon emission coefficient of the agricultural land use category is directly cited from reference [33]; different carbon emission coefficients of early, middle and late rice in different provinces are from reference [34].

Category	Carbon Source Factor	Carbon Emission Coefficient
Agricultural land utilization	Chemical fertilizer	0.8956 t(C)/t
	Pesticides	4.934 t(C)/t
	Agricultural film	5.180 t(C)/t
	Agricultural diesel oil	0.5927 t(C)/t
	Agricultural irrigation	0.26648 t(C)/hm^2
	Soil ploughing	0.3126 t(C)/hm^2
Rice planting	Early rice	2.38–17.51 g(CH_4)/m^2
	Middle-season rice	5.57–65.42 g(CH_4)/m^2
	Late rice	7.6–52.6 g(CH_4)/m^2

2.3. Urbanization Evaluation Index System

With reference to existing urbanization evaluation results, and based on the principles of scientific rigor, objectivity, and accessibility of indicators, an urbanization evaluation index system was constructed. This system includes 12 indicators such as population urbanization and economic urbanization. As shown in Table 3, except for per capita GDP and per capita disposable income of urban residents, which are indicators directly obtained from the statistical yearbook, the other indicators are mostly ratios of two or three indicators. This approach aims to reduce the excessive influence of the total value of the evaluation unit on the evaluation results.

Table 3. Urbanization evaluation index system.

Category	Index
Population urbanization	Proportion of urban population
	Proportion of employees in tertiary industries
Economic urbanization	GDP per capita
	Proportion of GDP accounted for by added value of secondary and tertiary industries
	Per capita disposable income of urban households
	Per capita total retail sales of consumer goods
Infrastructure	Highway mileage per 10,000 people
	Urban street lamp density
	Proportion of built-up area
Social service	Number of hospital beds per 10,000 people
Resources and environment	Per capita urban park area
Innovative R&D	Per capita educational expenditure

3. Methods and Data Sources

3.1. SBM Model Based on Non-Expected Output

In this paper, the SBM–DEA model was used to quantitatively measure agricultural eco-efficiency. Data envelopment analysis (DEA) was first proposed by Charles and Cooper in 1978 and is used to measure productivity. The Stochastic Block Model (SBM), based on non-expected output, is one of the expanded models of DEA, first proposed by Tone in 2001. This model not only considers the unexpected output of each decision-making unit but also effectively manages the relaxation of input–output variables, providing significant advantages over the traditional DEA model [35–37]. Tone proposed the SBM for non-expected output after introducing the model, as shown below.

$$E = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s\bar{\iota}}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)}$$

Among them, $x_0 = X\lambda + S^-; y_0^g = Y^g\lambda - S^g; y_0^b = Y^g\lambda + S^b; S^- \geq 0, S^g \geq 0, S^b \geq 0$.

In the formula, $X = (x_{ij}) \in R^{m\times n}$, $Y = (y_{ij}) \in R^{s\times n}$. That is, there are n evaluation units, m input indicators and s output indicators, among which S_1 is the expected output indicator and S_2 is the non-expected output indicator. S^- and S^b represent excess input and undesired output (redundancy), while S^g represents insufficient expected output. E is the value of agricultural eco-efficiency.

In order to compare and assess efficiency changes in the same decision-making unit at different time periods, the Malmquist index was introduced to measure the changes in total factor productivity from period t to period $t + 1$, specifically as follows:

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

Among them, $D^t\left(x^{t+1}, y^{t+1}\right), D^t\left(x^t, y^t\right)$, respectively, represent the distance functions between the decision units of periods $t + 1$ and t with the production frontier of period t as a reference; $D^{t+1}\left(x^{t+1}, y^{t+1}\right), D^{t+1}\left(x^t, y^t\right)$, respectively, represent the distance functions between the decision units of periods $t + 1$ and t with the production frontier of period $t + 1$ as a reference. When the Malmquist index is greater than 1, it indicates that the total factor productivity from period t to $t + 1$ is increasing. The Malmquist index can be decomposed into a technical efficiency index (EC) and a technological progress index (TC). When EC is greater than 1, it indicates technical efficiency improvement, and when TC is greater than 1, it indicates technological progress. Specifically:

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

Among them, $EC = \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t(x^t, y^t)}$, $TC = \left(\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D^t\left(x^t, y^t\right)}{D^{t+1}(x^t, y^t)}\right)^{1/2}$.

3.2. Entropy Method

The entropy method is a multi-index comprehensive evaluation technique. Determining index weights through the entropy method can effectively overcome the randomness problem that cannot be avoided by subjective weighting methods, and also effectively solve the problem of information overlap between multiple indicator variables [23]. This paper adopts the entropy method to measure the comprehensive index of urbanization.

Assuming that X_{ij} is the jth index of the ith decision unit, the steps of comprehensive evaluation using entropy method are as follows:

First, standardize the data. $x_{ij} = \frac{X_j - \min(X_j)}{\max(X_j) - \min(X_j)}$, where X_{ij} represents the standardized value of the jth indicator data for the ith decision-making unit, while max (X_j) and min (X_j) represent the maximum and minimum values of the jth indicator, respectively.

Second, determine the index weight. $y_{ij} = x_{ij}/\sum_{i=1}^{m} x_{ij}$ represents the weight of the jth indicator of the ith decision unit, and m represents the number of decision units.

Thirdly, entropy and coefficient of variation are calculated. Entropy is calculated by $e_i = -\frac{1}{\ln m}\sum_{i=1}^{m} y_{ij}\ln y_{ij}$, if $y_{ij} = 0$, define $\lim\limits_{y_{ij}\to 0} y_{ij}\ln y_{ij} = 0$, in order to make sense for the normalized value to be zero. The coefficient of variation is calculated by $g_j = 1 - e_j$.

Fourth, calculate the composite index. The weight of the jth index in the comprehensive evaluation of urbanization is determined by $w_j = g_i/\sum_{j=0}^{n} g_i$, and then the comprehensive index of urbanization is calculated by $Z_i = \sum_{j=0}^{n} w_j y_{ij}$.

3.3. Coupling Coordination Model

With reference to research results from existing scholars [23], a coupling degree model for agricultural eco-efficiency and comprehensive urbanization index was constructed to describe the level of interaction between the two systems, where E represents agricultural eco-efficiency, Z stands for the comprehensive urbanization index, and C denotes the coupling degree. The value range of C is [0, 1]. When the C value is closer to 1, it indicates that the interaction between agricultural eco-efficiency and urbanization is stronger, and the coupling degree between them is higher. When the C value is closer to 0, it indicates that the relationship between agricultural eco-efficiency and urbanization is weaker, and the coupling degree between the two is worse.

$$\mathrm{C} = \sqrt{\frac{E \times Z}{(E+Z)^2}}$$

The coupling coordination degree model was utilized to quantify the coupling coordination state between agricultural eco-efficiency and urbanization. Although the coupling degree model can effectively describe interactions between agricultural eco-efficiency and urbanization, it does not demonstrate overall coordination. Therefore, it is necessary to introduce the coupling coordination degree model to comprehensively evaluate the level of development and coordination between the two. The specific formula is as follows:

$$\mathrm{D} = \sqrt{\mathrm{CT}}$$

$$\mathrm{T} = \mathrm{a}E + bZ$$

In the formula, D represents the coupling coordination degree, with a value range of [0, 1]. When the D value approaches 1, it indicates that the degree of coordination between the two systems is closer. By contrast, as the D value approaches 0, it indicates that the relationship between the two variables is not significant, and the mutual influence is weak. T represents the Comprehensive Development Index, where "a" and "b" are undetermined coefficients for agricultural eco-efficiency and urbanization, with $a = b = 0.5$.

