REGIONAL DIFFERENCES, SPATIOTEMPORAL EVOLUTION, AND CONVERGENCE OF AGRICULTURAL GREEN DEVELOPMENT IN CHINA: A COMPARISON BASED ON TWO TYPES OF REGIONAL DIVISIONS

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Abstract. This study, aiming a comparative analysis of two types of regional divisions, employs multiple research methodologies, including the Dagum Gini coefficient, Kernel density estimation, Markov chains, and convergence analysis, to empirically examine regional differences, evolutionary trends, and convergence issues in China’s agricultural green development. Findings indicate that within the sample period, the overall level of China's agricultural green development as measured by the Dagum Gini coefficient shows a slight upward trend amid fluctuations, with disparities between regions being the primary cause of the overall regional differences in agricultural green development levels; All sample regions demonstrate a rightward shift over time in the centers and variance of Kernel density curves, indicating continuous improvements in the level of agricultural green development; There is a high degree of mobility between states of agricultural green development levels, with relative positions of various types of regions within the distribution being quite unstable and highly variable; σ-convergence is not evident, however, absolute β-convergence and conditional β-convergence are present; Comparative analysis of different regional divisions reveals that finer regional divisions provide more accurate estimation results, bringing the research findings closer to reality. Consequently, coarser regional divisions may introduce certain biases and potentially obscure some actual conditions.
Keywords: *agricultural green development, Dagum Gini coefficient, Kernel density estimation, Markov chains, convergence analysis*

Introduction

Over an extended period, China's high-input, high-consumption extensive agricultural development has increasingly exacerbated environmental and ecological issues, making a green transformation of agriculture urgently necessary (Song et al., 2023). Achieving agricultural green development has become a critical issue in the development of agriculture and rural areas in China today.

Agricultural green development is crucial not only for national food security, modernization of agriculture and rural areas, and improvement of people's livelihoods but it also represents a vital component of the entire natural ecosystem and socio-economic system responce to climate change and sustainable development (Zhang et al., 2021). In recent years, China has been committed to accelerate the green transformation of its development modes, promoting the greening and decarbonization of economic and social development, and forming green, low-carbon production and lifestyle methods. The "14th Five-Year Plan for National Agricultural Green Development" explicitly aims to significantly improve resource utilization, enhance the quality of the production environment, improve agricultural ecosystems, increase the supply of green products, and enhance the capacity to reduce emissions and sequester carbon.

Emphasizing sustainable development and pursuing a path of green development that fosters a harmonious coexistence of humans and nature are common features and systematic insights of developed agricultural countries globally. For China, a strong agriculture requires robust sustainable development capabilities (Jin et al., 2023). Agricultural green development is a stable and gradual process of change towards a set direction (Li, 2023), serving as an effective means to alleviate constraints on agricultural development (Singh, 2000). Environmental issues must be considered within the framework of sustainable agricultural economic development (Ruttan, 2002) and effective measures should be actively implemented (Scherer et al., 2018). Currently, China's agricultural green development has transitioned from a pollution control stage to a carbon reduction and sink enhancement stage, gradually establishing a pattern of agricultural green development and ecological value enhancement (Du et al., 2023). Efforts are being made to build an integrated industrial system that merges agricultural and ecological product production, combining ecological reproduction with economic reproduction to jointly enhance ecological and economic efficiencies (Li, 2022).

Current research on agricultural green development can broadly be categorized into three types. The first type of research focuses on analyzing factors influencing agricultural green development, such as finance (Amaruzaman, 2017), technological innovation (Karlsson et al., 2021), technical services (Gargano et al., 2021), agricultural insurance (Zhou et al., 2024), integration of rural industries (Tian et al., 2024), agricultural trade (Yang et al., 2024), agricultural water rights trading (Yao et al., 2023), digitalization (Pu Xujin et al., 2023), inclusive digital finance (Wang et al., 2023), agricultural mechanization (Kansanga, 2019; Wang et al., 2023), and environmental regulations (Ma et al., 2021). These studies propose hypotheses based on the theoretical mechanisms between agricultural green development and its influencing factors, construct empirical analysis models, and conduct quantitative analyses to verify the hypotheses. The second type of research involves measuring the level of agricultural green development and analyzing regional differences (Qi et al., 2018, 2020; Gong et al., 2020). These studies typically involve constructing an index system to calculate and compare the levels of agricultural green development across different regions. The third type of research analyzes the historical logic behind China's agricultural green development (Feng et al., 2021; Gao et al., 2023; Jin et al., 2024). These studies systematically trace the history of China's agricultural green development, identify key issues that need to be addressed in current agricultural green development, and offer relevant recommendations.

The aforementioned literature provides certain ideas for this study; however, existing research that is most closely aligned with our framework and involves regional disparity analysis still has significant room for expansion in two aspects. Firstly, the indicator systems constructed are missing many metrics, which impedes the scientific measurement of the levels of agricultural green development. Moreover, the analytical methods employed, such as the Theil index and other traditional tools, not only lack accuracy in identifying sources and contributions of disparities but also fail to effectively address issues of sample overlap across groups, which hinders precise assessments of the state of agricultural green development. Secondly, these studies only utilize one regional division standard when analyzing regional differences. Would different findings emerge if various

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regional division standards were employed? Are there relatively better regional division standards? These issues have not been addressed at all in existing studies.

How to further enhance the level of agricultural green development and promote sustainable agricultural green development is a very important topic. China's vast territory features significant heterogeneity in policy environments and resource endowments across different regions, potentially leading to noticeable differences in the levels and pace of agricultural green development, which in turn affects the achievement of high-quality agricultural green development. Therefore, accurately understanding the regional differences, spatiotemporal evolution, and convergence of agricultural green development holds substantial theoretical and practical value.

Compared to existing literature, this study makes marginal contributions in two aspects. Firstly, it employs an improved system of indicators for agricultural green development, utilizing multiple research methodologies including the Dagum Gini coefficient, Kernel density estimation, Markov chains, and convergence analysis to conduct empirical analysis, providing a scientific basis for more accurately assessing the regional disparities, distributional evolution, and convergence of China's agricultural green development at this stage. Secondly, during the analysis, the study adopts a layered subdivision approach, utilizing two methods of regional division, involving the division of sample areas into three regions: east, central, and west for the first method, and further subdividing these into seven major geographical areas for the second method, to conduct further analysis. The results of both regional division calculations are compared, thus providing guidance for such studies from the perspective of regional division.

Research Hypothesis

Due to differences in natural resource endowments, levels of socioeconomic development, and policy support, the levels of green agricultural development vary across regions, leading to significant regional disparities in China's agricultural green development.

First, from the dimension of natural resource endowments, China is vast, and there are significant differences among regions in terms of natural resource endowments such as geographic location, water resources, arable land resource, climate conditions, and biodiversity. Since agricultural development is closely related to natural endowments, these differences significantly affect regional agricultural green development. Natural resource endowments can directly affect agricultural green development through factors such as the production environment and can also have indirect effects through technological progress and other factors. Differences in natural resource endowments between regions can have varying degrees of impact on agricultural green development, resulting in disparities in the levels of agricultural green development across regions.

Second, from the dimension of socioeconomic development levels, there is considerable heterogeneity among regions. Overall, the socioeconomic development level in the eastern coastal regions is higher than that in the central and western regions, while the central region is higher than the western region. At a macro level, socioeconomic development influences agricultural green development through various factors, including technological innovation, financial support, fiscal support, and agricultural trade. Therefore, the heterogeneity in socioeconomic development levels among regions leads to disparities in agricultural green development levels.

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Third, from the dimension of policy support, agricultural green development requires strong policy backing to be realized. Only by establishing a sound and effective policy framework can sufficient momentum for agricultural green development be ensured. However, there are significant differences in the selection, combination, coordination, and implementation of policy tools among regions at present. This results in variations in the diversity, synergy, and integration of policy systems, leading to differing effectiveness of policy tools in supporting agricultural green development. The heterogeneous outcomes of policies result in regional disparities in agricultural green development levels.

Hypothesis 1: There are significant regional disparities in the level of agricultural green development in China.

In the process of promoting agricultural green development, many issues require inter-regional cooperation through consultation to be effectively resolved; such cooperation is both a driving force and a safeguard for agricultural green development. However, due to heavy administrative barriers and the independent actions of regions, issues such as the lack of a collaborative governance concept, difficulty in coordinating interests, and the inadequacy of consultation mechanisms have arisen. This has resulted in a fragmented approach to horizontally advancing agricultural green development across regions (Zhao et al., 2024), leading to a dilemma in regional cooperation. Regions have failed to form and utilize synergistic effects; when faced with agricultural green development issues that require joint regional action, they not only shirk responsibility but also exhibit indifference or even resistance to cooperative governance, leading to many deficiencies in the proactivity, stability, and reliability of regional cooperation, cooperation often has a noticeable degree of arbitrariness and informality, which directly results in a lack of effectiveness in addressing issues such as watershed ecological governance, soil restoration and remediation, and air pollution control, so the cross-regional issues that hinder agricultural green development are difficult to resolve effectively and thoroughly. Since the difficulties of regional cooperation usually occur in geographically adjacent regions, the difficulty of inter-regional cooperation will gradually emerge with the further refinement of regional division, resulting in a decline in the mobility between the levels of agricultural green development and a slowing down of the adjustment speed.

Hypothesis 2: With the gradual refinement of regional division, the fluidity between agricultural green development levels will decline, and the adjustment speed of spatial disequilibrium will slow down.

At present, China is comprehensively advancing the rural revitalization strategy, guiding agriculture and rural areas towards modernization. Agricultural green development, as an important component of the rural revitalization strategy, has also entered a phase of key breakthroughs and comprehensive promotion. The national level has continuously introduced various regulations and documents to establish a framework for promoting agricultural green development. Regions have also placed great importance on agricultural green development, practicing the concept of green development and seeking ways to transform agricultural green development, cultivating green production and management mode, and effectively promoting the green development of agriculture.

