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Analysis of Measurement, Regional Differences, Convergence and Dynamic Evolutionary Trends of the Green Production Level in Chinese Agriculture

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Abstract: The development of green agriculture is conducive to accelerating the agricultural modernization process, making a significance for the sustainable development of agriculture and the environment in China. This paper constructs a comprehensive evaluation model by selecting 17 representative indicators from the perspective of sustainability. Then, this paper uses the entropy value method to measure the level of green agricultural production in 31 provinces from 2011 to 2021. We use Dagum's Gini coefficient and decomposition method, the kernel density estimation method and spatial Markov chain analysis method to explore the main sources of spatial differences and dynamic evolution trends. The results show that: (1) The overall level of green production in Chinese agriculture is low, and the level in the central region is higher than that in eastern and western regions; (2) There are significant regional differences in the level of green production in China's agriculture, and this is likely to widen. The interaction of inter- and intra-regional differences is the main reason for overall differences; (3) The trend of polarization in the level of green agricultural production is more obvious in the eastern part of China, while it is weaker in central and western regions; (4) There is a spatial spillover effect in the dynamic evolution of China's agricultural green production level. And the longer the overall time, the more obvious the spillover effect is. This paper analyzes the past development of green agriculture in China, makes predictions and provides constructive suggestions for the improvement and development of green agricultural production in China in the future.

Keywords: green agriculture; production levels; spatial differences; dynamic evolution

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1. Introduction

Agriculture is the basic industry of China's national economy. At the same time, China is also a very important grain-producing country in the world. It has developed very rapidly in recent years. China's grain output has increased steadily. Total output rose from 305 million tons in 1978 to 687 million tons in 2022. Agricultural infrastructure has also been significantly improved, and production efficiency has risen sharply. Wheat yields increased from 1844.9 kg per hectare in 1978 to 5912.3 kg per hectare in 2022. Maize production has increased from 2802.7 kg per hectare to 6302.3 kg per hectare [1,2]. The standard of living and quality of life of rural residents have also changed dramatically. The Engel's coefficient of rural households has decreased from 67.7% in 1978 to 30.1%. The rapid development of China's agriculture has laid the foundation for the country's rapid economic development. At the same time, it has also made a great contribution to the development of world agriculture and the solution of the problem of food shortage [3,4]. But rapid development

has also brought about serious ecological and environmental problems [5,6]. At the same time, traditional agricultural production systems have a negative impact on ecological security. It threatens sustainable social, economic and environmental development [7]. As a major contributor to world food production, problems in China's agricultural production are bound to affect the world's food supply as well. Therefore, China urgently needs to build a resource-saving and environmentally friendly agricultural production system to achieve sustainable agricultural development.

Against the above background, green agriculture has become an effective way to mitigate the problem of agricultural pollution and promote sustainable agricultural development. Green agriculture combines the concepts of ecological balance, recycling development and green life [8,9]. Based on sustainable agricultural development, it is a new form that can effectively guarantee the quality and safety of agricultural products, protect the environment and promote sustainable development. The rapid development of green agriculture is largely dependent on efficient agricultural production. An increase in the level of green production in agriculture is consistent with the concept of the Sustainable Development Goals proposed by the United Nations and can also provide more food for the world. In recent years, the Chinese government has introduced a number of policies to promote green production methods, enhance the sustainability of agriculture and vigorously promote the development of green agriculture. Many studies have now focused on the level of green production in Chinese agriculture. These include the impacts of technological progress [10,11], environmental regulation [12,13] and green finance [14,15] on the level of green production in agriculture. Some studies have discussed methods and pathways to achieve green agricultural production [16,17]. Some scholars have also studied green production in agriculture outside of China. Koohafkan et al. (2012) [9] emphasized the importance of green agriculture production from the perspective of biodiversity and ecosystem resilience. Ray (2014) [18] found that modern technological products such as fertilisers and electricity are an important part of promoting the greening of Indian agriculture. Ahmed et al. (2022) [19] found that increasing the level of agricultural insurance or reducing the level of air pollution can contribute to the improvement of the level of green agriculture based on the data of 50 states in the US. It can be seen that for the sustainable development of agriculture and the alleviation of environmental problems, countries around the world have noticed the importance of green production in agriculture. As a major agricultural country in the world, China's level of green agricultural production is also in urgent need of further evaluation and analysis.

Assessing the current level of green production in China's agriculture is a key step in the gradual transformation of traditional agriculture into green agriculture. However, existing studies are not uniform in the selection of indicators to evaluate the level of green agricultural production [20,21]. Most studies have identified indicators at both the production process and output process levels of greening agriculture. However, these indicators are not sufficient to clarify the green and sustainable attributes of green agricultural production. Therefore, it is necessary to construct reasonable evaluation indicators from the perspective of sustainable and green development. China is a vast country with very different resource endowments, diverse climatic conditions and different economic levels. This has led to spatial differences in the level of green agricultural production [22–24]. This is not only detrimental to the joint promotion of agricultural green development in different regions, but also affects the synergistic formulation and implementation of agricultural green development policies. Therefore, it is necessary to clarify the current situation and sources of spatial differences in agricultural green production in various regions. This is of great significance to the precise formulation of regional agricultural green development policies, the reduction of regional differences in the level of agricultural green development and the promotion of coordinated regional development in agriculture. The convergence and future evolutionary trend of the level of green agricultural production are very closely related to the coordinated development among provinces. At the same time, the prediction of the future evolution trend can provide the government with the ability to formulate dif-

ferent policies according to the characteristics of the level of green agricultural production in different provinces. In summary, there has been no harmonization in the evaluation of green production levels in agriculture. Spatial differences may lead to differences in policy implementation. They urgently need to be further discussed and analyzed. This paper provides a new basis for the government to formulate relevant policies by constructing a new indicator system and analyzing the differences between eastern, central and western regions. At the same time, the prediction about the level of green agricultural production is of great significance to policy makers and relevant enterprises.

The paper measured the level of green production in agriculture based on data from 31 provinces in China from 2011 to 2021 using the entropy method and a comprehensive evaluation model. The paper then uses the Dagum's Gini coefficient, kernel density estimation and spatial Markov chains to provide a comprehensive analysis of the spatial variation, convergence and dynamic evolutionary trends. Compared with the existing studies, the innovations of this paper are as follows. First, this paper provides a comprehensive measure of the level of green production in Chinese agriculture from the perspective of sustainable development. Secondly, the paper analyses the location, shape, ductility and polarization trends of the distribution of green production levels in agriculture using kernel density estimation methods. Thirdly, this paper uses Markov chains to predict future trends in the level of greening of agriculture. Most of the existing studies focus on the current status of green production levels in agriculture but ignore the future evolutionary trends. This paper provides a more comprehensive insight into the level of green production in agriculture from a temporal perspective. At the same time, this paper's selection of more refined indicators enables the government to formulate more precise policies. This paper provides a scientific basis for the improvement of green agricultural development and the rational formulation of relevant policies in the region.