In order to conduct a more comprehensive analysis of the coupling and coordination between agricultural eco-efficiency and urbanization, we categorized the coupling degree (C value) and coupling coordination degree (D value) into grade intervals based on relevant research findings. The specific criteria are presented in Table 4.

Table 4. Value Range and Grade Division of Coupling Degree and Coupling Coordination Degree.

Index	Value Range	Level or Stage
Coupling degree (C)	$0 \leq C \leq 0.3$	Low-level coupling
	$0.3 < C \leq 0.5$	Antagonistic stage
	$0.5 < C \leq 0.8$	Running-in stage
	$0.8 < C \leq 1.0$	High-level coupling
Coupling coordination degree (D)	$0 \leq D \leq 0.2$	extreme imbalance
	$0.2 < D \leq 0.3$	severe imbalance
	$0.3 < D \leq 0.4$	moderate imbalance
	$0.4 < D \leq 0.5$	mild imbalance
	$0.5 < D \leq 0.6$	primary coordination
	$0.6 < D \leq 0.7$	intermediate coordination
	$0.7 < D \leq 0.8$	advanced coordination
	$0.8 < D \leq 1.0$	top coordination

3.4. Data Sources

In this paper, 31 provincial units in China are considered as evaluation units, excluding Hong Kong, Macao, and Taiwan from the evaluation area. The time scale is 2000–2020. A total of 25,389 data points were involved in the calculation of agricultural eco-efficiency value, agricultural carbon emission value, and comprehensive urbanization index. In the specific process of data acquisition, the primary source is derived from China economic and social big data research platform (https://data.cnki.net/). Any missing data for certain provinces or years is supplemented by referring to both the China Statistical Yearbook and provincial statistical yearbooks. In cases where these aforementioned data sources are unavailable, a substitution method utilizing the average value from previous years is employed to replace some of the missing data.

4. Results

4.1. Agricultural Eco-Efficiency at Different Scales

4.1.1. Temporal and Spatial Changes in Agricultural Eco-Efficiency

The calculation results of the SBM–DEA model indicate that agricultural eco-efficiency in China continued to improve from 2000 to 2020, showing an especially significant upward trend from 2015 to 2020. In the years 2000, 2005, 2010, 2015, and 2020, there were increases in the number of regions exhibiting effective agricultural eco-efficiency. In general, the average level of agricultural eco-efficiency in China was 0.493, 0.527, 0.527, and 0.606 in the years 2000, 2005, 2010, and 2015, respectively. The number of provincial units with agricultural eco-efficiency greater than or equal to 1.0 per year was initially limited to only 2–3 units. By the year 2020, there was significant improvement as the number of provincial units with agricultural eco-efficiency greater than or equal to 1.0 reached 24, while the average efficiency also increased substantially to approximately 0.959.

Agricultural eco-efficiency was assessed using the GIS natural fracture method. The results revealed an increase in the number of areas classified as moderate and above, with distinct spatial contiguity features. From 2000 to 2020, the percentage of provincial units with above-median agricultural eco-efficiency increased from 58.1% to 77.4%. Additionally, the minimum value of the middle level rose from 0.398 to 0.831 over the same period. As depicted in Figure 2, higher levels of agricultural eco-efficiency are primarily concentrated in southwest China, particularly along the Xinjiang-Guangdong axis, whereas moderate performance is mainly observed in northeast and eastern coastal regions.

4.1.2. Results of Agricultural Eco-Efficiency by Area Type

In China, there have been several rounds of adjustments to the definition and scope of the majority grain-producing areas, majority grain-consuming areas, and grain production–consumption balance areas. At present, the majority grain-producing areas include 13 provinces (autonomous regions), namely Hebei, Inner Mongolia, Jilin, Heilongjiang, Liaoning, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Sichuan. The areas with a balance between grain production and consumption include 11 provinces (autonomous regions): Shanxi, Ningxia, Qinghai, Gansu, Xizang, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi, and Xinjiang. The majority grain-consuming areas include seven provinces (cities): Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. The majority grain-producing regions play an essential role in ensuring food security, as their grain output contributes to nearly 80% of China's total production. Regional classification can enhance the precision and efficacy of targeted policies to a certain extent.