After the implementation of the rural revitalization strategy, agricultural green development has received stronger impetus and made more substantial progress. In this context, does the level of agricultural green development converge or diverge? Over the past few decades, China has been continuously improving its economic development system, deepening factor market reforms, breaking local protectionism and market segmentation, unblocking key bottlenecks that restrict economic circulation and

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promoting the smooth flow of commodity factor resources across a broader scope, accelerating the construction of a highly efficient, standardized, fair, and fully open national unified market, and providing a relatively complete factor market environment for agricultural green development. Based on the economic convergence theory in neoclassical economics, in the long run, the free flow of production factors equalizes factor returns, thereby promoting the convergence of economic disparities. The mobility of factors influences the evolution of agricultural green development; as the factor market environment improves, the mobility of factors increases. At this point, when compared to other regions, the development speed of low-level agricultural green development areas may exceed that of high-level regions due to the "learning effect" and the utilization of "latecomer advantages". This may lead to a gradual convergence of agricultural green development levels across regions. When referencing itself, the level of agricultural green development may converge to a stable state over time.

Hypothesis 3: There is a "catch-up effect" in China's agricultural green development, where low-level regions strive to reach high-level regions.

Hypothesis 4: The level of agricultural green development in China will converge to its own steady state over time.

Research Design

Research Methods

Dagum Gini Coefficient

There are many methods for analyzing spatial imbalance among variables, but most have notable shortcomings. For instance, standard deviation, coefficient of variation, weighted coefficient of variation, and traditional Gini coefficient cannot re-decompose regional differences, while the Theil index can decompose regional differences, it cannot describe the distribution of subsamples, and it also does not address the issue of cross-over overlap between samples, which affects measurement accuracy. In contrast, the Dagum Gini coefficient effectively addresses the sources of regional disparities and describes the distribution of subsamples. This effectively resolves the issue of cross-over overlap between samples, offering better accuracy, sensitivity, and applicability, thus better meeting the research needs of this paper.

This study utilizes the Dagum Gini coefficient and its decomposition method to describe the regional disparities in China's agricultural green development. Unlike the traditional Gini coefficient, the Dagum Gini coefficient introduces a parameter that adjusts the calculation of the Gini coefficient, making it more flexible. It represents an expansion and refinement of the traditional Gini coefficient.

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

$$\overline{Y}_h \leq \cdots \overline{Y}_j \leq \cdots \overline{Y}_k \tag{Eq.2}$$

In the above formula, G represents the overall Gini coefficient, with a higher value indicating greater overall disparity in agricultural green development; k denotes the number of regions divided; y_{ji}(y_{hr})represents the level of agricultural green development for any sample in the j(h) region; k denotes the number of regions divided; n_j(n_h)

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represents the number of provinces, cities, and autonomous regions in the j(h) region; and $\bar{y}$ represents the average of agricultural green development.

The Dagum Gini coefficient, according to subgroup decomposition, divides the overall Gini coefficient G into contributions from within-region disparities (G_w), between-region disparities (G_{nb}), and transvariation density contributions (G_t), such that $G= G_w+ G_b+ G_t$.

The within-region disparity coefficient (G_{jj}) measures the differences in agricultural green development among different provinces, cities, and autonomous regions within a region, calculated as follows:

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji}-y_{jr}|}{2n_j^2\bar{Y}_j} \qquad \text{(Eq.3)}$$

The between-region disparity coefficient (G_{jh}) measures the differences in agricultural green development between different regions, and is calculated as follows:

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji}-y_{jr}|}{n_j n_h(\bar{Y}_j+\bar{Y}_k)} \qquad \text{(Eq.4)}$$

Thus, the within-region disparity contribution (G_w) is:

$$G_w = \sum_{j=1}^{k} G_{jj}P_jS_j \qquad \text{(Eq.5)}$$

The between-region disparity contribution (G_{nb}) is given by:

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right) \qquad \text{(Eq.6)}$$

The transvariation density contribution (G_t) is:

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right) \qquad \text{(Eq.7)}$$

where, $p_j = \frac{n_j}{n}$, $s_j = \frac{n_j\bar{Y}_j}{n\bar{Y}}$, for j = 1, 2, 3, …, K. D_{jh} represents the degree of influence of the contribution rate of agricultural green development levels between regions j and h, calculated as follows:

$$D_{jh} = \frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}} \qquad \text{(Eq.8)}$$

where, d_{jh} is the difference in the contribution rates of agricultural green development levels between regions, calculated as the expected sum of all sample values where $y_{jt}-y_{hr} > 0$ for regions j and h; P_{jh} is the first moment of transvariation, calculated as the expected sum of all sample values where $y_{hr}-y_{jt} > 0$ for regions j and h. The specific calculations for d_{jh} and P_{jh} are as follows:

$$d_{jh} = \int_0^{\infty} dF_j(y)\int_0^{y}(y-x)dF_h(x) \qquad \text{(Eq.9)}$$

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$$P_{jh} = \int_0^\infty dF_h(y) \int_0^y (y - x) dF_j(x) \tag{Eq.10}$$

where, $F_j(F_h)$ denotes the cumulative density distribution function for region j(h).

Kernel Density Estimation

Kernel density estimation adapts well to different types of data distributions and helps address issues of distributional balance. This study employs this method to reveal the evolutionary characteristics of agricultural green development distribution and the absolute differences between regions, to show the spatiotemporal evolution process of the difference change of agricultural green development in different regions, serving as a complement and enhancement to the relative differences depicted by the Dagum Gini coefficient.

Kernel density estimation is a non-parametric method used to estimate the probability distribution of a random variable whose density function is unknown, employing a continuous density curve to depict the distribution's shape. It concretizes the variable's distribution location, shape, and spread, serving as a conventional method for studying uneven distributions. Unlike parametric estimation, Kernel density estimation does not assume any specifics about the model's structure and can freely determine the function form, thus it has less dependency on the model and offers greater robustness. Assuming f(x) is the density function of the random variable x, the probability density at point x is given by:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{Eq.11}$$

$$K(x) = \frac{1}{\sqrt{2p}} \exp\left(-\frac{x^2}{2}\right) \tag{Eq.12}$$

In the formula above, N represents the number of observations; K(x) is the kernel function, a type of weighting function or smoothing transformation; X_i is independent and identically distributed observations, x is the mean; h is the bandwidth.

Markov Chain Analysis

Markov chain is a Markov process with discrete time and states. This method can effectively reveal the state transition characteristics of regional agricultural green development levels, reflecting the internal dynamics and evolution of these levels. Utilizing Quah's (1996) Markov chain estimation method, this study conducts a dynamic evolution analysis of the level of agricultural green development, depicting the internal dynamics and evolutionary processes of agricultural green development levels. A Markov chain is a state space of a discrete-time stochastic process $\{X(t), t \in T\}$, which is the set of all possible values. For time t, any n random values, the Markov chain satisfies:

$$\begin{aligned} &P\{X(t_n) \le x_n | X(t_1) = x_1, X(t_2) = x_2, \cdots, X(t_{n-1}) = x_{n-1}\} \\ &= P\{X(t_n) \le x_n | X(t_{n-1}) = x_{n-1}\}, x_n \in R \end{aligned} \tag{Eq.13}$$

In this context, $X(t_n)$ represents the conditional distribution function given $X(t_i)=x_i$. Assuming that the transition probabilities depend only on states i and j, and are independent of n, a homogeneous Markov chain can be derived:

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$$P\{X_{n+1} = j|X_0 = i_0, X_1 = i_1, X_2 = i_2, \cdots, X_{n-1} = i_{n-1}, X_n = i\} = P\{X_{n+1} = j|X_n = i\} \quad \text{(Eq.14)}$$

The formula expresses the probability distribution of a random variable transitioning from one state space to another. If the level of agricultural green development in China is classified into N types, a Markov chain can generate an N×N dimensional state transition probability matrix P, calculated as follows:

$$P = p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1i} & \cdots \\ p_{21} & p_{22} & \cdots & p_{1j} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{i1} & p_{i2} & \cdots & p_{ij} & \cdots \\ \vdots & \vdots & \cdots & \vdots & \vdots \end{bmatrix} \quad \text{(Eq.15)}$$

$$p_{ij} \geq 0,\ \ i\ j \in N \quad \text{(Eq.16)}$$

$$\sum_{j \in N} p_{ij} = 1, i\ j \in N \quad \text{(Eq.17)}$$

In the formula above, p_{ij} represents the transition probability from agricultural green development state i to state j. It is typically estimated using the maximum likelihood method, calculated as follows:

$$p_{ij} = \frac{n_{ij}}{n_i} \quad \text{(Eq.18)}$$

In this formula, n_{ij} denotes the number of times a transition from state i to state j occurs within the sample period; n_i represents the total number of occurrences of state i.

Convergence Analysis

Convergence analysis can effectively reveal the evolving trends of spatial heterogeneity in agricultural green development across regions. This study utilizes this method to conduct relevant research.

(1) σ-Convergence

σ-Convergence measures the changes over time in the deviations of agricultural green development levels across different regions. A decrease in deviations indicates reduced dispersion among regions, signifying σ-convergence; an increase in deviations indicates growing dispersion, signifying no σ-convergence. This study uses the coefficient of variation to measure σ-convergence, defined as:

$$\sigma = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^{n} [y_{ij} - \bar{y}]^2}{n}} \quad \text{(Eq.19)}$$

In the above formula, y_{ij} represents the level of agricultural green development for the i-th sample in the j-th group, $\bar{y}$ represents the average level of agricultural green development within the j-th group, and n denotes the number of samples in the j-th group.

(2) β-Convergence

β-Convergence analyzes the evolutionary trends of agricultural green development from the perspective of growth rates; absolute β-Convergence measures the convergence

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of agricultural green development among different regions, conditional β-Convergence measures the convergence of agricultural green development towards its own state.

Absolute β-convergence, using other regions as references, reflects the "catch-up effect" of lower-level agricultural green development regions towards higher-level regions, modeled as follows:

$$\ln\left(\frac{y_{it}}{y_{i0}}\right)/T = \alpha_0 + \beta\ln(y_{i0}) + \varepsilon_{it} \quad \text{(Eq.20)}$$

In the formula above, if β is less than 0 and passes the significance test, then absolute β-convergence exists; otherwise, there is no absolute β-convergence.

Conditional β-convergence, using the region itself as a reference, reflects whether agricultural green development levels are converging towards their own steady state, modeled as follows:

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right)/T = \alpha_0 + \beta\ln(y_{it-1}) + \varepsilon_{it} \quad \text{(Eq.21)}$$

In the formula above, conditional β-convergence exists if β is less than zero and it passes the significance test; otherwise, there is no conditional β-convergence.