The remainder of this paper is organized as follows: Section 2 specifies the methodology used for the selection and use of indicators. Section 3 presents the results and makes an analysis. Section 4 discusses the current study of green agricultural production in China. Section 5 summarizes the findings and shortcomings of this paper and makes appropriate comments. The specific process and the methods used are shown in Figure 1.

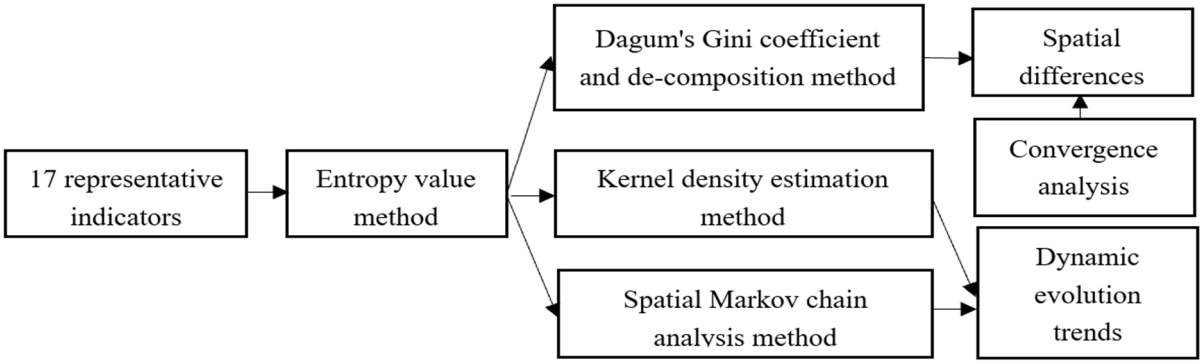


Figure 1. Methods and article structure.

2. Methodology and Data

2.1. Measurement of the Level of Green Production in Agriculture

Green agricultural production emphasizes the reduction of pollution and the efficient use of resources. The aim of green production is to achieve sustainable agricultural development. In this paper, we first consider the complexity of measuring the level of green agricultural production and the practicality and availability of data indicators. Then, this paper combines the research of previous scholars on ecological development and other aspects to highlight the characteristics of sustainable development in green agricultural production [25–27]. We finally selected 17 indicators of economic sustainability, environmental sustainability, resource sustainability and production sustainability to comprehensively

evaluate the level of green production in Chinese agriculture. The relevant indicators selected need to be closely related to green agricultural production. Based on the four areas mentioned above, we will describe the selected indicators in detail. Economic sustainability measures the long-term economic benefits of agricultural development. The indicators we have chosen include food production per unit area, total farmers' income, total green agricultural output, agricultural productivity and agricultural land yield. Indicators of environmental sustainability include fertilizer use intensity, pesticide use intensity, agricultural film use intensity, forest cover and cropland retention rate. Indicators of resource sustainability include agricultural machinery efficiency, agricultural water use efficiency, effective irrigation of agricultural land, electricity use in agriculture and financial inputs to agriculture. Indicators of production sustainability include the green variety certification index and the share of green food production base. The specific selection of indicators is shown in Table 1.

Table 1. Evaluation index system of China's agricultural green production level.

Form	Indicators	Calculation Method	
Economic sustainability	Food production per unit area	Total food production/area under food cultivation	+
	Total farmers' income	Total income of farmers during the year	+
	Total green agricultural output	Total output of green agricultural products during the year	+
	Agricultural productivity	Value added of primary sector/employees in primary sector	+
	Agricultural land yield	Total value of plantation production/area sown under crops	+
Environmental sustainability	Fertilizer use intensity	Fertilizer use/area sown to crops	−
	Pesticide use intensity	Pesticide use/area sown to crops	−
	Agricultural film use intensity	Agricultural film use/area sown to crops	−
	Forest cover	Forest area/total land area	+
	Cropland retention rate	Number of ecological fallow/total arable land	+
Resource sustainability	Agricultural machinery efficiency	Total power of agricultural machinery/total agricultural output	−
	Agricultural water use efficiency	Total agricultural water use/total agricultural output	−
	Effective irrigation of agricultural land	Effective irrigated area/cultivated area	+
	Electricity use in agriculture	Rural electricity consumption/rural population	−
	Financial inputs to agriculture	Expenditure on agriculture and forestry services/rural population	+
Production sustainability	Green variety certification	Number of certifications/the number for the base period	+
	Share of green food production base	Area of green food production base/area of arable land	+

In order to ensure the objectivity and accuracy of the evaluation of the level of green production in agriculture, we first need to standardize the raw data of the indicators and use the entropy value method to calculate the weights of the indicators. Then, we use the linear weighted summation method to calculate the comprehensive score of the agricultural green production level [28,29]. The specific formulas are as follows:

$$Z_{ij} = \frac{x_{ij} - minx_{ij}}{maxx_{ij} - minx_{ij}} \quad (1)$$

$$Z_{ij} = \frac{maxx_{ij} - x_{ij}}{maxx_{ij} - minx_{ij}} \tag{2}$$

In the formula, Z_{ij} denotes the standardised data for the j indicator for the i year or region. x_{ij} denotes the raw data for the j indicator for the i year or region. $maxx_{ij}$ denotes the maximum value in the evaluation sample for the j indicator. $minx_{ij}$ denotes the minimum value in the evaluation sample for the j indicator.

$$S_j = \frac{-\sum_{i=1}^{n} L_{ij} \times lnL_{ij}}{\ln n} \tag{3}$$

$$L_{ij} = \frac{Z_{ij} + 0.01}{\sum_{j=1}^{n} Z_{ij} + 0.01} \tag{4}$$

$$w_j = \frac{1 - S_j}{\sum_{j=1}^{m} 1 - S_j} \tag{5}$$

$$F = \sum_{j}^{m} x_{ij} w_j \tag{6}$$

In the formula, F represents the measured value of agricultural green production level, w_j represents the weight of evaluation indexes, m represents the number of indexes, S_j represents the entropy value and L_{ij} represents the proportion of evaluation indexes in the sample.