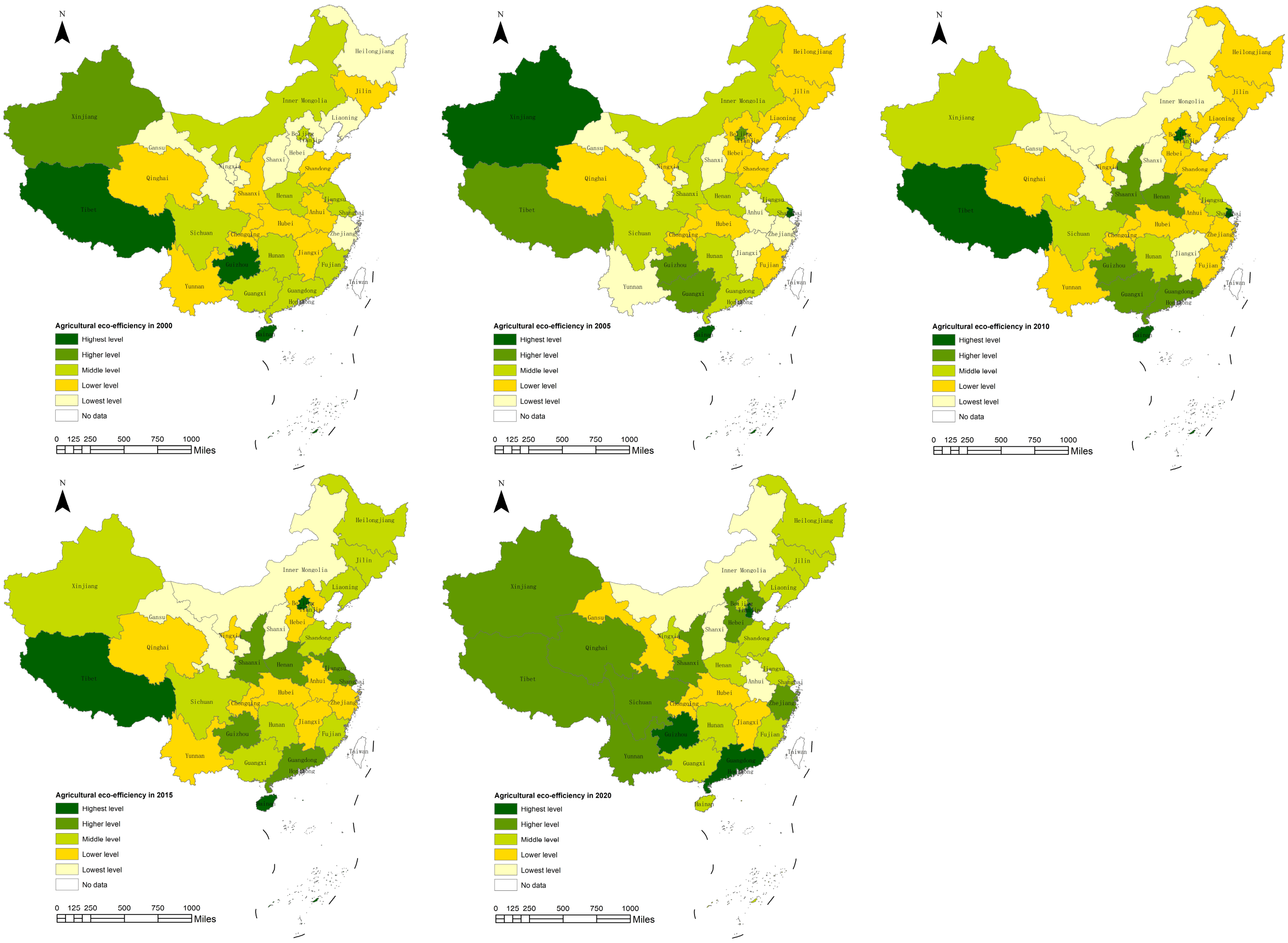

Figure 2. Spatial changes in agricultural eco-efficiency scores at different time nodes.

The areas with the highest average agricultural eco-efficiency are the mostly grain-consuming areas, followed by the grain production–consumption balance areas, and the lowest is the majority grain-producing areas. From 2000 to 2020, the average levels of agricultural eco-efficiency in the majority grain-consuming areas, grain production–consumption balance areas, and majority grain-producing areas increased from 0.571, 0.529, and 0.420 to 1.077, 0.942, and 0.909, respectively. Their rankings remained unchanged during this period. During this process, the average agricultural eco-efficiency of the majority grain-consuming areas showed significant fluctuations but also maintained the highest growth rate. In contrast, the annual fluctuations in the average agricultural eco-efficiency of the majority grain-producing areas and the grain production–consumption balance areas were relatively small, indicating a stable growth trajectory. The annual average agricultural eco-efficiency values can be seen in Figure 3. In 2020, there was no significant change in the ranking of agricultural eco-efficiency in the majority grain-consuming areas, grain production–consumption balance areas, or majority grain-producing areas. The agricultural eco-efficiency of each province in the main grain consumption areas exceeded 1.0. Particularly noteworthy are Tianjin and Guangdong, with agricultural ecological efficiencies of 1.23 and 1.22, respectively, the highest levels in the country. The agricultural eco-efficiency in the majority grain-producing areas ranged from 0.48 to 1.10. Approximately 70% of provinces exhibited agricultural eco-efficiency greater than or equal to 1.0, with no exceptionally high values observed. The agricultural eco-efficiency in the grain production–consumption balance areas ranged from 0.37 to 1.14. Shanxi had the lowest agricultural eco-efficiency, which was also the lowest level in the country. Specific values for each province can be found in Figure 4.

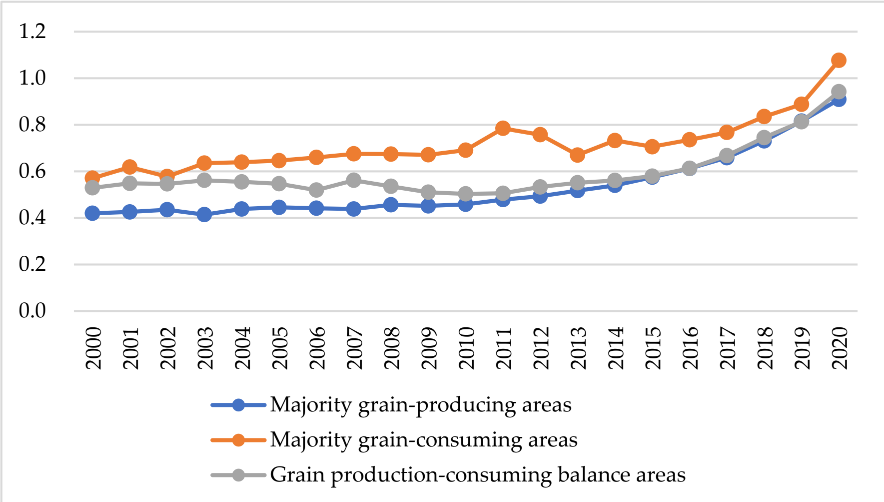

Figure 3. Change curve of mean agricultural eco-efficiency in each type of area.

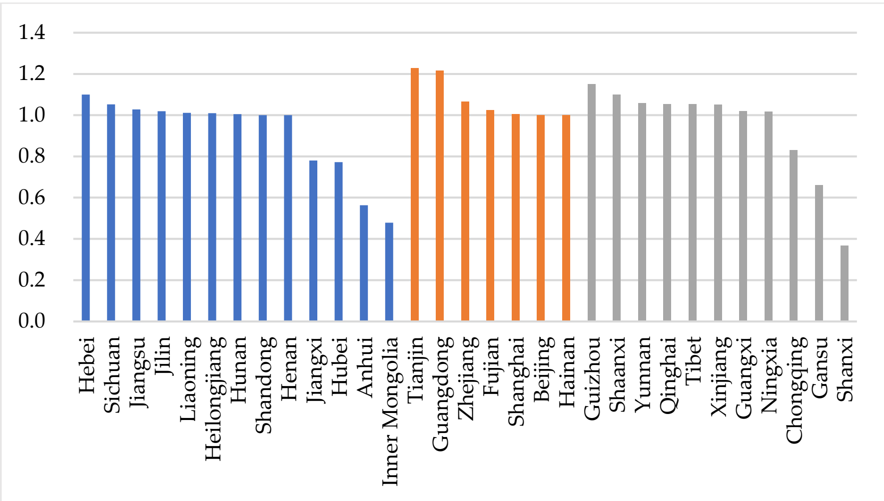

Figure 4. Comparison of agricultural eco-efficiency by province in 2020. Note: Blue shows provinces that are majority grain-producing areas, orange shows provinces that are majority grain-consuming areas, grey provinces that are grain production-consuming balance areas.