Based on the estimates of absolute and conditional convergence, the convergence rate can be further calculated as follows:

$$\nu = -\ln(1+\beta)/T \quad \text{(Eq.22)}$$

In the above formula, ν represents the rate of convergence, and T represents the time period.

Variable Description

To comprehensively reflect the state of agricultural green development, this article, considering the complexity of agricultural green development and the availability of research data, and referencing the "14th Five-Year National Plan for Agricultural Green Development" issued by China in 2021, draws on and adjusts the existing research findings of Zou et al. (2023), Su et al. (2021), and He et al. (2021). From the dimensions of resource utilization, green production, ecological environmental management, livelihood protection, and economic benefits, 25 indicators were selected to construct an indicator system for measuring the level of agricultural green development (*Table 1*), the level of agricultural green development was calculated by entropy method.

Data Sources

Due to the limited availability of some variable data, this study analyzes panel data from 2006 to 2022 for 30 provinces, cities, and autonomous regions in China, excluding Hong Kong, Macau, Taiwan, and Tibet. The sample data are sourced from the "China Rural Statistics Yearbook," "China Science and Technology Statistics Yearbook," "China Statistical Yearbook," "China Financial Yearbook," "China Leisure Agriculture Yearbook," "China Tertiary Industry Statistics Yearbook," and the National Greenhouse Data System. Linear interpolation is used to fill in missing data. Linear interpolation assumes that the change between data points is linear and estimates the data at other

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locations between these points by using a straight line between the known data points. The formula for linear interpolation is Y = Y1 + (Y2 - Y1) (X - X1) / (X2 - X1), where Y is the value to be interpolated, Y1 and X1 represent the most recent known data points before Y, and Y2 and X2 represent the most recent known data points after Y.

Table 1. *Evaluation indicator system for the level of agricultural green development*

Primary Indicator	Secondary Indicator	Definition
Resource Utilization	Agricultural Electricity Intensity	Agricultural electricity consumption / Total agricultural output
	Agricultural Water Intensity	Total agricultural water use / Total agricultural output
	Cropping Intensity Index	Cropped area / Arable land area
	Per Capita Arable Land	Rural population / Arable land area
Green Production	Pesticide Usage Intensity	Pesticide application / Cropped area
	Fertilizer Usage Intensity	Fertilizer application / Cropped area
	Agricultural Film Intensity	Agricultural film used / Cropped area
	Effective Irrigation Rate	Effectively irrigated area / Arable land area
	Agricultural Machinery Intensity	Total power of agricultural machinery / Cropped area
	Scale of Protected Agriculture	Area of protected agriculture / Arable land area
Ecological Environmental Management	Forest Coverage Rate	Forest-covered area / Provincial area
	Forest Stock Volume	Total volume of timber in forests
	Soil Erosion Control Rate	Soil erosion controlled area / Provincial area
	Wetland Area Ratio	Wetland area / Jurisdictional area
	Natural Reserve Area Ratio	Natural reserve area / National territory
	Level of Ecological Afforestation	Area of ecological afforestation
	Artificial Ecological Water Replenishment	Volume of water replenished in artificial ecological environments
	Disaster Resistance Index	(Disaster-affected area - disaster-stricken area) / Disaster-affected area
	Unit Value COD Emission Intensity	COD emissions from agriculture / Total agricultural output
	Unit Value Ammonia Nitrogen Emission Intensity	Ammonia nitrogen emissions from agriculture / Total agricultural output
Livelihood Security	Rural Medical Security	Number of rural doctors and health workers per thousand rural population
	Rural Social Security	Minimum living security expenditures
Economic Benefits	Urban-Rural Income Ratio	Urban resident income / Rural resident income
	Contribution Rate of Agricultural Services	Output value of agricultural services / Primary industry output
	Level of Development of Recreational Agriculture	Operating income from recreational agriculture / Total output of agriculture, forestry, animal husbandry, and fishery

Results

Dagum Gini Coefficient and Its Decomposition

This study initially divides the sample into three major regions: East, Central, and West. Based on the Dagum Gini coefficient and its decomposition method, it calculates the overall Gini coefficient for agricultural green development and the situation by region.

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The second column of *Table 2* reports the overall Gini coefficient for agricultural green development across China, according to the calculation results, there are significant regional differences in China's agricultural green development levels, verifying Hypothesis 1. According to the calculations, the overall Gini coefficient fluctuated slightly within the range of 0.099 to 0.123, showing a "rise-fall-rise-fall-rise" pattern with an average of 0.1111. The years 2008, 2009, and 2013 had Gini coefficients significantly above the average, with fourteen other years being either below or slightly above the average. The average annual growth rate of the Gini coefficient during the sample period was 0.22%, showing a slight upward trend amidst fluctuations. From 2006 to 2013, the growth was faster, with an average annual increase of 0.99%, particularly between 2006 and 2009, when it reached 2.32%. However, it then stabilized, with Gini coefficients around 0.113 from 2019 to 2022, showing more decreasing trend compared to the peak (0.123). This change might be attributed to the comprehensive advancement of the China’s Rural Revitalization Strategy, which improved the previously uneven levels of agricultural green development.

Table 2. *Gini coefficients and contribution rates of agricultural green development*

Time	Gini Coefficient				Contribution Rate (%)		
	Overall	Within-region disparity	Between-region disparity	transvariation density	Within-region disparity	Between-region disparity	transvariation density
2006	0.105	0.032	0.016	0.057	30.859%	15.120%	54.021%
2007	0.112	0.034	0.018	0.059	30.815%	16.507%	52.678%
2008	0.120	0.037	0.013	0.070	31.052%	10.597%	58.351%
2009	0.123	0.039	0.006	0.078	31.455%	5.031%	63.515%
2010	0.115	0.036	0.005	0.073	31.299%	4.740%	63.961%
2011	0.109	0.034	0.012	0.063	31.299%	10.782%	57.919%
2012	0.114	0.035	0.017	0.061	31.160%	15.302%	53.538%
2013	0.123	0.038	0.043	0.043	30.582%	34.708%	34.710%
2014	0.104	0.032	0.024	0.048	30.815%	23.434%	45.751%
2015	0.105	0.032	0.018	0.055	30.614%	17.408%	51.978%
2016	0.105	0.032	0.023	0.050	30.613%	21.600%	47.787%
2017	0.099	0.031	0.016	0.052	31.244%	16.594%	52.162%
2018	0.101	0.031	0.020	0.050	30.273%	19.843%	49.884%
2019	0.112	0.035	0.027	0.050	31.144%	24.448%	44.409%
2020	0.115	0.035	0.023	0.057	30.699%	19.847%	49.454%
2021	0.113	0.035	0.037	0.041	30.887%	32.635%	36.479%
2022	0.114	0.035	0.038	0.041	30.926%	32.919%	36.155%

The transvariation density Gini coefficient reflects the overlapping phenomena of agricultural green development levels between the East, Central, and West regions. Although it decreased at an annual rate of 0.89% during the sample period, it was consistently higher than the contributions of within-region and between-region disparities. In nine sample years, its contribution rate exceeded 50%, reaching as high as 63.961% in 2010, and remained the primary cause of the overall regional disparities in agricultural green development levels until 2022. Furthermore, the average within-region Gini coefficient (0.0343) is significantly higher than the between-region average (0.0209), indicating that the internal imbalances within the East, Central, and West regions have a greater impact on the disparities in agricultural green development levels compared to the disparities between these regions.

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Table 3 reports on the decomposition of the Dagum Gini coefficient for agricultural green development. According to the calculations, in terms of within-region Gini coefficients, fluctuations in the Eastern region are slightly larger, with a maximum and minimum difference of 0.037, while the differences for the Central and Western regions are 0.029 and 0.030, respectively. The within-region Gini coefficient in the Eastern region has shown an increasing trend over the sample period, with an average annual growth rate of 0.75%, whereas the Gini coefficients in the Central and Western regions have decreased, with average annual rates of -0.18% and -0.11%, respectively. From the perspective of Gini coefficient levels, those of the Eastern and Central regions are relatively close, while the Western region consistently shows significantly higher values; the average within-region Gini coefficient is lowest in the Central region (0.0822), followed by the Eastern region (0.0868), and the highest in the Western region (0.1473), indicating that agricultural green development levels are relatively more balanced among the provinces, cities, and autonomous regions within the Central and Eastern regions, whereas the imbalance within the Western region is more severe than in the Central and Eastern regions.

Table 3. *Decomposition of Dagum gini coefficient for agricultural green development levels*

Time	Within-region Disparity			Between-region Disparity		
	East	Central	West	East-Central	East-West	Central-West
2006	0.076	0.076	0.151	0.078	0.129	0.128
2007	0.082	0.088	0.150	0.092	0.132	0.132
2008	0.086	0.099	0.163	0.097	0.141	0.143
2009	0.095	0.099	0.163	0.102	0.142	0.145
2010	0.085	0.087	0.161	0.090	0.136	0.138
2011	0.083	0.085	0.148	0.087	0.129	0.128
2012	0.085	0.095	0.151	0.093	0.133	0.134
2013	0.108	0.089	0.135	0.111	0.149	0.131
2014	0.086	0.073	0.133	0.083	0.128	0.121
2015	0.080	0.072	0.147	0.079	0.131	0.128
2016	0.082	0.075	0.140	0.081	0.128	0.128
2017	0.078	0.075	0.133	0.079	0.118	0.117
2018	0.071	0.075	0.143	0.076	0.123	0.128
2019	0.096	0.076	0.142	0.090	0.137	0.129
2020	0.085	0.092	0.154	0.091	0.138	0.142
2021	0.098	0.070	0.145	0.090	0.143	0.128
2022	0.100	0.071	0.145	0.092	0.144	0.129

Regarding between-region Gini coefficients, from an evolutionary perspective, the Gini coefficients between East-Central, East-West, and Central-West have all shown an increasing trend during the sample period, with average annual growth rates of 0.45%, 0.30%, and 0.02%, respectively. From the level of Gini coefficients, the average Gini coefficient between the Eastern and Western regions is 0.1342, the highest among the three regional comparisons, followed by the average between the Central and Western regions (0.1311), and the smallest between the Eastern and Central regions (0.0889). This indicates that the disparity in agricultural green development levels between the Eastern and Western regions is large, highlighting significant regional imbalances, while the gap between the Eastern and Central regions is relatively smaller.