2.2. Dagum's Gini Coefficient

This paper uses Dagum's Gini coefficient decomposition to describe the regional differences in the level of green production in agriculture. According to the Gini coefficient proposed by Dagum (1997) [30], the Gini coefficient is defined as shown in Equation (7). Then, we decompose the Gini coefficient into three parts: The contribution of intra-regional disparity, the contribution of inter-regional net value disparity and the contribution of hypervariable density. Equations (8) and (9) represent the Gini coefficient and the contribution of intra-area disparity in the area. Equations (10) and (11) show the contribution of inter-regional Gini coefficient and inter-regional net worth gap for regions j and h. D_{jh} is the relative impact of the level of green agricultural production per unit between regions j and h. Equation (12) represents the contribution of hyper-variance density. y_{ji} (y_{hr}) is the level of agricultural green production in any province in the region. y is the average of the level of agricultural green production in all provinces, n is the number of provinces and k is the number of regional divisions. n_j is the number of provinces in the region.

$$G = \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2n^2 \overline{y}} \tag{7}$$

$$G_{jj} = \frac{\frac{1}{2\overline{Y}_j} \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{hr}|}{n_j^2} \tag{8}$$

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \tag{9}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{n_j n_h (\overline{Y}_j + \overline{Y}_h)} \tag{10}$$

$$G_{nb} = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \tag{11}$$

$$G_t = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right) \tag{12}$$

2.3. Kernel Density Estimation Method

Kernel density estimation is a nonparametric estimation method. It has become a common method for studying unbalanced distributions because of the robustness of its estimation results [31–33]. This method is mainly used to estimate the probability density of a random variable. A continuous density profile describes the distribution pattern of a random variable. Therefore, we use the kernel density estimation method to analyze the patterns, extensions and polarization trends in the level of green production in agriculture. Assuming that the density function of the random variable X is $f(x)$, the probability density at point x can be estimated by Equation (13), where N is the number of observations, h is the bandwidth and K is the kernel function. In this paper, the more commonly used Gaussian kernel function is chosen for estimation. The expression of the Gaussian kernel function is shown in Equation (14). Since there is no definite function expression for nonparametric estimation, we need to examine the changes in the distribution by graphical comparison.

$$f(x) == \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{13}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{x^2}{2}\right) \tag{14}$$

2.4. Convergence Analysis

If there is convergence in the level of greening of agriculture between provinces, this means that the rate of increase in the level of greening of agriculture in a province is negatively correlated with the initial level. This leads to a tendency for the difference in green agricultural production levels between two provinces to decrease. This section constructs the α-convergence test and β-convergence test [34,35]. The specific models are as follows:

$$\alpha_i = \sqrt{\frac{\sum_{i=1}^{n}(x_{it} - \overline{x}_t)^2}{n}} \tag{15}$$

$$\alpha = \theta + \delta \times t + \varepsilon \tag{16}$$

i and t denote provinces and years, respectively. α denotes the standard deviation of the green agricultural production level. x denotes the green agricultural production level. α convergence test focuses on reflecting the relative degree of difference in the level of green agricultural production in provinces and regions. In order to better examine the test, we constructed Equation (16). θ is the constant term. t is the time trend term. ε is the error term. If δ is less than 0 and significant at a certain level, it indicates that the difference in the level of green agricultural production is decreasing year by year. And there is an overall α convergence.

$$\frac{1}{T} Ln\left(\frac{Ln\ x_{it}}{Ln\ x_{i0}}\right) = \alpha + \beta Ln\ x_{i0} + \mu_{it} \tag{17}$$

$$\beta = \left[\frac{-\left(1 - e^{\lambda T}\right)}{T}\right] \tag{18}$$

T denotes the span of years from the base period to the present. x denotes the level of green agricultural production. If the coefficient of the initial green agricultural production level is negative, then there is absolute β-convergence.

2.5. Markov Chain Analysis Methods

The Markov chain is a process of events in which the transition of any state is only related to the state at the previous moment in time. And it is a stochastic process in which the future state is only related to the current state. Letting $\{X_t, t \in T\}$ be a finite-valued stochastic process which satisfies any $X_t \in S, t \in T = \{0, 1, 2 \cdots\}$, where S is the state space and the random variables can be discrete or continuous, we can obtain the following equation:

$$P\{X_t = x_t | X_0 = x_0, X_1 = x_1, \cdots, X_{t-1} = x_{t-1}\} = P\{X_t = x_t | X_{t-1} = x_{t-1}\} \quad (19)$$

We call $\{X_t, t \in T\}$ a Markov chain or Markov process, and denote p_{ij}= $(X_t = i \mid X_{t-1} = j)$ as the transfer probability of a Markov chain with n states being in state j at moment $(t-1)$ to state i at moment t. Its one-step transfer probability matrix is shown below:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \quad (20)$$

when the transfer probability matrix P is constant, the state of the system after k steps of state transfer can be obtained from the Chapman–Kolmogorov equation as follows [36]:

$$S^{(k)} = S^{(0)} \cdot P^{(k)} = S^{(1)} \cdot P^{(k-1)} = \cdots = S^{(k-1)} \cdot P \quad (21)$$

The traditional Markov chain examines the probability distribution of the transfer of the level of agricultural green production of a region to a high-level state or a low-level state and a smooth transfer under different time horizons [37,38]. The level of green agricultural production is not randomly distributed in geographic space. However, its regional correlation and dependence in geospatial terms cannot be ignored. Spatial Markov chains incorporate the concept of spatial lag. It makes up for the fact that traditional Markov chains ignore spatial interactions [39,40]. The spatial Markov chain introduces a spatial weight matrix to calculate the weighted average value of neighboring regions. It can fully consider the state of the neighborhood of a spatial unit. For location i with neighborhood j, the type of spatial lag for location i is determined by the spatial lag operator. The specific formula is as follows:

$$Lag = \sum_{i=1}^{n} x_i w_{ij} \quad (22)$$

where Lag is the spatial lag operator, x_i is the attribute value of the regional cell and w_{ij} is the weight of the observation in domain j on the spatial lag operator at location i. The spatial lag operator for each region can determine the type of spatial lag for each region. The traditional $k * k$ Markov matrix is decomposed into k conditional transfer probability matrices conditioned on the spatial lag type of cell i at the initial moment. Through the spatial lag type Markov transfer matrix, we can determine whether the level of agricultural green production in neighboring provinces will have an impact on the transfer of the regional agricultural green production level.

2.6. Data Sources

China first introduced the concept of green agriculture at the beginning of the twentieth century. The government has continued to introduce a variety of subsidy policies to enhance support for the sustainable development of green agriculture. From 2004 to 2011, the development of green agriculture showed steady growth. Based on the background of policy implementation and data availability, we select 31 provinces in China from 2011 to 2021 as the research object. Food production per unit area, total income of farmers, total output value of green agriculture, agricultural productivity, agricultural land yield,

fertilizer use intensity, pesticide use intensity, agricultural film use intensity, agricultural machinery efficiency, agricultural water use efficiency, agricultural electricity use and agricultural financial inputs are measured from the China Statistical Yearbook and the China Rural Statistical Yearbook. Forest coverage rate and cropland retention rate are measured from the China Agricultural Statistical Yearbook. The data on the green variety certification index and the proportion of the area of green food raw material production bases come from the Annual Report of Green Food Statistics.