4.1.3. Main Determinants of Eco-Efficiency in Agriculture

Technological efficiency and progress are crucial factors influencing agricultural eco-efficiency. Figures 5 and 6 display the proportion of provinces with technological efficiency and technological progress greater than 1, respectively. In terms of technological efficiency, the proportion of provinces with technological efficiency ≥1 in majority grain-producing and grain-consuming areas shows a significant fluctuating upward trend. This trend is particularly noticeable in majority grain-consuming areas, where the proportion of provinces with technological efficiency ≥1 consistently remains at the highest level. Beijing is the only region among the majority grain-consuming areas that maintained a technological efficiency of ≥1 throughout the entire period. This suggests that technological efficiency plays a crucial role in enhancing agricultural eco-efficiency in majority grain-consuming areas. Conversely, the proportion of provinces with technological efficiency ≥1 that are grain production–consumption balance areas is generally decreasing, especially more significantly after 2008. In terms of technological progress, the percentage of provinces with technological advancement greater than or equal to 1 is increasing in majority grain-producing, majority grain-consuming, and grain production–consumption balance areas. The proportion of provinces with technological progress of at least 1 among the majority grain-producing areas has consistently remained above 90% in recent years. Technological progress is a crucial factor in enhancing agricultural eco-efficiency in majority grain-producing regions.

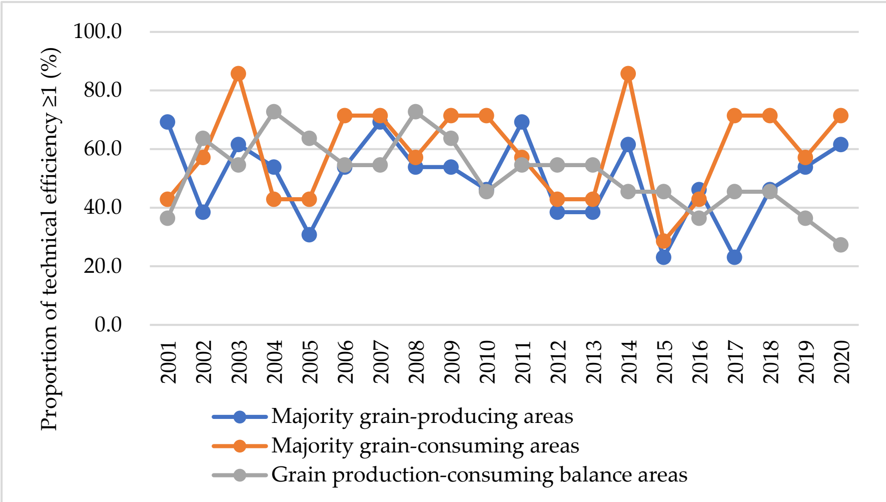

Figure 5. The proportion curve of provinces with technical efficiency greater than 1.

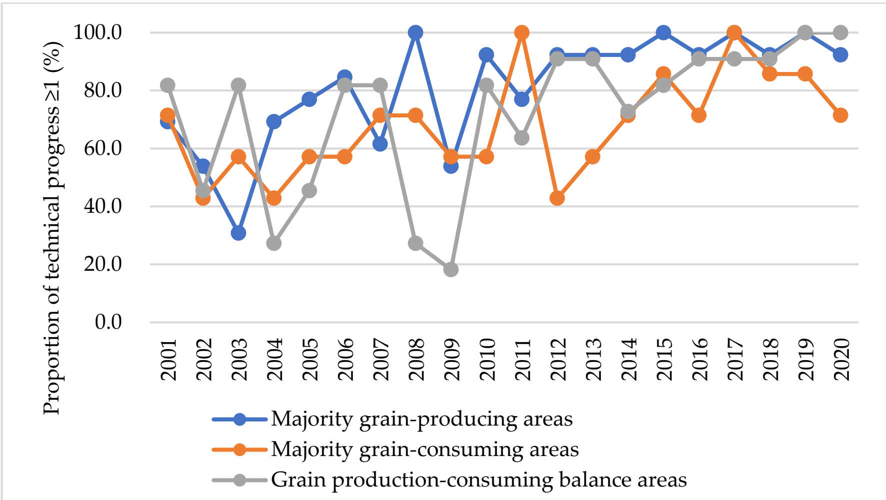

Figure 6. The proportion curve of provinces with technological progress greater than 1.

4.2. Comprehensive Evaluation of Urbanization

The results of the comprehensive urbanization index, calculated based on the entropy method, indicate significant variations in the overall level of urbanization in China. There are numerous regions with low values, yet the general trend demonstrates positive development. Figure 7 illustrates the comprehensive level of urbanization and its changes at each time node. The provincial units included in the highest level of comprehensive urbanization have not changed, while the comprehensive urbanization index of Shanghai and Beijing has fluctuated around 0.8 for a long time. In some years, the two have swapped positions but have consistently ranked in the top two. The level of urbanization is comprehensively distributed across the border area connecting Liaoning and Guangdong. There is an increase in the number of intermediate and lower levels in the southwest region, and an overall decrease in the number of lower levels.