Considering that the division into East, Central, and West regions is rather coarse, this study further divides the sample into seven major geographical regions to observe the disparities and trends in agricultural green development at a more detailed level. *Table 4* reports the Gini coefficients and contribution rates for agricultural green development levels calculated by dividing into seven major geographical regions. The results indicate that, after further subdivision, the impact of within-region imbalances on disparities in agricultural green development levels significantly reduces, while the influence of between-region disparities significantly increases. Over time, within the sample period, both the within-region disparities and transvariation densities show a decreasing trend, with average annual growth rates of -0.20% and -1.23%, respectively. In contrast, between-region disparities are increasing, with the Gini coefficient growing from 0.030 in 2006 to 0.063 in 2022, an average annual growth rate of 2.03%. The contribution rate of between-region disparities first exceeded the contribution rate of transvariation densities in 2011. Between 2011 and 2018, the contribution rates of between-region disparities and transvariation densities varied, but since 2019, the contribution rate of between-region disparities has consistently exceeded that of transvariation densities, becoming the primary cause of overall regional disparities in agricultural green development levels.

Table 4. *Gini coefficients and contribution rates for agricultural green development across seven major geographical regions*

Time	Gini Coefficient			Contribution Rate (%)		
	Within-region disparity	Between-region disparity	transvariation density	Within-region disparity	Between-region disparity	transvariation density
2006	0.014	0.030	0.060	13.269%	28.999%	57.732%
2007	0.015	0.042	0.055	13.035%	37.370%	49.595%
2008	0.016	0.041	0.063	13.091%	34.334%	52.575%
2009	0.016	0.043	0.063	13.338%	35.264%	51.398%
2010	0.015	0.044	0.055	13.368%	38.361%	48.271%
2011	0.014	0.048	0.047	12.959%	44.058%	42.983%
2012	0.015	0.049	0.050	13.115%	43.193%	43.691%
2013	0.016	0.062	0.045	12.802%	50.542%	36.656%
2014	0.012	0.045	0.046	11.976%	43.535%	44.489%
2015	0.013	0.042	0.051	12.037%	39.456%	48.507%
2016	0.012	0.050	0.043	11.489%	47.613%	40.898%
2017	0.012	0.045	0.042	12.359%	45.018%	42.622%
2018	0.012	0.041	0.048	12.309%	40.160%	47.531%
2019	0.013	0.060	0.039	11.571%	53.692%	34.736%
2020	0.013	0.053	0.049	11.354%	46.383%	42.263%
2021	0.013	0.062	0.038	11.610%	54.729%	33.661%
2022	0.013	0.063	0.038	11.578%	55.235%	33.187%

Compared to findings from the division into East, Central, and West regions, conclusions drawn from dividing into seven major geographical regions align more closely with the actual situation in China. This suggests that a finer regional division in the decomposition of the Dagum Gini coefficient yields findings that are more reflective of reality, whereas a coarser regional division may introduce some degree of bias.

Table 5 reports the Dagum Gini coefficients within the seven major geographical regions regarding the level of agricultural green development. The data show that during the sample period, from an evolutionary perspective, the internal Gini coefficients in the East China, South China, and Southwest regions have shown a decreasing trend, with annual rates of -1.30%, -2.80%, and -0.37% respectively. The rate of decrease in South China is relatively faster, indicating that the issue of uneven green agricultural development within these regions is gradually alleviating. Conversely, the Central China, North China, Northeast, and Northwest regions have exhibited an increasing trend in their internal Gini coefficients, with annual rates of 0.35%, 1.44%, 0.46%, and 0.43% respectively, suggesting that the disparity in green agricultural development within these areas has become more pronounced over time.

Table 5. *Decomposition of intra-regional Dagum gini coefficients for agricultural green development levels across seven major geographical regions*

Time	East China	South China	Central China	North China	Northeast	Northwest	Southwest
2006	0.081	0.077	0.065	0.059	0.038	0.106	0.179
2007	0.089	0.068	0.050	0.077	0.048	0.097	0.171
2008	0.088	0.068	0.082	0.092	0.054	0.100	0.185
2009	0.099	0.047	0.085	0.105	0.072	0.097	0.177
2010	0.094	0.038	0.071	0.091	0.060	0.112	0.158
2011	0.089	0.035	0.073	0.084	0.053	0.096	0.146
2012	0.094	0.042	0.075	0.091	0.066	0.100	0.148
2013	0.115	0.019	0.045	0.096	0.073	0.074	0.156
2014	0.079	0.017	0.028	0.072	0.072	0.077	0.152
2015	0.072	0.036	0.028	0.080	0.053	0.090	0.155
2016	0.064	0.028	0.033	0.085	0.056	0.080	0.149
2017	0.070	0.032	0.030	0.086	0.055	0.083	0.137
2018	0.056	0.029	0.034	0.088	0.062	0.114	0.142
2019	0.051	0.029	0.046	0.103	0.055	0.123	0.138
2020	0.038	0.067	0.039	0.114	0.069	0.118	0.159
2021	0.051	0.025	0.073	0.098	0.045	0.123	0.156
2022	0.050	0.027	0.074	0.100	0.045	0.124	0.156

From the perspective of Gini coefficient levels, the Southwest region has the highest mean internal Gini coefficient (0.1567), significantly above the other six regions. Despite a downward trend during the sample period, its Gini coefficient remained the highest in 2022, likely linked to the "sinking" status of Yunnan and Guizhou provinces. The Northwest region, with a mean internal Gini coefficient of 0.1008, ranked second. Unlike the Southwest, the Northwest has shown a noticeable upward trend, steadily approaching the Southwest's levels. Without corrective measures, it may surpass the Southwest in the coming years, becoming the most uneven region in terms of green agricultural development. The mean internal Gini coefficients for North China and East China are 0.0895 and 0.0753 respectively, with North China's rate of increase being the highest, necessitating focused attention to this issue. The mean coefficients for South China, Central China, and the Northeast are relatively low at 0.0402, 0.0548, and 0.0574 respectively, indicating a more balanced level of green agricultural development among the provinces, cities, and autonomous regions within these areas.

Tables 6, 7, and 8 present the decomposition of Dagum Gini coefficients between regions within the seven major geographical areas regarding agricultural green development. According to the estimations, the inter-regional Gini coefficients between East China-Central China, East China-Southwest, South China-Northeast, South China-Southwest, Central China-Northeast, Central China-Southwest, Northeast-Southwest, and Northwest-Southwest have shown a declining trend during the sample period, with annual average rates of -0.52%, -0.41%, -1.09%, -0.19%, -0.34%, -0.44%, -0.14%, and -0.22% respectively, indicating a gradual narrowing of disparities in green agricultural development. Conversely, the inter-regional Gini coefficients between East China-South China, East China-North China, East China-Northeast, East China-Northwest, South China-Central China, South China-North China, Central China-North China, Central China-Northwest, North China-Northeast, North China-Northwest, North China-Southwest, and Northeast-Northwest have shown an increasing trend, with annual average rates of 0.88%, 0.44%, 0.32%, 0.42%, 0.77%, 1.67%, 0.70%, 0.58%, 2.29%, 1.39%, 0.12%, and 0.22% respectively, indicating a gradual widening of disparities over time.

Table 6. *Decomposition of inter-regional Dagum gini coefficients for agricultural green development levels across seven major geographical regions*

Time	East China - South China	East China – Central China	East China - North China	East China - Northeast	East China - Northwest	East China - Southwest
2006	0.092	0.086	0.074	0.071	0.108	0.162
2007	0.097	0.100	0.090	0.077	0.115	0.157
2008	0.099	0.105	0.097	0.080	0.116	0.173
2009	0.090	0.098	0.111	0.094	0.117	0.173
2010	0.079	0.088	0.101	0.087	0.118	0.160
2011	0.076	0.086	0.099	0.090	0.114	0.145
2012	0.080	0.089	0.105	0.094	0.122	0.143
2013	0.144	0.108	0.110	0.103	0.154	0.163
2014	0.106	0.073	0.081	0.087	0.118	0.141
2015	0.103	0.066	0.082	0.073	0.119	0.146
2016	0.121	0.063	0.080	0.074	0.126	0.142
2017	0.096	0.059	0.082	0.073	0.109	0.128
2018	0.092	0.051	0.079	0.067	0.111	0.137
2019	0.108	0.052	0.098	0.080	0.122	0.131
2020	0.082	0.041	0.113	0.074	0.113	0.150
2021	0.125	0.071	0.086	0.078	0.125	0.139
2022	0.127	0.071	0.087	0.080	0.126	0.139

From the level of Gini coefficients, the inter-regional Gini coefficient between Northwest-Southwest is the highest (0.1699), followed by South China-Southwest and North China-Southwest with averages of 0.1591 and 0.1511 respectively, ranking second and third, indicating significant disparities in green agricultural development. Additionally, imbalances are relatively pronounced between Central China-Southwest (0.1501), East China-Southwest (0.1488), Northeast-Southwest (0.1479), North China-Northwest (0.1388), South China-North China (0.1224), and Northeast-Northwest (0.1128). The smallest mean Gini coefficient is between Central China-Northeast (0.0759), followed by East China-Central China (0.0769), East China-Northeast (0.0813),

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South China-Central China (0.0845), South China-Northeast (0.0878), South China-Northwest (0.0886), Central China-North China (0.0922), North China-Northeast (0.0924), and East China-North China (0.0926), where disparities in green agricultural development are relatively small and imbalances are less pronounced.