3. Empirical Results and Analyses

3.1. Measurement of Green Production Levels

Based on the comprehensive evaluation model, we calculated the green production level of Chinese agriculture from 2011 to 2021 at national, regional and provincial levels. From Table 2, China's agricultural green production level shows a decline followed by a rise, and then moves from a slow decline to a rise. The overall trend is W-shaped. The green production level reaches 0.2901 in 2021, with a slight increase compared with 2011. The level of green production in agriculture in the eastern region shows a trend of increasing and then decreasing. The level of green production in 2021 reaches 0.2601, which is lower than the national average. The overall trend in the central region is more like that of the whole country. The western region shows a fluctuating upward trend. The level of agricultural green production in the western region rises by 10 per cent from 2011 to 2021. The level of agricultural green production in the western region has long been lower than the national average over the same period, but the difference is not very large. The central region's agricultural green production level is higher than the national average in the study period. The eastern region is higher than the national average during the period 2012–2016 and lower than the national average for the rest of the period. In summary, the difference between the central and western regions is the largest but is evolving in a narrowing trend.

The level of green production in China's agriculture varies widely among provinces, with Jiangxi (0.5296), Heilongjiang (0.4942) and Jiangsu (0.4089) having a level of green production of more than 0.4 in 2011, and 17 provinces having a level of green production of less than 0.3. Among them, Hainan (0.1703), Shaanxi (0.1826), Yunnan (0.1835) and Guizhou (0.1973) have an agricultural green production level of less than 0.2, which is at a lower level in the country. The reason may be that Jiangxi Province is an important national production base for green and organic agricultural products. The proportion of the area of green food raw material production bases to the area of arable land in the province is 0. 2068. And the intensity of chemical fertilizer application in the province is 252.12 kg per hectare, which is much lower than the national average of 349.34 kg per hectare. The quality of arable land in Heilongjiang Province is high. The intensity of fertilizer application in the province is low. It is the second lowest in China, at 176.78 kg per hectare. The intensity of agricultural film use is also low. It is in the third lowest position in the country, with only 5.71 kg per hectare. Jiangsu Province is in the middle of the range in terms of resource sustainability, environmental sustainability and production sustainability. There is a lack of green raw material production bases in Hainan, Shaanxi, Yunnan and Guizhou. Hainan and Shaanxi have a very high fertilizer application intensity due to the cultivation of high fertilizer-consuming crops such as economic or horticultural crops. In addition, Hainan has a high temperature and high humidity climate, so the frequency of pests and diseases is high and harmful. Therefore, the intensity of pesticide use is also the highest. Therefore, the level of green agricultural production in these four provinces is relatively backward. In 2021, the provinces with agricultural green production levels above 0.4 include Shanxi, Shanghai, Chongqing and Jiangsu. However, the level of green production in agriculture in most provinces is still below 0.3. This may stem from increased consumer recognition and acceptance of green products and increased government subsidies. This has driven green changes in agriculture in Shanxi, Shanghai, Chongqing and Jiangsu. If we take 2011 as the base period, the green variety certification index of these provinces has risen by 19.846, 24.333, 18.510 and 1.066. In addition, the intensity of pesticide and fertilizer

use has been reduced in all four provinces in the context of sustainable development and increased government penalties. And Shanghai and Jiangsu have achieved significant results in terms of resource sustainability. Unlike previous studies, this paper analyzes the possible reasons for the differences in the level of green agricultural production between provinces [41,42]. At the same time, the use of sustainability indicators can provide fresh insights for government policy development.

Table 2. Evaluation results of the level of green production in agriculture.

Region	Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
East	Beijing	0.2946	0.2103	0.2540	0.2157	0.2008	0.2390	0.2003	0.1667	0.1551	0.1293	0.2066
	Tianjin	0.3122	0.2354	0.2742	0.2830	0.2787	0.2857	0.2646	0.2235	0.2179	0.1975	0.2573
	Hebei	0.3267	0.3902	0.3312	0.2772	0.2685	0.3043	0.2999	0.2962	0.3241	0.2937	0.3112
	Liaoning	0.2617	0.1796	0.1495	0.1430	0.1827	0.2090	0.1826	0.1873	0.1874	0.1493	0.1832
	Shanghai	0.2437	0.1950	0.2814	0.2647	0.2855	0.2882	0.2657	0.2424	0.4626	0.5947	0.5324
	Jiangsu	0.4089	0.3856	0.5405	0.5891	0.5843	0.6358	0.5524	0.5170	0.5085	0.4233	0.5145
	Zhejiang	0.2263	0.1812	0.2023	0.1990	0.2185	0.2491	0.2185	0.2044	0.2133	0.1915	0.2104
	Fujian	0.2921	0.2440	0.3009	0.3335	0.3480	0.3781	0.3295	0.2546	0.2748	0.2462	0.3002
	Shandong	0.2653	0.2058	0.2282	0.2251	0.2558	0.2860	0.2657	0.2540	0.2611	0.2470	0.2494
	Guangdong	0.2673	0.2036	0.2430	0.2381	0.2514	0.2798	0.2475	0.2185	0.2362	0.2115	0.2397
	Hainan	0.1703	0.1223	0.1406	0.1360	0.1489	0.1680	0.1695	0.1477	0.1831	0.1694	0.1556
Central	Shanxi	0.2030	0.1587	0.1674	0.1748	0.2078	0.1953	0.2004	0.2359	0.3089	0.6069	0.6061
	Jilin	0.2296	0.1701	0.1482	0.1462	0.1526	0.1832	0.1694	0.1889	0.1859	0.1703	0.1744
	Heilongjiang	0.4942	0.4354	0.3995	0.4561	0.4721	0.5464	0.4811	0.4658	0.4427	0.3601	0.3953
	Anhui	0.3670	0.2693	0.2757	0.3059	0.3406	0.3907	0.3475	0.3538	0.3653	0.3311	0.3347
	Jiangxi	0.5296	0.3583	0.3249	0.3459	0.4449	0.5074	0.4407	0.4227	0.4144	0.3534	0.4142
	Henan	0.2550	0.1946	0.2193	0.2146	0.2291	0.2668	0.2293	0.2310	0.2488	0.2535	0.2342
	Hubei	0.2773	0.2113	0.2127	0.2229	0.2445	0.2803	0.2464	0.2459	0.2504	0.2254	0.2417
	Hunan	0.3987	0.3162	0.3456	0.3775	0.3859	0.4247	0.3762	0.3549	0.3623	0.3389	0.3681
West	Inner Mongolia	0.2712	0.2441	0.2502	0.2676	0.2928	0.3290	0.3017	0.3011	0.3059	0.2786	0.2842
	Guangxi	0.2106	0.1621	0.1679	0.1685	0.1791	0.2066	0.1843	0.1896	0.1922	0.1963	0.1857
	Chongqing	0.2282	0.1942	0.2018	0.2013	0.2355	0.2249	0.2385	0.2697	0.3443	0.4955	0.4934
	Sichuan	0.3163	0.2502	0.2624	0.2745	0.2878	0.3330	0.2952	0.3025	0.3067	0.2865	0.2915
	Guizhou	0.1973	0.1478	0.1491	0.1385	0.1459	0.1821	0.1595	0.1774	0.2096	0.2388	0.2446
	Yunnan	0.1835	0.1412	0.1427	0.1423	0.1532	0.1764	0.1666	0.1682	0.1911	0.2066	0.1672
	Tibet	0.2740	0.1755	0.1717	0.1693	0.2116	0.2345	0.2408	0.4622	0.2413	0.3315	0.2512
	Shaanxi	0.1826	0.1363	0.1456	0.1412	0.1483	0.1809	0.1704	0.1854	0.1795	0.1779	0.1648
	Gansu	0.2017	0.1734	0.1564	0.1367	0.1584	0.1917	0.1844	0.2169	0.2589	0.2390	0.2417
	Qinghai	0.3303	0.2823	0.3185	0.1902	0.3314	0.3738	0.4329	0.4315	0.4308	0.3559	0.3478
	Ningxia	0.2923	0.2156	0.1756	0.1385	0.2740	0.3043	0.2632	0.1718	0.2615	0.2053	0.2302
	Xinjiang	0.3474	0.2984	0.3047	0.2409	0.3713	0.4106	0.3900	0.3545	0.3519	0.3265	0.3396
Average	National	0.2858	0.2287	0.2415	0.2373	0.2674	0.2989	0.2747	0.2723	0.2863	0.2849	0.2901
	East	0.2790	0.2321	0.2678	0.2640	0.2748	0.3021	0.2724	0.2466	0.2749	0.2594	0.2601
	Mid	0.3443	0.2642	0.2617	0.2805	0.3097	0.3493	0.3114	0.3124	0.3223	0.3299	0.3304
	West	0.2529	0.2018	0.2039	0.1841	0.2325	0.2623	0.2523	0.2692	0.2728	0.2782	0.2789