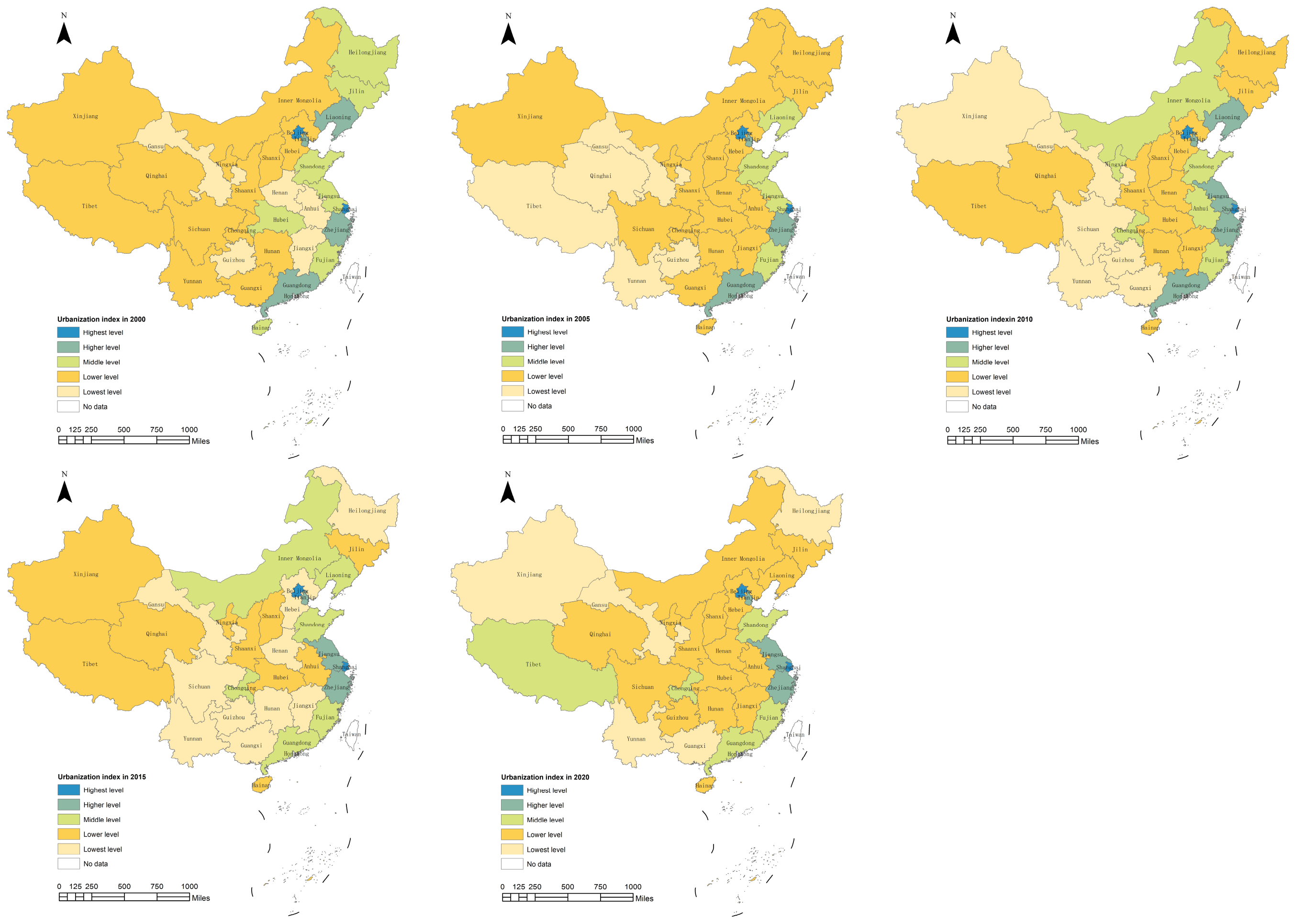

Figure 7. Spatial changes in comprehensive urbanization index from 2000 to 2020.

Calculation of the comprehensive urbanization index assigns high weights to six indicators, namely GDP per capita, per capita disposable income of urban households, per capita retail sales of social consumer goods, proportion of built-up areas, highway mileage per 10,000 people, and per capita education funding. From the 2020 data, Shanghai and Beijing exhibited a GDP per capita of 156,000 and 165,000 CNY, respectively. The per capita disposable income of urban households was 76,437 CNY in Shanghai and 75,602 CNY in Beijing. Additionally, the per capita total retail sales of social consumer goods reached 64,063.1 CNY in Shanghai and 62,660.6 CNY in Beijing, securing their positions as the top two cities nationwide. Furthermore, the proportion of built-up areas accounted for 19.7% in Shanghai and 8.74% in Beijing. The road mileage amounted to approximately 0.08 km per 10,000 people. Per capita education expenditure ranked among the top three, with figures standing at 5679.7 CNY for Shanghai and 6758.7 CNY for Beijing within China's context. The comprehensive urbanization index in Shanghai and Beijing is notably superior to other regions. This is primarily attributed to their high-weight indicators ranking among the top two or three nationwide, exhibiting virtually no deficiencies, and significantly surpassing the index values of other regions.

4.3. Coupling and Coordination Analysis of Agricultural Eco-Efficiency and Urbanization Level

4.3.1. Coupling Results of Agricultural Eco-Efficiency and Urbanization Level

From 2000 to 2020, the level of coupling degree between agricultural eco-efficiency and urbanization in 31 provincial units in China generally remained at a low level of coupling or an antagonistic stage. Among them, Guizhou, Tibet, and Heilongjiang displayed low-level coupling ($C \leq 0.3$) during some years, while other regions in all years were in the antagonistic stage (0.3 < C ≤ 0.5). The antagonistic stage refers to a stage where the total effect of the two is less than the sum of their individual effects. Although no provincial units entered the running-in stage and high-level coupling stage, the degree of coupling between agricultural eco-efficiency and urbanization in six provincial units, including Beijing, Tianjin, Shanxi, Liaoning, Shanghai, and Zhejiang, was greater than or equal to 0.49 in more than half of the years. This value was very close to the threshold for the running-in stage.

The spatial distribution of the highest and second-highest levels of coupling between agricultural eco-efficiency and urbanization in 2000, as depicted in Figure 8, primarily exhibited strong spatial continuity along the Heilongjiang–Guangdong axis. By 2020, there was a reduction in the number of provincial units falling within the highest and second-highest levels, resulting in a more dispersed spatial distribution with less pronounced contiguous characteristics. Notably, regions such as Heilongjiang and Jilin, which were previously classified at higher levels, were downgraded to lower levels, including the lowest level. Furthermore, the western region of China is predominantly characterized by middle levels or below, with most provincial units oscillating between second-lowest and lowest levels.