Table 7. *Decomposition of inter-regional Dagum gini coefficients for agricultural green development levels across seven major geographical regions*

Time	South China - Central China	South China - North China	South China - Northeast	South China - Northwest	South China - Southwest	Central China - North China	Central China - Northeast	Central China - Northwest	Central China - Southwest
2006	0.076	0.088	0.093	0.104	0.166	0.082	0.084	0.097	0.166
2007	0.067	0.106	0.089	0.095	0.166	0.116	0.094	0.090	0.169
2008	0.087	0.114	0.084	0.091	0.183	0.115	0.099	0.106	0.182
2009	0.083	0.115	0.096	0.088	0.182	0.111	0.094	0.113	0.176
2010	0.066	0.100	0.083	0.095	0.165	0.096	0.084	0.109	0.162
2011	0.070	0.100	0.087	0.082	0.149	0.089	0.075	0.113	0.141
2012	0.074	0.105	0.092	0.087	0.149	0.095	0.081	0.120	0.142
2013	0.066	0.136	0.126	0.063	0.162	0.094	0.091	0.083	0.152
2014	0.093	0.117	0.113	0.065	0.154	0.062	0.073	0.093	0.141
2015	0.093	0.110	0.109	0.080	0.161	0.063	0.056	0.100	0.147
2016	0.090	0.127	0.095	0.072	0.159	0.074	0.054	0.092	0.146
2017	0.096	0.116	0.082	0.077	0.143	0.072	0.054	0.095	0.128
2018	0.091	0.110	0.077	0.096	0.149	0.075	0.057	0.106	0.137
2019	0.098	0.161	0.060	0.100	0.145	0.102	0.070	0.118	0.132
2020	0.088	0.154	0.083	0.104	0.161	0.111	0.079	0.118	0.148
2021	0.098	0.159	0.061	0.103	0.155	0.105	0.072	0.119	0.141
2022	0.101	0.162	0.062	0.104	0.155	0.106	0.074	0.120	0.141

Table 8. *Decomposition of inter-regional Dagum gini coefficients for agricultural green development levels across seven major geographical regions*

Time	North China - Northeast	North China - Northwest	North China - Southwest	Northeast - Northwest	Northeast - Southwest	Northwest - Southwest
2006	0.053	0.098	0.158	0.096	0.155	0.167
2007	0.071	0.122	0.156	0.100	0.155	0.171
2008	0.084	0.130	0.170	0.101	0.173	0.188
2009	0.097	0.135	0.168	0.116	0.168	0.193
2010	0.082	0.133	0.153	0.117	0.154	0.190
2011	0.074	0.139	0.135	0.127	0.135	0.177
2012	0.085	0.150	0.137	0.137	0.137	0.180
2013	0.093	0.142	0.159	0.138	0.143	0.162
2014	0.082	0.123	0.142	0.128	0.139	0.158
2015	0.076	0.125	0.146	0.124	0.146	0.175
2016	0.086	0.133	0.141	0.108	0.147	0.170
2017	0.087	0.128	0.128	0.097	0.131	0.159
2018	0.090	0.132	0.141	0.107	0.140	0.161
2019	0.136	0.170	0.150	0.106	0.140	0.155
2020	0.133	0.175	0.157	0.109	0.157	0.173
2021	0.119	0.161	0.163	0.103	0.147	0.155
2022	0.122	0.163	0.165	0.104	0.147	0.154

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Kernel Density Estimation

This study takes 2006, 2010, 2015, 2019 and 2022 for example, Kernel density estimation is used to analyze the dynamic distribution trends of agricultural green development levels within the sample period (*Figures 1-11*).

From the perspective of distribution position, the centers and change areas of the distribution curves for all sample regions shift to the right over time, indicating a continuous improvement in the level of green agricultural development. Significant shifts are observed in the overall China, Eastern, Central, East China, South China, Central China, North China, Northeast, and Northwest regions, indicating relatively substantial improvements in green agricultural development levels within these sample regions.

From the perspective of distribution shape, the peak heights decrease for overall China, Eastern, Western, Central China, North China, and Northwest regions; the peak heights for the central, East China, Northeast, and Southwest regions change little; the peak height for South China rises. Regarding peak widths, overall China, Eastern, Western, Central China, North China, and Northwest regions experience an increase, indicating a trend of widening absolute disparities in green agricultural development levels; the peak widths of the central, East China, Northeast, and Southwest regions show no significant change; the peak width of South China decreases significantly, suggesting a reduction in the dispersion of green agricultural development levels and a decrease in absolute disparities.

From the perspective of distribution extension, there is a certain degree of right-skew in overall China, Eastern, and Western regions, indicating a trend of increasing disparities between areas with higher and lower levels of green agricultural development.

From the perspective of polarization trends, the Eastern, North China, and Northwest regions initially exhibit bimodal or multimodal distributions, indicating early signs of polarization or multi-level differentiation in these areas. However, over time, these distributions have transitioned to unimodal; no apparent multimodal distributions occur in the remaining regions during the sample period, predominantly showing unimodal distributions, indicating the absence of polarization. The weakening of polarization in various sample regions might be attributed to the implementation of China's Rural Revitalization Strategy, which has provided support in terms of funding, policies, and personnel to green agricultural development, thereby mitigating issues of polarization or multi-level differentiation.

Markov Chain Analysis

This study categorizes the levels of agricultural green development into four types from low to high: Type I, defined as low level, is below the overall average level of agricultural green development; Type II, defined as moderately low, ranges from 0-10% of the overall average; Type III, defined as moderately high, ranges from 11%-20% of the overall average; and Type IV, defined as high level, is above 21% of the overall average.

Table 9 reports the maximum likelihood estimates of the transition probabilities for levels of agricultural green development. According to the estimates, in the overall Chinese sample, for Type I, 53.1% of areas remain at a low level by year-end, 9.9% rise to a moderately low level, 12.5% advance to a moderately high level, and 24.5% escalate to a high level. For Type II, 7.7% remain at moderately low level by year-end, while 73.1% drop to low level, and 16.7% and 2.60% ascend to moderately high and high levels, respectively.

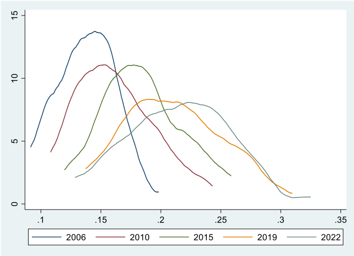

***Figure 1.** Kernel density of the overall China*

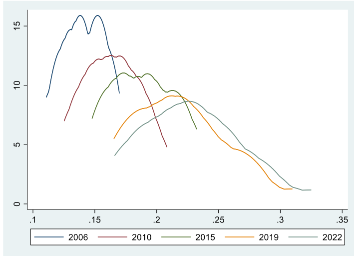

***Figure 2.** Kernel density of the eastern region*

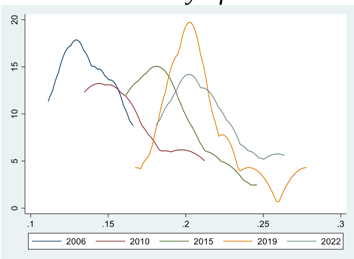

***Figure 3.** Kernel density of the central region*

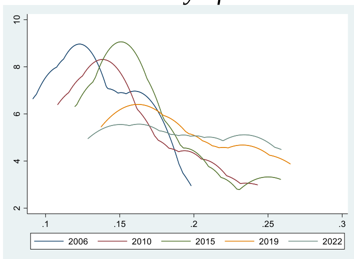

***Figure 4.** Kernel density of the western region*

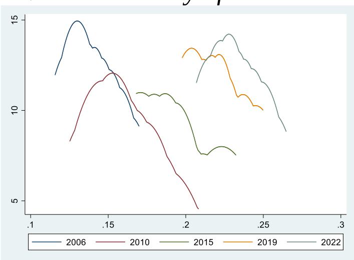

***Figure 5.** Kernel density of the eastern region*

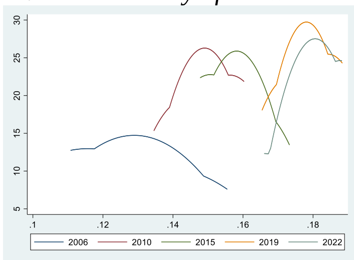

***Figure 6.** Kernel density of the southern region*

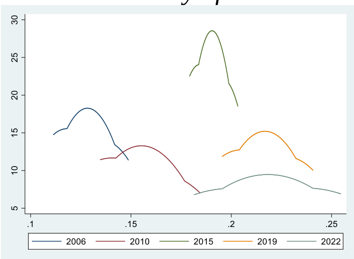

***Figure 7.** Kernel density of the the central region*

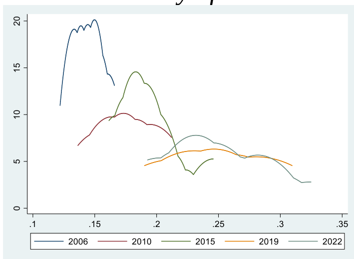

***Figure 8.** Kernel density of the northern region*

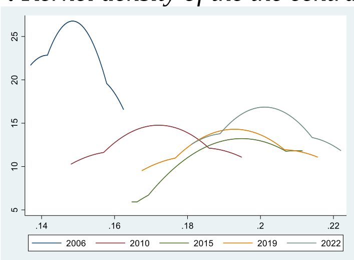

***Figure 9.** Kernel density of the northeastern region*

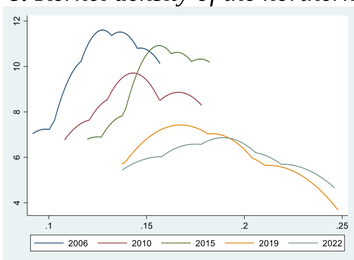

***Figure 10.** Kernel density of the northwestern region*

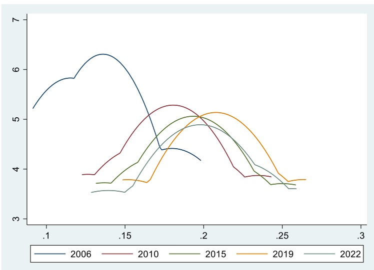

***Figure 11.** Kernel density of the southwestern region*

Table 9. *Markov chain transition probability matrix for agricultural green development levels*