In terms of spatial distribution, the spatial imbalance in the level of green production in Chinese agriculture is relatively significant. In 2011, the green production level of agriculture in the central and eastern regions was significantly higher than that in the western region. Jiangxi, Heilongjiang and Jiangsu all scored more than 0.4. We found that the dynamic evolution of the spatial distribution of China's agricultural green production level is significantly characterized by the spread of low-level areas to the east. At the same time, the level of agricultural green production in the western region has a higher degree of agglomeration. Overall, the level of green production in Chinese agriculture shows significant spatial imbalance characteristics.

3.2. Measurement of Regional Differences

The specific Gini coefficient measurements are shown in Table 3. From Table 3, the intra-regional differences in China's agricultural green production level are rising in fluctuation. The overall Gini coefficient reaches 0.2172 by 2021. This is an increase of 0.0578 from 2011. This reflects the possibility of further expansion of China's agricultural green production level under the influence of factors such as resource endowment, cultivation structure, technological level, environmental regulation and macro policies. On further analysis, we find that the Gini coefficients of the eastern, central and western regions are growing at an average annual rate of 9.42 per cent, 0.22 per cent and 2.86 per cent. In 2021, the Gini coefficients of the eastern, central and western regions reach 0.2521, 0.1912 and 0.1646. Although the changes in the internal disparities of the three regions are different from 2011 to 2021, the disparities within the eastern, central and western regions are all on a widening trend. Differences within the eastern region grew at the fastest rate, followed by the western region, with the central region being the most stable. The most obvious differences in the results are found in the eastern region, followed by the central region and the western region. This is mainly since the eastern region has a large north-south span. The region's climatic conditions, resource endowment and level of economic development vary significantly. This leads to large differences in the intensity of environmental regulations, crop types and fertilizer application intensity across provinces. This further leads to intra-regional differences in the level of green production.

Table 3. Gini coefficient and decomposition results of green production levels in agriculture.

Year	Total	Intra-Regional Gap			Inter-Regional Gap			Contribution Rate		
		East	Middle	West	E–M	E–W	M–W	Intra	Inter	Den
2011	0.1594	0.1121	0.1874	0.1278	0.1837	0.1309	0.2081	28.72	41.04	30.24
2012	0.1849	0.1737	0.1951	0.1489	0.1992	0.1775	0.2071	30.77	31.58	37.65
2013	0.1967	0.1950	0.1817	0.1612	0.1958	0.2131	0.2049	30.88	31.82	37.30
2014	0.2199	0.2155	0.2039	0.1448	0.2231	0.2325	0.2542	28.67	42.36	28.96
2015	0.2073	0.1942	0.2012	0.1810	0.2193	0.2012	0.2309	30.98	30.17	38.85
2016	0.2026	0.1803	0.2096	0.1683	0.2221	0.1914	0.2308	30.31	30.54	39.15
2017	0.1966	0.1768	0.1970	0.1853	0.2092	0.1884	0.2147	31.76	22.65	45.59
2018	0.1987	0.1803	0.1681	0.2008	0.2113	0.2042	0.2004	31.77	24.86	43.37
2019	0.1809	0.2081	0.1466	0.1517	0.2035	0.1877	0.1681	31.95	18.50	49.55
2020	0.1982	0.2302	0.1590	0.1643	0.2249	0.1989	0.1801	31.66	20.34	47.81
2021	0.2161	0.2521	0.1912	0.1646	0.2577	0.2226	0.1961	31.35	23.09	45.56

Second, we analyzed inter-regional differences. Inter-regional differences in the level of green agricultural production show a fluctuating trend. Compared with 2011, the inter-regional difference in the center–west has narrowed slightly. The inter-regional differences in east–central and east–west have both increased. And the east–central difference is the largest. The possible reason is that the eastern region is economically developed and has certain geographic advantages. These have had an obvious effect on the promotion of agriculture. In contrast, the western region is resource poor and lags in economic and technological development, so the effect of green productivity improvement is less satisfactory. It is difficult to narrow the development gap with the eastern region. The interaction between the inter- and intra-regional differences is the main cause of the overall differences. And this influence is gradually increasing. To achieve the coordinated development of regional agricultural greening, the government should firstly reduce the intra-regional disparities. At the same time, the government should also take differentiated measures to grant full play to the advantages of each region.

3.3. Dynamic Evolution Based on Kernel Density Estimation

In order to examine the distribution dynamics of the national and three major regions' agricultural green production level from 2011 to 2021, this paper draws a three-dimensional

curve of kernel density using Matlab 2020a software. According to Figure 2a, the position of the main peak of the distribution curve of the national level of green production in agriculture shows a slight shift from left to right. This indicates that the overall level of national agricultural green development has basically changed little. The height of the main peak declines in repeated fluctuations and its width widens. This indicates that the degree of regional development imbalance is increasing. There is a small side peak in the 2011–2014, 2018 and 2020 plots. This indicates that the phenomenon of polarization in the level of green production in the country disappears and then tends to appear gradually. Compared with 2011, the lateral peak of the density curve for the country in 2021 is shifted to the right and extended with a right trailing tail. This indicates that more provinces have higher green production levels as agricultural green development advances.