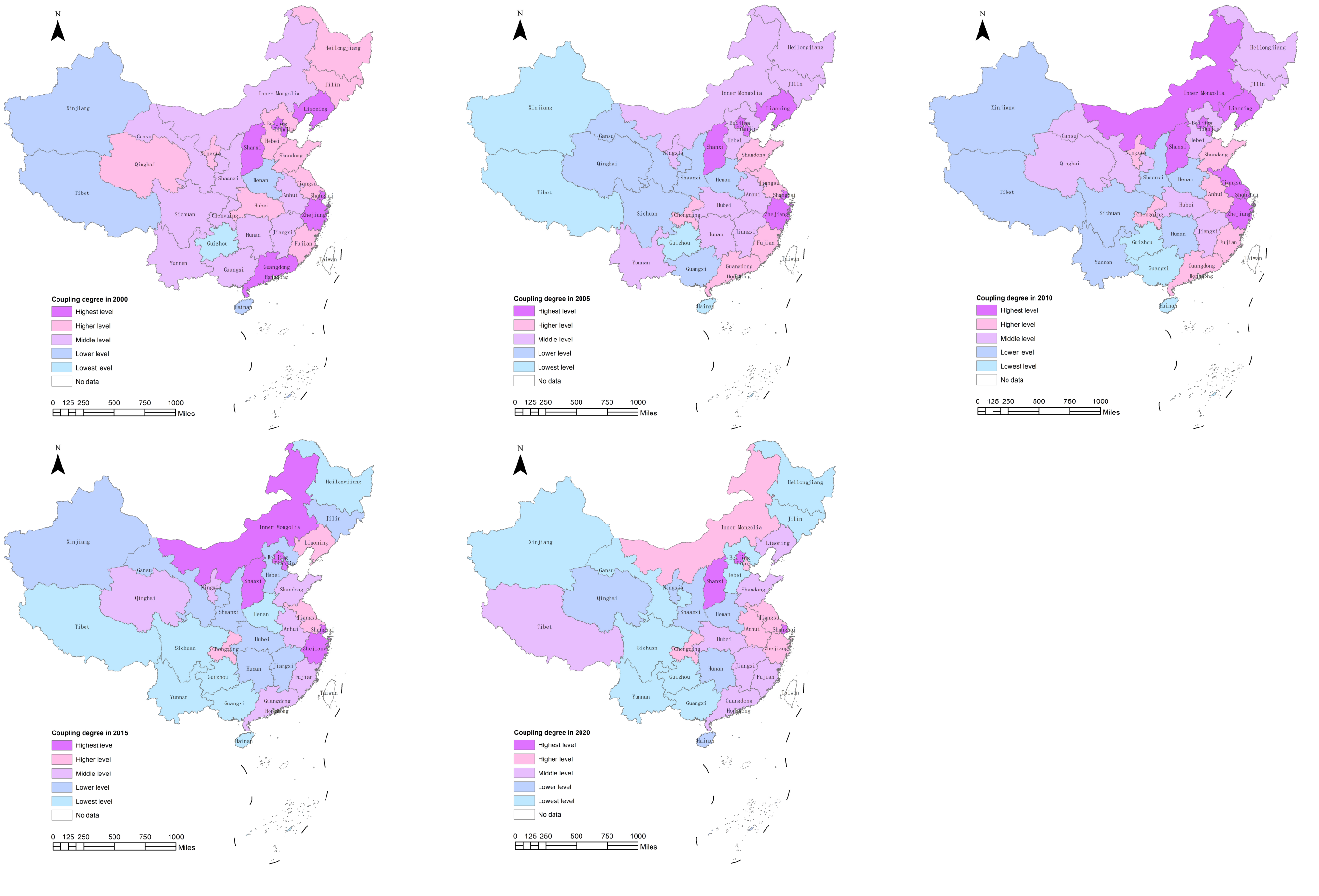

Figure 8. Spatial changes in the coupling of agricultural eco-efficiency and urbanization from 2000 to 2020.

4.3.2. The Coupling and Coordination Results of Agricultural Eco-Efficiency and Urbanization Level

According to the criteria for classification of coupling coordination degree, the level of coupling coordination between China's agricultural eco-efficiency and urbanization is transitioning from discoordination to coordination. Table 5 displays the variations in the coupling coordination levels at various time points. In 2000, the level of coupling coordination between China's agricultural eco-efficiency and urbanization was categorized into four levels: "severe discoordination", "moderate discoordination", "mild discoordination", and "primary coordination". The proportions of provinces included in each level were 6.45%, 67.74%, 19.35%, and 6.45%, respectively, with the "moderate discoordination" level including over two-thirds of provinces. In 2005, 2010, 2015, and 2020, the coupling coordination level between China's agricultural eco-efficiency and urbanization became increasingly synchronized. The level of severe discoordination gradually diminished, giving way to the emergence of the moderate coordination level. By 2020, the spectrum of coordination levels expanded to include "moderate discoordination", "mild discoordination", "primary coordination", and "moderate coordination". The proportion of provinces classified under the "moderate discoordination" level decreased from 67.74% to 19.35%, making the "mild discoordination" level currently the largest category.

Table 5. Classification of coupling coordination levels at multiple time nodes.

Coupling Coordination Level	2000	2005	2010	2015	2020
intermediate coordination		Shanghai	Shanghai	Beijing	Shanghai
primary coordination	Shanghai	Beijing	Beijing	Shanghai	Beijing
	Beijing		Tianjin	Tianjin	Tianjin
mild imbalance	Tianjin	Guangdong	Guangdong	Jiangsu	Zhejiang
	Guangdong	Tianjin	Jiangsu	Guangdong	Jiangsu
	Hainan	Jiangsu	Hainan	Liaoning	Guangdong
	Tibet	Hainan	Zhejiang	Tibet	Fujian
	Jiangsu	Xinjiang	Tibet	Zhejiang	Tibet
	Xinjiang	Zhejiang	Liaoning	Hainan	Shandong
moderate imbalance	Zhejiang	Liaoning	Fujian	Shaanxi	Chongqing
	Fujian	Inner Mongolia	Shaanxi	Fujian	Shaanxi
	Liaoning	Fujian	Shandong	Shandong	Liaoning
	Shandong	Shandong	Chongqing	Chongqing	Qinghai
	Sichuan	Guangxi	Henan	Jilin	Ningxia
	Hubei	Chongqing	Ningxia	Ningxia	Guizhou
	Jilin	Henan	Anhui	Henan	Hainan
	Inner Mongolia	Shaanxi	Hebei	Qinghai	Hunan
	Guizhou	Tibet	Hunan	Xinjiang	Sichuan
	Guangxi	Hunan	Jilin	Inner Mongolia	Hebei
	Hunan	Ningxia	Guangxi	Hunan	Henan
	Chongqing	Sichuan	Sichuan	Anhui	Jilin
	Henan	Heilongjiang	Hubei	Hubei	Xinjiang
	Shaanxi	Jilin	Inner Mongolia	Heilongjiang	Yunnan
	Heilongjiang	Hubei	Heilongjiang	Sichuan	Hubei
	Qinghai	Hebei	Qinghai	Guizhou	Jiangxi
	Hebei	Jiangxi	Xinjiang	Hebei	Heilongjiang
	Ningxia	Anhui	Jiangxi	Guangxi	Anhui
	Anhui	Shanxi	Guizhou	Jiangxi	Guangxi
	Yunnan	Guizhou	Yunnan	Yunnan	Inner Mongolia
	Jiangxi	Yunnan	Shanxi	Shanxi	Gansu
severe imbalance	Shanxi	Qinghai	Gansu	Gansu	Shanxi
	Gansu	Gansu			

Note: Provinces with the same background color belong to the same coupling coordination level.

Overall, the coupling coordination degree between China's agricultural eco-efficiency and urbanization does not exceed 0.7, indicating that there is still significant potential for further improvement. Currently, the coupling coordination degrees in Shanghai and Beijing are 0.641 and 0.626, respectively. Meanwhile, Tianjin, Zhejiang, Jiangsu, and Guangdong have coupling coordination degrees above 0.5, positioning them as the regions with the highest coupling coordination between China's agricultural eco-efficiency and urbanization. It is not difficult to find that the coupling coordination degrees in majority grain-consuming areas are generally higher. Meanwhile, most majority grain-producing areas and regions with a balance between grain production and consumption are predominantly experiencing a "mild imbalance" or "moderate imbalance". In particular, the coupling coordination degrees in majority grain-producing provinces such as Heilongjiang, Anhui, and Inner Mongolia are only 0.396, 0.394, and 0.372, respectively. This indicates that these areas require attention.