Region	t/t+1	Type I	Type II	Type III	Type IV
Overall China	TypeI	0.531	0.099	0.125	0.245
	TypeII	0.731	0.077	0.167	0.026
	TypeIII	0.494	0.208	0.169	0.130
	TypeIV	0.412	0.350	0.225	0.013
Eastern Region	TypeI	0.455	0.168	0.228	0.149
	TypeII	0.421	0.158	0.368	0.053
	TypeIII	0.553	0.277	0.170	0.000
	TypeIV	0.765	0.118	0.118	0.000
Central Region	TypeI	0.457	0.185	0.185	0.174
	TypeII	0.826	0.000	0.087	0.087
	TypeIII	0.789	0.211	0.000	0.000
	TypeIV	0.944	0.056	0.000	0.000
Western Region	TypeI	0.439	0.037	0.061	0.463
	TypeII	0.720	0.280	0.000	0.000
	TypeIII	0.875	0.125	0.000	0.000
	TypeIV	0.541	0.378	0.081	0.000
East China	TypeI	0.703	0.016	0.172	0.109
	TypeII	0.609	0.348	0.043	0.000
	TypeIII	0.190	0.524	0.143	0.143
	TypeIV	0.100	0.300	0.600	0.000
South China	TypeI	0.273	0.591	0.091	0.045
	TypeII	0.560	0.440	0.000	0.000
	TypeIII	0.500	0.500	0.000	0.000
	TypeIV	1.000	0.000	0.000	0.000
Central China	TypeI	0.484	0.194	0.258	0.065
	TypeII	1.000	0.000	0.000	0.000
	TypeIII	0.778	0.222	0.000	0.000
	TypeIV	1.000	0.000	0.000	0.000
North China	TypeI	0.132	0.421	0.105	0.342
	TypeII	0.960	0.000	0.000	0.040
	TypeIII	0.600	0.200	0.200	0.000
	TypeIV	0.313	0.563	0.000	0.125
Northeast China	TypeI	0.000	0.000	0.625	0.375
	TypeII	0.600	0.200	0.200	0.000
	TypeIII	0.524	0.095	0.333	0.048
	TypeIV	0.250	0.125	0.500	0.125
Northwest China	TypeI	0.541	0.162	0.027	0.270
	TypeII	0.444	0.167	0.333	0.056
	TypeIII	0.474	0.368	0.158	0.000
	TypeIV	0.000	0.100	0.900	0.000
Southwest China	TypeI	0.000	0.000	0.412	0.588
	TypeII	0.000	0.000	0.882	0.118
	TypeIII	0.500	0.500	0.000	0.000
	TypeIV	0.455	0.545	0.000	0.000

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For Type III, 16.9% remain at moderately high level by year-end, 20.8% and 49.4% fall to moderately low and low levels, respectively, with 13% rising to high level. For Type IV, 1.3% stay at high level by year-end, with 22.5%, 35%, and 41.2% dropping to moderately high, moderately low, and low levels, respectively. This indicates high mobility between levels of green agricultural development in the overall Chinese sample, with relatively unstable positions and significant variability, particularly evident in areas at low and moderately low levels.

According to the maximum likelihood estimates of transition probabilities for agricultural green development levels in the Eastern, Central, and Western regions, mobility between levels within these regions is lower compared to the overall Chinese sample. The Central and Western regions exhibit even lower mobility than the Eastern region, with relatively stable positions in higher and high levels of green agricultural development distribution.

Based on the maximum likelihood estimates of transition probabilities for agricultural green development levels across the seven major geographic regions, mobility between levels further decreases under finer regional segmentation, with each type maintaining a more stable position in the distribution of green agricultural development levels. This indicates a slow adjustment speed for spatial inequalities in green agricultural development levels, suggesting the need for greater focus on the application of regulatory tools, verifying Hypothesis 2.

Convergence Analysis

Table 10 reports the results of the σ convergence tests for the levels of agricultural green development in China overall and in different regions from 2006 to 2022, based on the coefficient of variation (CV). The results indicate that the coefficient of variation for China as a whole exhibits a pattern of "rise-fall-rise-fall-rise," slightly increasing amidst fluctuations. This suggests that although there are periods of convergence, the overall trend remains divergent.

Table 10. *σ Convergence of agricultural green development levels*

Time	Overall	Eastern	Central	Western	East China	South China	Central China	North China	Northeast China	Northwest China	Southwest China
2006	0.1851	0.1329	0.1328	0.2734	0.1442	0.1486	0.1204	0.1049	0.0710	0.1940	0.3364
2007	0.1962	0.1446	0.1641	0.2721	0.1596	0.1310	0.1043	0.1390	0.0903	0.1788	0.3231
2008	0.2121	0.1509	0.1802	0.2989	0.1572	0.1242	0.1698	0.1667	0.1046	0.1786	0.3477
2009	0.2193	0.1670	0.1870	0.2996	0.1793	0.0870	0.1685	0.1903	0.1325	0.1821	0.3336
2010	0.2045	0.1487	0.1637	0.2906	0.1672	0.0720	0.1369	0.1633	0.1111	0.2064	0.3023
2011	0.1938	0.1462	0.1589	0.2702	0.1662	0.0690	0.1363	0.1524	0.1010	0.1766	0.2725
2012	0.2025	0.1507	0.1778	0.2747	0.1748	0.0778	0.1373	0.1683	0.1235	0.1837	0.2785
2013	0.2219	0.1973	0.1856	0.2461	0.2132	0.0341	0.0956	0.1754	0.1451	0.1353	0.3040
2014	0.1838	0.1528	0.1355	0.2458	0.1515	0.0329	0.0538	0.1325	0.1427	0.1398	0.2883
2015	0.1868	0.1405	0.1357	0.2693	0.1364	0.0689	0.0519	0.1473	0.1095	0.1680	0.2947
2016	0.1850	0.1443	0.1357	0.2597	0.1167	0.0558	0.0613	0.1520	0.1123	0.1509	0.2898
2017	0.1764	0.1383	0.1411	0.2417	0.1268	0.0592	0.0600	0.1575	0.1067	0.1583	0.2569
2018	0.1795	0.1278	0.1401	0.2570	0.1016	0.0533	0.0676	0.1652	0.1137	0.2089	0.2769
2019	0.1983	0.1756	0.1430	0.2559	0.0947	0.0533	0.0856	0.1845	0.1023	0.2222	0.2703
2020	0.2036	0.1530	0.1709	0.2769	0.0672	0.1302	0.0722	0.2088	0.1311	0.2122	0.3058
2021	0.2016	0.1772	0.1268	0.2608	0.0898	0.0515	0.1350	0.1777	0.0829	0.2199	0.2987
2022	0.2039	0.1811	0.1283	0.2610	0.0886	0.0568	0.1366	0.1823	0.0833	0.2211	0.2982

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From a regional perspective, when divided into East, Central, and West, the coefficient of variation for the eastern region shows an upward trend, indicating that the disparities in the level of agricultural green development are widening, with no σ convergence. In contrast, the coefficients of variation for the Central and Western regions are decreasing, suggesting that disparities in the levels of agricultural green development in these areas are gradually narrowing over time, indicating the presence of σ convergence.

When divided into the seven major geographical regions, a more detailed and diversified σ convergence situation can be observed. The coefficients of variation for the Central China, North China, Northeast, and Northwest regions are on the rise, with North China showing the largest increase. These regions exhibit significant σ divergence, with disparities in the levels of agricultural green development widening over time. In contrast, the coefficients of variation for the East China, South China, and Southwest regions are decreasing, indicating σ convergence in these areas, with regional disparities steadily diminishing over time.

Estimates of absolute β convergence and conditional β convergence were conducted by using the Two-way Fixed Effects Model. *Table 11* reports the test results of absolute β convergence for the overall Chinese, Eastern, Central, and Western regions' levels of agricultural green development. According to the estimates, the β coefficients for all four sample regions are negative and have passed the 1% significance test, indicating the presence of absolute β convergence in these regions. This demonstrates a "catch-up effect" from lower-level areas to higher-level areas in terms of agricultural green development, verifying Hypothesis 3. Regarding the speed of convergence, the overall convergence rate for China is 0.0305; among the three regions, the Eastern region has the fastest convergence rate at 0.0343, followed by the Central region at 0.0258, and the Western region at 0.0255.

Table 11. *Absolute β convergence of agricultural green development levels in China, eastern, central, and western regions*

Coefficient	Overall	Eastern	Central	Western
β	-0.4041^{***}	-0.4423^{***}	-0.3547^{***}	-0.3519^{***}
c	-0.6700^{***}	-0.7339^{***}	-0.7148^{***}	-0.7585^{***}
R^2	0.4118	0.3895	0.5834	0.5269
F-test	6.75^{***}	3.88^{***}	6.94^{***}	5.52^{***}
Time	Control	Control	Control	Control
Region	Control	Control	Control	Control

Table 12 reports the results of the absolute β convergence tests for the levels of agricultural green development across the seven major geographical regions. According to the estimates, the β coefficients for all sample regions are negative; apart from the Central China region, the β coefficients for the other six regions have passed the significance test, indicating the presence of absolute β convergence in these six regions, whereas Central China does not exhibit absolute β convergence. Regarding the speed of convergence, the East China region has the fastest convergence rate at 0.0768, followed by North China at 0.0307, and then the Southwest region at 0.0287.

Table 13 reports the results of the conditional β convergence tests for the levels of agricultural green development in the overall Chinese, Eastern, Central, and Western regions. According to the estimates, the β coefficients for all four sample regions are negative and have passed the 1% significance test, indicating that there is conditional β

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convergence in these regions. Over time, the levels of agricultural green development in each sample region converge towards their own steady-state levels, verifying Hypothesis 4. Regarding the speed of convergence, the overall convergence rate for China is 0.0075. Among the three regions, the Central and Eastern regions have relatively faster convergence rates at 0.0086 and 0.0080, respectively, while the Western region has a slower convergence rate of 0.0057.

Table 12. *Absolute β convergence of agricultural green development levels across seven major regions*

Coefficient	East China	South China	Central China	North China	Northeast China	Northwest China	Southwest China
β	-0.7289^{***}	-0.1980^{**}	-0.1967	-0.4067^{***}	-0.3653^{***}	-0.3007^{***}	-0.3857^{***}
c	-1.2928^{***}	-0.3622^{**}	-0.3786	-0.6559^{***}	-0.6615^{***}	-0.5551^{***}	-0.8207^{***}
R^2	0.5036	0.7103	0.7437	0.4961	0.7251	0.4479	0.7693
F-test	4.10^{***}	3.95^{***}	4.68^{***}	2.90^{***}	4.25^{***}	2.39^{***}	7.72^{***}
Time	Control	Control	Control	Control	Control	Control	Control
Individual	Control	Control	Control	Control	Control	Control	Control

Table 13. *Conditional β convergence of agricultural green development levels in China, eastern, central, and western regions*

Coefficient	Overall	Eastern	Central	Western
β	-0.1191^{***}	-0.1278^{***}	-0.1366^{***}	-0.0916^{***}
c	0.0244^{***}	0.0260^{***}	0.0177^{***}	0.0116^{***}
R^2	0.4087	0.3871	0.6232	0.4995
F-test	6.67^{***}	3.84^{***}	8.20^{***}	4.95^{***}
Time	Control	Control	Control	Control
Region	Control	Control	Control	Control

Table 14 reports the results of the conditional β convergence tests for the levels of agricultural green development across the seven major geographical regions. According to the estimates, the β coefficients for all sample regions are negative; apart from the Central China region, the β coefficients for the other six regions have passed the significance test. This indicates that these six regions exhibit conditional β convergence, whereas the Central China region does not show conditional β convergence and instead demonstrates a diverging state in its agricultural green development levels. Regarding the speed of convergence, the East China region has the fastest convergence rate at 0.0172, followed by the Northeast region at 0.0076, and the Southwest region at 0.0063.