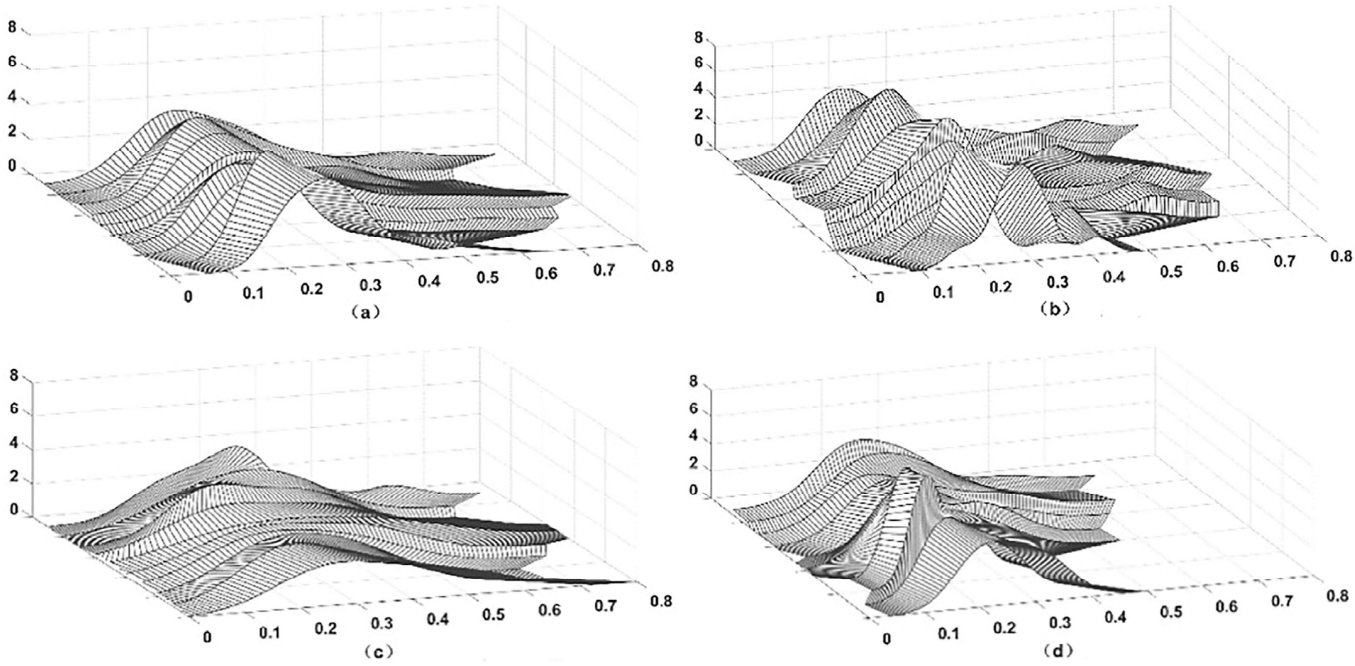


Figure 2. (**a**) Dynamic evolution of green production levels in agriculture in China (**b**) Dynamic evolution in the eastern region (**c**) Dynamic evolution in the central region (**d**) Dynamic evolution in the western region.

According to Figure 2b, the position of the main peak of the density curve in the eastern region shows a left–right–left trend. The level of green agricultural production shows a recurrent fluctuation process of decreasing, then increasing and then decreasing. However, the shape of the main peak changes from sharp to flat, and the position of the main peak and the side peaks first expands and then narrows. This indicates that the polarization trend of the agricultural green production level is more obvious in the eastern region. In 2021, the number of side peaks increases, the height of side peaks decreases and the right trailing extension widens. This indicates that the polarization of the agricultural green production level in the eastern region increases, and the absolute difference tends to widen. According to Figure 2c, the trend of the main peak position change in the distribution curve of the green production level of agriculture in the central region is a left–right–left–right trend. The green development level has experienced two rounds of decreasing and then increasing. The shape of the main peak becomes flat to sharp, and the peak value of the side peaks is lower. This indicates that the level of agricultural green production in the central region has a certain gradient effect, and the degree of polarization is weak. According to Figure 2d, the position of the main peak of the distribution curve of the level of green production in agriculture in the western region changes in a left–right trend. The shape of the peak first narrows and then widens, and the height of the peak first rises and then falls.

This indicates that the level of green production in the western region first decreases and then gradually becomes better. Regional differences first narrow and then widen, and the trend of polarization gradually disappears.

3.4. Results of Convergence Analysis

The α-convergence statistics for the level of green production in agriculture are shown in Table 4. At the national level, there is little difference in the level of agricultural green production among provinces. The overall level remains between 0.22 and 0.28. It shows a fluctuating upward trend before 2016 and a fluctuating downward trend after 2016. At the regional level, the overall evolution trend is basically the same as that at the national level. Overall, there is an increasing trend in the α-convergence statistics between 2011 and 2021. This suggests that the gap in agricultural green production levels is evolving in a diffuse manner.

Table 4. α-convergence statistics of green production levels in agriculture.

Year	Total	East	Central	West
2011	0.22	0.23	0.25	0.19
2012	0.23	0.24	0.25	0.20
2013	0.26	0.24	0.26	0.18
2014	0.25	0.25	0.26	0.17
2015	0.28	0.27	0.25	0.19
2016	0.27	0.29	0.27	0.23
2017	0.25	0.28	0.24	0.20
2018	0.26	0.25	0.26	0.26
2019	0.24	0.25	0.23	0.25
2020	0.23	0.26	0.20	0.23

In order to further ensure the accuracy of the conclusion, this paper further tests the convergence of α. The results are shown in Table 5. According to the setting of δ value and the test results in this paper, except for the negative δ value of the samples from the eastern region, the δ values of the samples from the whole country, the central region and the western region are positive. The δ-values of the national and western regions are significant at the five-percent level. This indicates that there is no significant α-convergence at the national level and in the western region.

Table 5. Tests for α convergence.

	Total	East	Central	West
δ	0.0072 **	−0.0068	0.0059	0.0077 **
	(0.0190)	(0.0147)	(0.0142)	(0.0249)
Constant	0.6123	1.4516	0.0620	0.9641
	(1.2719)	(1.2627)	(0.0543)	(0.6624)
F	19.2430	10.1966	14.0145	14.3920
R2	0.7070	0.5762	0.4336	0.6215
Samples	11	11	11	11

Note: All explanatory variables in this table are α convergence values. Robustness standard errors are in parentheses. ** respectively indicate that the significance is 5%.

Table 6 reflects the results of β convergence estimation. Table 6 shows that the β-values for the national, eastern, central and western regions are all greater than 0. The β-value in the eastern region is significant at the 5% level. This indicates that there is no obvious β-convergence at the national level or from the regional perspective. At present, the national level and the three major regions have not yet formed a catching-up effect on the developed provinces and regions in agricultural green production.