4.4. Grain Production and Self-Sufficiency Capacity at Different Levels of Coupling Coordination

4.4.1. Grain Production in Provinces with Varying Levels of Coupling Coordination

Provinces with higher levels of coordination between agricultural eco-efficiency and urbanization tend to have lower grain production. In 2020, the proportions of grain production in the four categories of "intermediate coordination", "primary coordination", "mild imbalance", and "moderate imbalance" were 0.18%, 8.7%, 62.4%, and 28.7%, respectively. The proportions of grain production in the "mild imbalance" and "moderate imbalance" categories have already exceeded 90%, essentially covering the regions with high grain production in China. Table 6 illustrates changes in the proportions of grain production at various coupling coordination levels from 2000 to 2020. Provinces at the "intermediate coordination" level have had the lowest proportion of grain production for an extended period, with a decreasing trend from 0.41% to 0.18%. Provinces at the "primary coordination" level have seen their proportion of grain production increase from less than 1% to 8.71%. This increase is primarily attributed to provinces with higher grain production, such as Jiangsu and Guangdong, transitioning from the "mild imbalance" level to the "primary coordination" level. Consequently, this transition has led to an increase in the proportion of grain production at the "primary coordination" level. Provinces at the "mild imbalance" level have seen their proportion of grain production increase from 13.1% to 62.4%, making it the level with the highest proportion of grain production among all levels. This is partly because this level includes a larger number of provinces, and also because some provinces in this tier have higher grain production. Provinces such as Henan and Shandong produce over 50 million tons of grain, while Jilin, Hebei, Sichuan, and Hunan produce over 30 million tons of grain. The average grain production at this level is 21.986 million tons. Provinces at the "moderate imbalance" level have shown a significant decrease in the proportion of grain production, dropping from 82.8% to 28.7%. This trend is primarily due to the decreasing number of provinces at this level each year, as most of the majority grain-producing provinces are transitioning to the "mild imbalance" level in terms of coupling coordination. However, provinces at the "moderate imbalance" level still have relatively high grain production overall: no province produces less than 10 million tons of grain, and the average grain production exceeds 30 million tons. Provinces with high grain production, such as Heilongjiang, Anhui, and Inner Mongolia, reach 75.41 million tons, 40.19 million tons, and 36.64 million tons, respectively. Promoting coupling coordination between agricultural eco-efficiency and urbanization without compromising grain supply capacity remains a challenging issue.

Table 6. The proportion of grain production at different coupling coordination levels (%).

Coupling Coordination Level	2000	2005	2010	2015	2020
intermediate coordination		0.41	0.44	0.28	0.18
primary coordination	0.7		0.3	5.7	8.7
mild imbalance	13.1	16.2	26.1	34.8	62.4
moderate imbalance	82.8	81.5	73.2	59.2	28.7
severe imbalance	3.4	1.9			

4.4.2. Grain Self-Sufficiency in Provinces with Varying Levels of Coupling Coordination

The introduction of self-sufficiency in grain here is a beneficial addition to the assessment of grain production in the previous subsection. It aims to collectively illustrate the food security capabilities of provinces at various levels of coupling coordination, considering both total quantity and per capita quantity. The Food and Agriculture Organization of the United Nations believes that one of the important criteria for food security is that per capita grain production reaches 400 kg or more. Therefore, the total regional grain quantity indicator is one aspect of food security. It requires the introduction of a population quantity indicator to assess whether per capita grain production in the region reaches 400 kg or more.

Provinces at the "Intermediate Coordination" and "Primary Coordination" levels are unable to achieve self-sufficiency in grain production. Provinces at the "Mild Imbalance" level have the ability to be self-sufficient in grain production, while provinces at the "Moderate Imbalance" level have a grain self-sufficiency capacity that is more than double the benchmark. Table 7 presents these results in two aspects: the per capita grain production of each province in 2000, 2010, and 2020, and the per capita grain production at each coupling level during the same period. (1) The per capita grain production of provinces at the "Intermediate Coordination" level decreased from 58.1 kg to 26.1 kg. Provinces such as Beijing and Shanghai have low grain production and high populations at this level, necessitating grain supply from other regions. (2) The per capita grain production of provinces at the "Primary Coordination" level increased from 106.1 kg to 201.6 kg, but it still did not reach the level of grain self-sufficiency. Additionally, the overall per capita grain production at this level increased not because the included provinces significantly improved their per capita grain production, but because Beijing and Shanghai, due to their low per capita grain production, entered the "Intermediate Coordination" level. Jiangsu, a majority grain-producing province, also reached this level, thereby raising the average standard. (3) The per capita grain production of provinces at the "Mild Imbalance" level increased from 322.6 kg to 493.3 kg, reaching the stage of grain self-sufficiency. This shift is primarily attributed to provinces such as Ningxia, Hunan, Sichuan, Hebei, Henan, Jilin, Xinjiang, Yunnan, Hubei, and Jiangxi moving from a state of "Moderate Imbalance" to "Mild Imbalance". These provinces achieved per capita grain production of over 400 kg, with Jilin notably surpassing 1500 kg per capita. (4) The per capita grain production of provinces at the "Moderate Imbalance" level increased from 392.5 kg to 846.7 kg. Although the number of provinces at this level is decreasing, the overall per capita grain production of these provinces remains at a very high level. In particular, Heilongjiang and Inner Mongolia have per capita grain production of 2367.7 kg and 1523.5 kg, respectively. From Table 7, it can be seen that in 2020, among the provinces ranking in the bottom 15 in coupling coordination, only Guangxi has a per capita grain production below 400 kg, while the per capita grain production of other provinces ranges from 401.6 kg to 2367.7 kg, with an average of 646.4 kg. In conclusion, regions with lower levels of coupling coordination have stronger capabilities for grain self-sufficiency.

Table 7. Grain self-sufficiency capacity at different levels of coupling coordination (kg).

	2000			2010			2020		
		Grain Production per Capita (by Province)	**Grain Production per Capita (by Grade)**		**Grain Production per Capita (by Province)**	**Grain Production per Capita (by Grade)**		**Grain Production per Capita (by Province)**	**Grain Production per Capita (by Grade)**
intermediate coordination				Shanghai	57.3	58.1	Shanghai	36.6	26.1
primary coordination	Shanghai	106.0	106.1	Beijing	59.0		Beijing	14.2	
	Beijing	106.3		Tianjin	123.6	123.6	Tianjin	164.4	201.6
mild imbalance	Tianjin	123.9	322.6	Guangdong	119.6	297.5	Zhejiang	93.9	
	Guangdong	228.4		Jiangsu	417.5		Jiangsu	440.0	
	Hainan	253.0		Hainan	191.7		Guangdong	100.6	
	Tibet	373.0		Zhejiang	126.0		Fujian	120.8	493.3
	Jiangsu	424.0		Tibet	303.1		Tibet	282.2	
	Xinjiang	444.2		Liaoning	412.3		Shandong	536.5	