Table 14. *Conditional β convergence of agricultural green development levels across seven major regions*

Coefficient	East China	South China	Central China	North China	Northeast China	Northwest China	Southwest China
β	-0.2540^{***}	-0.0846^{***}	-0.0644	-0.0963^{***}	-0.1211^{***}	-0.0568^{*}	-0.1013^{***}
c	0.0444^{***}	0.0137^{***}	0.0098	0.0215^{***}	0.0200^{***}	0.0099^{**}	0.0137^{***}
R^2	0.5604	0.7268	0.7398	0.4955^{***}	0.7413	0.3973	0.7546
F-test	5.16^{***}	4.29^{***}	4.58^{***}	2.90^{***}	4.62^{***}	1.94^{***}	7.12^{***}
Time	Control	Control	Control	Control	Control	Control	Control
Individual	Control	Control	Control	Control	Control	Control	Control

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The results of the convergence analysis indicate that there are differences in the convergence analysis results calculated based on different regional divisions. Relatively speaking, finer regional divisions can observe more accurate estimation results, while coarser regional divisions may obscure some actual situations.

Discussion

As China's agricultural green development enters a comprehensive advancement phase, are there regional differences in agricultural green development? What are the sources of these differences? How do the spatial and temporal evolution processes of agricultural green development vary across different regions? What are the characteristics of state transitions? Are the evolving trends converging or diverging? Answering these questions will help enhance the overall coordination of agricultural green development and strengthen regional coordinated development capabilities.

To address these questions, this study employs research methods including the Dagum Gini coefficient, kernel density estimation, Markov chains, σ-convergence, and β-convergence to analyze regional differences, sources, evolving trends, and convergence in China's agricultural green development levels.

Our research finds that the level of agricultural green development in China has shown a continuous upward trend during the sample period, consistent with the conclusions of Wei et al. (2018). The driving forces for this improvement may stem from agricultural technological innovation (Wang et al., 2020), agricultural industrial clustering (Xue et al., 2020), rural industrial integration (Liu et al., 2024), and organizational and environmental factors (Sun, 2024).

However, despite this growth trend, there are significant regional disparities in agricultural green development in China. Moreover, under more detailed regional divisions, the disparities between regions have become the primary reason for the overall regional differences in agricultural green development levels. This finding aligns closely with the conclusions of Jin (2019), Tu et al. (2019), Lu et al. (2022), and Yang et al. (2019). Similarly, studies by Li et al. (2023), Ma et al. (2022), and Gao et al. (2020) focusing on smaller regional areas have yielded similar findings.

As regional divisions become more detailed, the fluidity of agricultural green development begins to decline, and the spatial adjustment speed of agricultural green development levels also gradually slows. Regarding this finding, we did not identify corresponding existing literature as evidence. However, the widespread issue of difficulty in regional cooperation in China has also been noted in research across other economic fields, such as in the labor market (Ye et al., 2018) and tourism development (Li et al., 2016; Lyu et al., 2021), providing indirect support for the findings of this study. In convergence analysis, we found that there is absolute β-convergence and conditional β-convergence in China's agricultural green development levels, but σ-convergence is not significant. This finding is somewhat consistent with the research by Zheng et al. (2022), but it differs significantly from the findings of Liu et al. (2024) and Qi et al. (2020), and the differences may be attributed to variations in sample scope, indicator construction, and method selection.

Currently, related studies typically use only one method for regional difference analysis; however, this research employs two progressively refined regional division methods for analysis.

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A comparative analysis of the results from both regional divisions revealed that the results from coarse regional divisions deviate from real-world conditions, additionally, more detailed regional divisions better identify the regional differences and sources of agricultural green development and align more closely with real-world conditions. We also did not find existing literature that employs similar analytical methods for comparison. This presents a significant opportunity for further exploration, requiring validation through subsequent related research. Furthermore, there is still considerable ambiguity regarding the spatial adjustment speed and convergence of agricultural green development levels, warranting further investigation.

Conclusions and Implications

Research Conclusions

This study utilizes the Dagum Gini coefficient, Kernel density estimation, Markov chain analysis, and convergence analysis, employing two types of regional divisions for comparative analysis to empirically examine the regional differences, evolutionary trends, and convergence issues in China's agricultural green development, yielding the following conclusions:

The decomposition of the Dagum Gini coefficient reveals a slight upward trend in the overall level of China's agricultural green development amidst fluctuations during the sample period. When divided into Eastern, Central, and Western regions, internal imbalances have a greater impact on disparities in agricultural green development levels than inter-regional differences. When categorized into the seven major geographical regions, the impact of internal imbalances significantly decreases, while the influence of inter-regional disparities markedly increases, becoming the main cause of overall regional disparities in agricultural green development levels.

Kernel density estimation finds that the centers and change areas of distribution curves for all sample regions shift to the right over time, indicating a continuous improvement in the level of agricultural green development. Absolute disparities in the levels of agricultural green development are increasing in the overall China, Eastern, Western, Central China, North China, and Northwest regions; however, the dispersion of agricultural green development levels in South China decreases, reducing absolute disparities. Over time, there is a trend of increasing disparities between areas with higher and lower levels of agricultural green development in the overall China, Eastern, and Western regions. No polarization phenomena exist in any sample regions over time.

Markov chain analysis reveals that in the overall Chinese sample, there is high mobility between different states of agricultural green development levels, with the relative positions of each type of region in the distribution of agricultural green development levels being quite unstable and highly variable, particularly evident in regions at low and moderately low levels. When divided into Eastern, Central, and Western regions, the mobility between states of agricultural green development levels in all three regions is lower than in the overall Chinese sample, with mobility in Central and Western regions being lower than in the Eastern region, making these two regions more stable in terms of high and very high levels of agricultural green development. When divided into the seven major geographical regions, the mobility between states of agricultural green development levels further decreases, with the relative positions of each type of region in the distribution being more stable, indicating a slow adjustment pace for spatial inequalities in agricultural green development levels, suggesting the need for greater emphasis on the application of regulatory tools.

Convergence analysis reveals that the overall sample of China's agricultural green development levels exhibits a divergent trend, with no significant σ convergence; however, absolute β convergence and conditional β convergence are present, indicating not only a "catch-up effect" from lower-level areas to higher-level areas but also that, over time, the agricultural green development levels of each sample area converge towards their own steady-state levels. When divided into Eastern, Central, and Western regions, there is no σ convergence in the Eastern region, but σ convergence exists in the Central and Western regions; all three regions exhibit both absolute β convergence and conditional β convergence. When divided into the seven major geographical regions, significant σ divergence is observed in the Central, North, Northeast, and Northwest regions, while σ convergence is present in the East, South, and Southwest regions; apart from the Central region, the other six regions exhibit both absolute β convergence and conditional β convergence.

Comparative analysis of different regional divisions finds that more detailed regional divisions provide more accurate estimation results during analyses of regional differences, spatiotemporal evolution, and convergence. The research findings thus obtained are relatively closer to reality. In contrast, coarser regional divisions might introduce some biases and could potentially obscure some actual conditions.

This study holds significant practical implications for enhancing the overall coordination of agricultural green development in China and strengthening regional coordinated development capabilities. Meanwhile, the analytical approach of employing two regional divisions and conducting comparative analysis also provides important reference value for future studies on regional differences.

Research Implications

As China's Rural Revitalization Strategy continues to be comprehensively advanced, agricultural green development has entered a more intensive phase of promotion. Based on the conclusions above, the following policy implications are drawn:

(1) Continue to promote the enhancement of agricultural green development levels. In terms of how to further improve agricultural green development levels, focus on key aspects such as the protection and utilization of agricultural resources, prevention and control of non-point source pollution in agriculture, and ecological protection and restoration, strengthen the research and development of agricultural green technology innovation and the promotion and application of the results. Emphasize policy incentives, education and outreach, and regulatory measures to refine institutional systems and working mechanisms, further promoting a green transformation in agricultural development methods.

(2) Strengthen more targeted intra-regional development strategies. Firstly, develop targeted development policies tailored to the characteristics and comparative advantages of different regions to achieve focused development, encouraging areas to design their own development directions, paths, and models that best suit their characteristics, promote the speed of regional agricultural green development through the differentiation strategy to give play to the advantages. Secondly, use regions that are pioneers in agricultural green development as bases, concentrate resource advantage, create distinctive regional brands of agricultural green development, cultivate regional agricultural green development benchmark and give play to its leading effect.

(3) Coordinate inter-regional development comprehensively. Pay attention to the impact of inter-regional differences on high-quality agricultural green development, improve the top-level system, strengthen policy intervention and regulation, manage differences within regions in the global framework to achieve coordinated regional development at multiple levels, multi-form and all-dimensional situation. First, improve government cooperation by enhancing the benefit distribution mechanism, refining assessment and supervision systems, increasing incentive mechanisms, reducing transaction costs, and standardizing implementation, actively seek effective cooperation paths that maximize benefits and minimize costs, break the local government cooperation dilemma, establish a sound cross-regional consultation and cooperation system, and effectively address the regional challenges and fragmented governance faced by agricultural green development, achieve co-governance and sharing. Second, increase guidance and support for regions lagging in agricultural green development. On one hand, learn from advanced cases, summarize transferable experiences, and enhance their ability to effectively identify weaknesses and resolve developmental constraints, thus increasing the pace of agricultural green development in lagging regions and improving their catch-up capabilities. On the other hand, utilize platforms and projects as vehicles for cooperation, establishing interregional spatial linkage mechanisms, playing spatial spillover effect, leveraging complementary resource advantages and technological spillovers to foster collaboration that "supports the weak", and encouraging advanced regions in agricultural green development to assist and uplift lagging areas to realize common development and prosperity.