Table 6. Tests for β-convergence.

	Total	East	Central	West
β	0.0245	0.0151 **	0.0168	0.0400
	(3.2250)	(1.7905)	(1.2676)	(3.6495)
Constant	0.1622	0.2648	0.3984	0.1898
	(2.0424)	(2.6601)	(2.9074)	(2.3290)
F	12.8362	13.4973	13.4096	14.1809
R2	0.8762	0.6210	0.7239	1.0430
Samples	11	11	11	11

Note: All explanatory variables in this table are β convergence values. Robustness standard errors are in parentheses. ** respectively indicate that the significance is 5%.

3.5. Dynamic Evolution Based on Markov Chains

We first used the convergence test and the kernel density estimation method to examine the distributional characteristics and its evolutionary process. However, they are not able to clarify the specific transfer pattern of the green production level of agriculture in China and each region. In this section, we measure the transfer probabilities between states under different time durations based on traditional Markov chain and spatial Markov chain analysis methods. This will provide a comprehensive explanation of the transfer trends and differences in the level of green production in agriculture. Without considering the influence of spatial factors, we first measure the state transfer probability of the green production level in Chinese agriculture based on the traditional Markov chain. The results are shown in Table 7. If the level of agricultural green production in a region is at a low level, the probability that the region will be stable after 1 year is 71%. The probability that the region will continue to have a low production level after 3 years drops to 46%. After 5 years, this probability drops further to 43%. At the medium–low and medium–high levels, the probability of them shifting smoothly after 1 year is 54% and 53%. The probability of a smooth shift after 3 years drops to 39%. After 5 years, the probability of maintaining the status is further reduced to 28% and 38%. In contrast, the probability of a smooth shift is always between 71 and 83% for high-level areas under different time periods. Similar to the results of the convergence test, the probability of low- and high-level regions maintaining their status is higher than that of medium–low- and medium–high-level regions after one, three and five years. This suggests that low-level regions have yet to catch up with high-level regions. Previous studies have not paid attention to this. They only considered some regional differences and spatial–temporal characteristics [43,44].

Table 7. Traditional Markov shift probabilities for green production levels in agriculture.

Time	Category	Low	Medium–Low	Medium–High	High
T = 1	Low	0.71	0.26	0.03	0.00
	Medium–Low	0.21	0.54	0.19	0.06
	Medium–High	0.08	0.17	0.53	0.22
	High	0.00	0.05	0.16	0.79
T = 2	Low	0.63	0.34	0.02	0.02
	Medium–Low	0.16	0.47	0.30	0.08
	Medium–High	0.08	0.13	0.50	0.30
	High	0.00	0.04	0.25	0.71
T = 3	Low	0.46	0.48	0.05	0.00
	Medium–Low	0.16	0.39	0.32	0.13
	Medium–High	0.09	0.18	0.39	0.34
	High	0.02	0.04	0.16	0.78
T = 4	Low	0.33	0.58	0.06	0.02
	Medium–Low	0.13	0.35	0.38	0.15
	Medium–High	0.08	0.13	0.42	0.38
	High	0.00	0.02	0.21	0.76
T = 5	Low	0.43	0.50	0.08	0.00
	Medium–Low	0.10	0.28	0.43	0.20
	Medium–High	0.03	0.20	0.38	0.40
	High	0.00	0.03	0.14	0.83

High-level areas will have a cyclical cumulative effect, thus maintaining their lead in the long term. In addition, the probability that a low-level area will rise to a higher level after a shift is 26%. This probability rises to 48% after 3 years and reaches 50% after 5 years. The probability that a low–medium- and high–medium-level area will move to a higher level at 1 year is 19% and 22%. This increases to 31% and 34% after 3 years and reaches 43% and 40% after 5 years. This suggests that the probability of regions at low, low–medium and high–medium levels moving to higher levels increases over time. However, the higher the level, the more difficult it is to shift upwards. The probability of a region at a relatively high level of production moving to a higher level is lower. The reason for this may be that the transformation and development of agriculture in recent years has achieved certain results, but it is difficult to continue to improve the level of green production in agriculture.

This paper further uses spatial Markov chains to analyze the spatial transfer patterns of agricultural green production levels. It is also used to identify the influence of spatial factors on the dynamic evolution of the regional agricultural green production level. Table 8 shows the results of the significance test of the spatial Markov shift probabilities for different time durations. The Q-statistic values are significant at 5%, 1%, 10% and 5% levels for lengths of 1, 2, 3 and 5 years. This means that spatial factors are very important in influencing the level of agricultural green production in each region. This suggests the existence of spatial spillover effects in the dynamic evolution of the level of green agricultural production in China.

Table 8. Results of the test for spatial effects in the shift process.

Time	Q	Degree of Freedom	Chi-Square Value	*p*
1	57.79 **	33.12	19	27.20
2	72.52 ***	38.14	21	29.62
3	79.06 *	27.47	22	30.81
4	100.07 *	29.58	20	28.41
5	108.41 **	27.63	16	23.54

Note: *, ** and *** respectively indicate that the significance is 10%, 5% and 1%.

To further analyze the specific impact of spatial effects, this paper introduces a geographic weighting matrix. It is used to measure the spatial transfer probability of the level of green agricultural production in China under different time periods. The results are shown in Table 9. When the area surrounding a low-level area also has a low level of green production, the probability that it will remain a low-level area after a one-step shift is 74%. The probability drops to 47% when the length of time is 5 years. When a low-level area is surrounded by a low–medium level, the probability that it will remain a low-level area after a one-step shift is 70%. The probability drops to 45% when the length of time is 5 years. If the area surrounding the low-level area is medium–high or high, the probability of the area remaining in the same state after a one-step shift is 77% and 56%. The probability drops to 33% and 40% when the length of time is 5 years. From the above, it is evident that spatial factors play an important role in the process of regional agricultural green development. When the level of agricultural green production in the surrounding areas of low-level regions is low, it is more difficult for low-level regions to improve their own level of agricultural green production. And with high-level areas as neighbors, this can increase the probability of upward transfer of the region. And with the longer time, this spatial spillover effect becomes more obvious. Based on Table 9, we can also draw the following conclusions. Firstly, the shift probability on the main diagonal is the largest at a duration of 1 year, irrespective of the level of the surrounding area. This is consistent with the results without spatial considerations. This proves that it is more difficult to break the path dependence of agricultural production in a short period of time. Secondly, agricultural green production in high-level areas is highly robust. Its probability of maintaining its original state under different influences is higher than 50%. On the other

hand, the dynamic evolution of the level of agricultural green production in low-level areas is strongly influenced by the spatial spillover effects of the surrounding areas.

Table 9. Probability of spatial shift in the level of green production in agriculture.