Table 7. *Cont.*

	2000			2010			2020		
		Grain Production per Capita (by Province)	Grain Production per Capita (by Grade)		Grain Production per Capita (by Province)	Grain Production per Capita (by Grade)		Grain Production per Capita (by Province)	Grain Production per Capita (by Grade)
moderate imbalance	Zhejiang	264.8	392.5	Fujian	158.3	297.5	Chongqing	337.3	493.3
	Fujian	250.6		Shaanxi	317.5		Shaanxi	322.5	
	Liaoning	272.5		Shandong	469.6		Liaoning	549.2	
	Shandong	426.5		Chongqing	374.6		Qinghai	180.7	
	Sichuan	414.8		Henan	593.5	523.0	Ningxia	527.8	
	Hubei	372.2		Ningxia	563.0		Guizhou	274.4	
	Jilin	610.7		Anhui	538.5		Hainan	143.8	
	Inner Mongolia	523.6		Hebei	433.8		Hunan	453.8	
	Guizhou	309.2		Hunan	438.6		Sichuan	421.5	
	Guangxi	321.8		Jilin	1015.9		Hebei	508.8	
	Hunan	438.1		Guangxi	298.1		Henan	686.9	
	Chongqing	365.9		Sichuan	400.7		Jilin	1580.0	
	Henan	432.3		Hubei	402.3		Xinjiang	612.4	
	Shaanxi	298.9		Inner Mongolia	948.3		Yunnan	401.6	
	Heilongjiang	668.6		Heilongjiang	1469.6		Hubei	472.2	
	Qinghai	160.0		Qinghai	181.6		Jiangxi	478.9	
	Hebei	382.2		Xinjiang	637.2		Heilongjiang	2367.7	846.7
	Ningxia	456.2		Jiangxi	445.9		Anhui	658.5	
	Anhui	393.3		Guizhou	319.7		Guangxi	273.3	
	Yunnan	346.1		Yunnan	358.5		Inner Mongolia	1523.5	
	Jiangxi	389.2		Shanxi	309.9		Gansu	480.4	
severe imbalance	Shanxi	262.7	269.9	Gansu	370.6		Shanxi	407.8	
	Gansu	279.0							

Note: Provinces with the same background color belong to the same coupling coordination level, and red characters indicate regions where per capita grain production exceeds 400 kg.

5. Discussion

Firstly, how can we improve agricultural eco-efficiency in the main grain-producing areas without compromising grain production capacity? Based on the technical efficiency and technological progress values calculated in the SBM–DEA model, improving technical efficiency can be seen as a critical strategy to effectively enhance agricultural eco-efficiency in the primary grain-producing regions [38,39]. In recent years, the proportion of provinces in the main grain-producing areas with technological progress of 1 or higher has consistently remained above 90% due to the limited scope for technological advancements to improve agricultural eco-efficiency. Technological progress is the driving factor behind achieving the current level of agricultural eco-efficiency in the main grain-producing areas. However, further enhancing agricultural eco-efficiency requires fully utilizing technical efficiency while preserving the benefits of technological progress. In majority grain-producing regions, majority grain-consuming regions, and areas where grain production and consumption are balanced, the percentage of provinces with technical efficiency ≥ 1 is lower than that with technological progress $\geq$1. This suggests significant potential for improving overall technical efficiency [40]. Provinces such as Inner Mongolia, Heilongjiang, Jiangsu, Anhui, Jiangxi, Hubei, Hunan, and Sichuan, which are majority grain-producing regions, generally exhibit lower technical efficiency. Instances of technical efficiency below 1.0 were observed multiple times in the past five years. For primarily grain-producing regions, it is essential to develop specific investment policies [41,42], build or enhance agricultural infrastructure, expedite the research and dissemination of agricultural scientific advancements [43–46], comprehensively improve the expertise of agricultural producers, prevent technology waste and losses, and enhance the overall efficiency of the agricultural production process [47,48].

In regions with higher levels of coupling coordination between agricultural eco-efficiency and urbanization, how can grain self-sufficiency be achieved? Among the top 50% of provinces in China in terms of their ranking of coupling coordination between agricultural eco-efficiency and urbanization, only Jiangsu, Shandong, Liaoning, and Ningxia have per capita grain production exceeding 400 kg. The challenge of achieving grain self-sufficiency in regions with high levels of coupling coordination needs to be tackled from both production and trade perspectives. From a production perspective, some regions experiencing rapid urbanization no longer have the option to expand grain cultivation areas. Therefore, enhancing grain yield levels and promoting green agriculture are the primary methods to boost grain production [49,50]. By strengthening scientific breeding, fertilization, and irrigation techniques, reducing environmental pollution, and improving the ecological environment, the quality of grain products can be enhanced while increasing grain production [51,52]. From a trade perspective, the focus is on guiding the establishment of stable production and sales cooperation mechanisms between the mainly grain-consuming areas, grain production and consumption balance areas, and mainly grain-producing areas [53]. This involves establishing grain production, storage, and processing facilities in different regions, and encouraging various market participants to actively engage in grain production and sales collaboration. This ensures a continuous grain supply to majority grain-consuming areas and fosters innovative models of diversified cooperation in grain production and sales [54].

6. Conclusions

First, agricultural eco-efficiency was comprehensively enhanced, with significant spatial disparities observed. The results obtained from the SBM–DEA model indicate a consistent improvement in agricultural eco-efficiency across all provincial units in China during the period from 2000 to 2020. In 2000, only 9.7% of regions exhibited agricultural eco-efficiency equal to or greater than 1. However, since 2016, this proportion has witnessed a rapid increase, and by 2020, it reached an impressive figure of 77.4%. In terms of different types of regions, the average agricultural eco-efficiency in the majority grain-consuming areas, grain production–consumption balance areas, and majority grain-producing areas in 2020 was 1.08, 0.94, and 0.91, respectively. The majority grain-producing regions are the primary areas of agricultural production in China, exhibiting the lowest agricultural eco-efficiency. There is not much difference in scores among provincial units within this category, and there is still a long way to go to promote the synchronous development of grain production efficiency and ecological efficiency.

Secondly, the level of coupling coordination between agricultural eco-efficiency and urbanization is transitioning from imbalance to coordination. According to the calculation results of the coupling degree between agricultural eco-efficiency and urbanization, it can be observed that from 2000 to 2020, except for certain years in Guizhou, Tibet, and Heilongjiang where the coupling degree was less than 0.3, the coupling degree in other provinces fell above 0.3.

Thirdly, the higher the level of coupling coordination between agricultural eco-efficiency and urbanization in a province, the weaker its relative food security guarantee capability. Between 2000 and 2020, the combined proportion of grain production in provinces classified as "intermediate coordination" and "primary coordination" levels in China consistently remained below 10%. Per capita grain production also decreased to 26.1 kg and 201.6 kg, respectively, in regions that are unable to be self-sufficient in the long term and have a higher level of urbanization in China. Provinces classified as having a "mild imbalance" witnessed a significant increase in their proportion of grain production, rising from 13.1% to 62.4%. Additionally, their per capita grain production surged from 322.6 kg to 493.3 kg, making them the group with the highest proportion of grain production across all levels. Calculated based on the food security threshold of 400 kg per capita, they also simultaneously achieve self-sufficiency in grain. Provinces classified as having a "moderate imbalance" experienced a decrease in their share of grain production from 82.8% to 28.7%. Although the number of provinces at this level has decreased, it includes major grain-producing provinces such as Heilongjiang, Anhui, and Inner Mongolia. The average grain production at this level exceeds 30 million tons, and per capita grain production has increased from 392.5 kg to 846.7 kg, making it the region with the highest per capita grain production in China. In conclusion, the degree of coupling coordination is inversely proportional to the ability to ensure food security.

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