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REFERENCES

[1] Amaruzaman, S., Leimona, B., van Noordwijk, M., Lusiana, B. (2017): Discourses on the performance gap of agriculutre in a green economy: a q-methodology study in Indonesia. – International Journal of Biodiversity Science, Ecosystem Services & Management 13(1): 233-247.

[2] Du, Z. X., Hu, L. X. (2023): The achievements and interpretationgs of the high-quality agricultural development in China since the 18th national congress of the communist party of China. – Chinese Rural Economy 1: 2-17.

[3] Feng, D. M., Xu, T. C. (2021): The historical retrospect and logical evolution of Chian's agricultural green development. – Chinese Rural Economy 10: 90-99.

[4] Gao, J., Ge, Z. H. (2020): Regional difference and trend analysis of agricultural green development level in Jiansu province. – Chinese Journal of Agricultural Resources and Regional Planning 41(12): 14-22.

[5] Gao, Q., Chen, H. Y., Zhang, X. L. (2023): Evolution and focal features of China's agricultural green development policies: text analysis based on attention perspective. – Resource Science 45(12): 2433-2448.

[6] Gargano, G., Licciardo, F., Verrascina, M., Zanetti, B. (2021): The agroecological approach as a model for multifunctional agriculture and farming towards the European green deal 2030: some evidence from the Italian experience. – Sustainability 13(4): 2215.

[7] Gong, Q. W, Li, X. M. (2020): Construction and measurement of agricultural green development index: 2005-2018. – Reform 1: 133-145.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_10711099

[8] He, K., Li, F. L., Zhang, J. B., Li, X. T. (2021): Green development levels and regional differences of agriculture in the Yangtze River economic belt. – Journal of Huazhong Agricultural University 40(3): 43-51.
[9] Jin, S. M. (2019): Evaluation of green agricultural development level and regional differences among provinces in China. – Seeker 2: 89-95.
[10] Jin, W. C., Jin, S. Z. (2023): Accelerating Chian's transformation into an agricultural powerhouse: present basis, international experiences and path selection. – Chinese Rural Economy 1: 18-32.
[11] Jin, S. Q., Zhang, Z. X., Hu, Y., Du, Z. X. (2024): Historical logic, theoretical interpretation, and practical exploration of China's agricultural green transformation. – Chinese Rural Economy 3: 4-19.
[12] Kansanga, M., Andersen, P., Kpienbaareh, D., Mason-Renton, S., Atuoye, K., Sano, Y., Antabe, R., Luginaah, I. (2019): Traditional agriculture in transition: examining the impacts of agricultural modernization on smallholder farming in Ghana under the new green revolution. – International Journal of Sustainable Development & World Ecology 26(1): 11-24.
[13] Karlsson, M., Hovelsrud, G. K. (2021): Everyone comes with their own shade of green: negotiating the meaning of transformation in Norway's agriculture and fisheries sectors. – Journal of Rural Studies 81: 259-268.
[14] Li, Q. Y., Zhong, S. Y. (2016): Spatial imbalance and its evolution of China's tourism industry specialization development: based on empirical study of Dagum Gini coefficient and Markov chain. – Economic Geography 36(12): 197-203.
[15] Li, Z. (2022): The green development of agriculture in China: institutional evolution and practical action. – Seeker 5: 97-105.
[16] Li, Z. (2023): The green development of agriculture in China: innovation and evolution. – Chinese Rural Economy 2: 2-16.
[17] Li, F. F., Zhou, X., Zhou, Y. X. (2023): Evaluation and regional difference analysis of agricultural green development level in Bohai rim region. – Chinese Journal of Agricultural Resources and Regional Planning 44(3): 118-129.
[18] Liu, S., Xie, Y. C. (2024): Does the integration of rural tertiary industries promote the green development of agriculture? Empirical test based on major grain producing areas. – Chinese Journal of Agricultural Resources and Regional Planning 8: 1-14.
[19] Liu, X., Chen, Y. T. (2024): Analysis of spatiotemporal differences and convergence of agricultural green totalfactor productivity in the yellow river basin. – Scientific Decision Making 2: 122-131.
[20] Lyu, Y. Q., Wang, Y. J., Miruibangguli, M., Wang, L. (2021): Spatial disequilibrium and dynamic evolution of tourism facilities development level in China. – Statistics & Decision 37(12): 52-56.
[21] Lyu, M., Huang, Y., Chen, R. (2022): Regional difference analysis of green agriculture in China. – Rural Economy 12: 78-87.
[22] Ma, G. Q., Tan, Y. W. (2021): Impact of environmental regulation on agricultural green total factor productivity: analysis based on the panel threshold model. – Journal of Agrotechnical Economics 5: 77-92.
[23] Ma, X. D., Hu, Y., Huang, B. (2022): Spatial-temporal characteristics and influencing factors of rural green development in Jiangsu province. – Economy Geography 42(4): 159-167.
[24] Pu, X. J., Ma, K. X., Wang, Y. F. (2023): Analysis on the impact of rural digitization on promoting green and high-quality agricultural development. – Chinese Journal of Agricultural Resources and Regional Planning 11: 1-12.
[25] Qi, Y. B., Han, S. Y., Deng, X. (2020): China's green agriculture development: production level measurement, regional spatial difference and convergence analysis. – Journal of Agrotechnical Economics 4: 51-65.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_10711099

[26] Qi, Y. B., Han, S. Y., Hu, X. (2021): Measurement, regional spatial difference and convergence Analysis. – Journal of Agrotechnical Economics 4: 51-65.
[27] Quah, D. T. (1996): Twin peaks: growth and convergence in models of distribution dynamics. – Economic Journal 106: 1045-1055.
[28] Ruttan, V. M. (2002): Productivity growth in world agriculture: sources and constraints. – Journal of Economic Perspectives 16(4): 161-184.
[29] Scherer, L. A., Verburg, P. H., Schulp, C. J. E. (2018): Opportunities for sustainable intensification in European agriculture. – Global Environmental Change 48: 43-55.
[30] Singh, R. B. (2000): Environmental consequences of agricultural development: a case study from the green revolution state of Haryana, India. – Agriculture, Ecosystems & Environment 1-3: 97-103.
[31] Song, H. Y., Jiang, F., Zhang, Y. (2023): Achievements and experience of Chian's rural development and reform in the new era. – Chinese Rural Economy 3: 2-21.
[32] Su, K., Meng, H. B., Zhang, H. (2021): Construction of the green development indicators for agriculture and its prediction in the 14th five-year plan in China. – Transactions of the Chinese Society of Agricultural Engineering 37(20): 287-294.
[33] Sun, Z. Y., Jiang, L. D., Yu, Z. P. (2024): Research on the multiple driving paths of China's agricultural green development from the perspective of configuration: based on fuzzy-set qualitative comparative analysis. – Journal of Agro-Forestry Economics and Management 4: 1-12.
[34] Tian, C. H., Li, L., Liao, B. (2024): Can integration of rural primary, secondary and tertiary industries promote agricultural green development? A case study of 579 counties in China's Yangtze River economic belt. – Journal of Natural Resources 39(3): 601-619.
[35] Tu, Z. G., Gan, T. Q. (2019): Research on the regional difference and dynamic mechanism of agricultural green development in China. – Wuhan University Journal (Philosophy & Social Science) 72(3): 165-178.
[36] Wang, L. J., Jia, B. H., Xin, L. Y. (2020): Research on the driving factors of agricultural green development in Tianjin. – Chinese journal of Agricultural Resources and Regional Planning 41(11): 56-63.
[37] Wang, L., Ma, J. M. (2023): Mechanism and effect of digital financial inclusion affecting green development of agriculture. – Journal of South China Agricultural University (Social Science Edition) 6: 14-27.
[38] Wang, Y. Q., Xu, L., Cao, L. (2023): Agricultural mechanization and agricultural green development under the "dual carbon" goal. – Journal of Huazhong Agricultural University (Social Sciences Edition) 6: 56-69.
[39] Wei, Q., Zhang, B., Jin, S. Q. (2018): A Study on construction and regional comparison of agricultural green development index in China. – Issues in Agricultural Economy 11: 11-20.
[40] Xue, L., Shen, Y., Xu, C. H. (2020): A research on spillover effects of agricultural agglomeration on agricultural green development efficiency. – Economic Survey 37(3): 45-53.
[41] Yang, Q., Wang, J., Li, C., Liu, X. P. (2019): The spatial differentiation of agricultural green total factor productivity and its driving factor recognition in China. – Journal of Quantitative & Technological Economics 10: 21-37.
[42] Yang, L. N., Zhang, X. Y. (2024): Does agricultural product trade promote green agricultural development in China? From the perspective of agricultural green total factor productivity. – Finance and Trade Research 2: 31-41.
[43] Yao, P., Li, H. Z. (2023): Can agricultural water rights trade promote agricultural green development? – Chinese Rural Economy 2: 17-40.
[44] Ye, C. H., Chen, L. T., Tian, Y. (2018): Spatial disequilibrium of labor market development level in the Yangtze River economic belt: based on Dagum Gini coefficient and Markov chain method. – East China Economic Management 32(8): 58-64.

[45] Zhang, L. X., Bai, Y. L., Sun, M. X., Xu, X. B. (2021): Views on agricultural green production from the perspective of system science. – Issues in Agricultural Economy 10: 42-50.
[46] Zhao, M. J., Zhou, C. H. (2024): High-quality promotion of green agricultural development: multi-objective synergy and multi-centered governance. – Journal of Chian Agricultural University (Social Sciences) 41(5): 1-16.
[47] Zheng, G. T., Chen, C. B., Zhang, K. H., Xing, M. H., Jiang, F. (2022): Dynamic evolution and convergence analysis of total factor productivity of agricultural environment in China. – Chinese Journal of Agricultural Resources and Regional Planning 43(1): 40-49.
[48] Zhou, Y. S., Yin, Z. J. (2024): Does agricultural insurance promote the green development of agriculture in Chian? – Journal of Huazhong Agricultural University (Social Sciences Edition) 1: 49-61.
[49] Zou, Y. Y., Kong, L. L., Ma, T. Y. (2023): Measurement of agricultural green development level and its influencing factors under the protection of black land. – Journal of Northeast Agricultural University (Social Science Edition) 21(3): 52-62.

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