T = 1	Category	Low	Medium–Low	Medium–High	High	T = 5	Category	Low	Medium–Low	Medium–High	High
Low	Low	0.74	0.19	0.07	0.00	Low	Low	0.47	0.47	0.07	0.00
	Medium–Low	0.40	0.40	0.00	0.20		Medium–Low	0.00	0.50	0.00	0.50
	Medium–High	0.11	0.11	0.56	0.22		Medium–High	0.00	0.14	0.36	0.50
	High	0.00	0.00	0.08	0.92		High	0.00	0.00	0.11	0.89
Medium–Low	Low	0.70	0.30	0.00	0.00	Medium–Low	Low	0.45	0.36	0.18	0.00
	Medium–Low	0.17	0.58	0.25	0.00		Medium–Low	0.13	0.19	0.44	0.25
	Medium–High	0.00	0.22	0.67	0.11		Medium–High	0.00	0.00	0.33	0.67
	High	0.00	0.06	0.19	0.75		High	0.00	0.00	0.10	0.90
Medium–High	Low	0.77	0.23	0.00	0.00	Medium–High	Low	0.33	0.67	0.00	0.00
	Medium–Low	0.20	0.60	0.20	0.00		Medium–Low	0.11	0.11	0.44	0.33
	Medium–High	0.11	0.11	0.47	0.32		Medium–High	0.00	0.27	0.45	0.27
	High	0.00	0.00	0.10	0.90		High	0.00	0.00	0.18	0.82
High	Low	0.56	0.44	0.00	0.00	High	Low	0.40	0.60	0.00	0.00
	Medium–Low	0.22	0.48	0.17	0.13		Medium–Low	0.08	0.46	0.46	0.00
	Medium–High	0.06	0.29	0.47	0.18		Medium–High	0.08	0.25	0.33	0.33
	High	0.00	0.14	0.29	0.57		High	0.00	0.20	0.20	0.60

4. Discussion

Existing researches about green agricultural production in China have widely explored various aspects in green agriculture such as green food and green technology progress [45,46], with a focus on the past development. This paper focuses on the green agricultural production level, in line with numerous studies [17,43,47,48]. Some of them only present theory and models about agricultural green production or are from a single perspective such as the farmer's [17,47,48], lacking data analysis from a comprehensive perspective. Li et al. (2020) [47] collect first-hand data of 645 grain growers and use a structural equation model to explore the impacts of farmers' perceptions on agriculture green production willingness. And game models between the government and farmers, and farmers and agricultural enterprises, are established to attempt to obtain the best stable strategy for better green technology diffusion [48], with Shen et al. (2020) [17] addressing the significance, challenges, framework, pathways and potential solutions for realizing agricultural green development in China.

Only Liu et al. (2022) [43], based on data from 1987–2017 in China, systematically sort the agricultural green production goals from five dimensions: supply capacity, resource utilization, environment quality, ecosystem maintenance and farmers' lives, and construct an agricultural green production assessment index system. And they show that Chinese agriculture has achieved great increases in production and efficiency in the past years, with a great regional imbalance in the green growth of agriculture in China. Specifically, more than 70% of the top 10 leading regions in the country are located in the eastern part of the country, while 50% of the 10 most-undeveloped regions are located in the western part. And this paper, using abundant models widely used in various research areas, confirms the overall level of green production in Chinese agriculture, regional difference and its reasons. Most importantly, this paper carries out a depth analysis on the future trend of polarization in the level of green agricultural production and the spatial spillover effect in the dynamic evolution of China's agricultural green production level.

Figure 3 is presented here to highlight the study of green agricultural production in China.

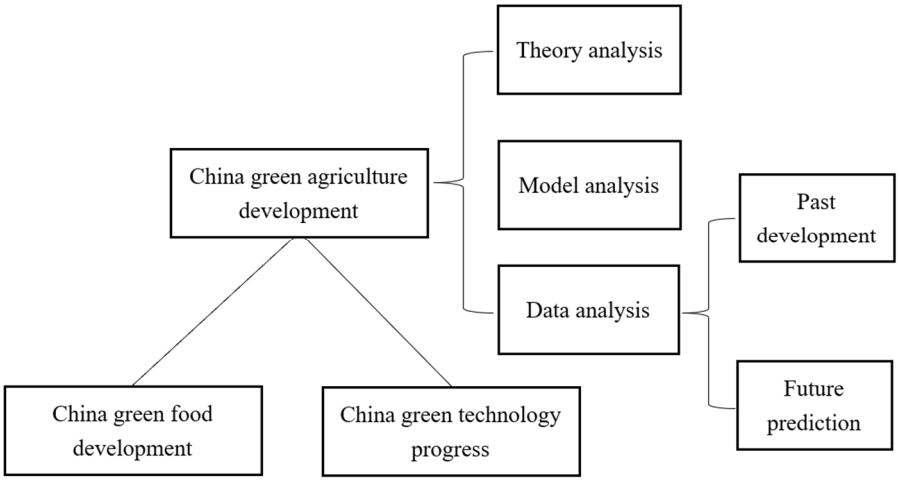


Figure 3. Study of green agricultural production in China.

5. Conclusions

This paper examines the level, spatial variation and dynamic evolution of green agricultural production levels in 31 provinces in China from 2011 to 2021. This paper uses a comprehensive evaluation model, entropy method, Gini coefficient decomposition, convergence test, kernel density estimation and Markov chain for a comprehensive analysis. The conclusions drawn in this paper are as follows: First, China's level of green agricultural production has repeatedly fluctuated at a low level, and the degree of uneven regional development is increasing. The level of green agricultural production in the central region is higher than that in the eastern and western regions. Secondly, differences within the eastern, central and western regions are all on a widening trend. The interaction between inter- and intra-regional differences is the main cause of the overall differences. Third, the possibility of upward shifts increases over time for low, medium–low and medium–high level regions. However, the higher the level, the more difficult it is to shift upwards. Fourth, there is a spatial spillover effect in the dynamic evolution of China's agricultural green production level. Being a neighbor of a high-level region can increase the probability of upward shifts. And this spatial spillover effect becomes more obvious over time.

However, this paper still has the following limitations. Follow-up articles could have chosen more targeted areas to obtain accurate conclusions. For example, Northeast China is a major grain-producing province in China, but no research has focused on the level of green production in the region. Second, this paper provides a new sustainable perspective on the level of green production in agriculture, but there may still be missing indicators. We need to examine the level of green agricultural production from a more comprehensive perspective.

Based on these conclusions, we make the following policy recommendations. First, China should focus on improving the level of green agricultural production. It should focus on promoting new modern agricultural production technology systems represented by sustainability. It is also necessary to support the transformation of traditional agricultural production systems into green agricultural production systems. Secondly, the government should promote inter-regional exchanges and the spread of green production technologies. This will reduce regional differences and create a good synergistic development situation. Third, the government should introduce many incentives to encourage provinces with lower levels of production to catch up with those with higher levels. At the same time, provinces with higher levels of green production should play an active leadership role. This can further expand spatial spillover effects.

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