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Study on Regional Differences, Dynamic Evolution and Convergence of Nutrition-Sensitive Agricultural Development in China

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Abstract: This article constructs an evaluation index system for the development of nutrition-sensitive agriculture in China and measures the development level of nutrition-sensitive agriculture using the entropy method, based on the panel data of 31 provinces from 2000 to 2022. The Dagum Gini coefficient is employed to analyze the magnitude and sources of regional differences in the development level between the whole country and the four major regions. The Kernel density estimation method is applied to describe the dynamic evolutionary characteristics of the development level in different regions. Furthermore, this study delves into the σ convergence and β convergence characteristics of the development level. The results show the following: (a) The level of nutrition-sensitive agricultural development at the national level and in the four major regions has been rising year by year, with a clear spatial pattern of "high in the east and low in the west". (b) There are significant regional differences at the national level and in the four major regions, which tend to widen. (c) The dynamic evolution characteristics of the development level of nutrition-sensitive agriculture in various regions differ greatly, with polarization in the national, eastern, western and northeastern regions. (d) There is no σ convergence in the development level of nutrition-sensitive agriculture in the country or in the four major regions, but there is absolute β convergence and conditional β convergence in all of them, with the northeastern and central regions having faster convergence speeds; the "catching-up effect" is obvious. The report concludes by outlining the policy ramifications for implementing a methodical and comprehensive strategy approach to support regionally coordinated development plans for leapfrogging and upgrading.

Keywords: nutrition-sensitive agriculture; regional differences; dynamic evolution; convergence

Citation: Gu, Y.; Qi, C.; Liu, F.; Dong, Y.; Zhang, H. Study on Regional Differences, Dynamic Evolution and Convergence of Nutrition-Sensitive Agricultural Development in China. *Agriculture* **2024**, *14*, 2034. https://doi.org/10.3390/agriculture14112034

Academic Editors: Katerina Melfou and Alexandros Theodoridis

Received: 22 October 2024
Revised: 9 November 2024
Accepted: 11 November 2024
Published: 12 November 2024

1. Introduction

Cereal is the lifeblood of the people, and food is the head of government. Agriculture has long provided humans with food and clothing, serving as the foundation for survival and economic progress. Currently, the global agriculture sector is facing a significant problem in dealing with ever-increasing nutritional and dietary problems [1]. The State of Food Security and Nutrition in the World 2024 shows that many countries face multiple forms of malnutrition, and global hunger levels remain high for the third year in a row, with between 713 million and 757 million people facing hunger in 2023, up about 152 million from 2019, while approximately 2.33 billion people worldwide faced moderate or severe food insecurity in 2023 [2]. As a large agricultural country and the world's most populous country, China has made great progress in agricultural production and nutritional health over recent decades [3]. According to the National Bureau of Statistics, China's total grain output has been stable at more than 650 million tons for nine consecutive years, reaching 695 million tons in 2023, and per capita grain possession has reached 493.31 kg, which is higher than the internationally recognized per capita grain safety line of 400 kg for 16 consecutive years, achieving the strategic bottom-line criterion of "basic self-sufficiency in grains and absolute security in food grains". However, new problems and challenges have emerged other than having enough to eat; dietary irrationality and malnutrition leading to hidden hunger (deficiencies in vitamins, minerals and other micronutrients), overweight and obesity, and the high incidence of chronic diseases such as dyslipidemia are rapidly becoming prominent health problems. The Scientific Research Report on Dietary Guidelines for Chinese Residents (2021) concluded that Chinese residents on the whole consume insufficient whole grains, dark-colored vegetables, fruits, milk, fish, shrimp and beans, and that there is a disparity between urban and rural development, with rural residents consuming significantly less animal-based foods, dark-colored vegetables and fruits compared to their urban counterparts. The degree of food diversity in rural areas urgently needs improvement [4]. Faced with the dual issues of over- and under-nutrition, China must urgently build a new agricultural system that suits its national conditions and meets its people's nutritional demands.

In 2011, The Food and Agriculture Organization of the United Nations (FAO) initially developed the Approach to Nutrition-Sensitive Agricultural Development, which aimed to focus on the unique relationship between agriculture, food and nutrition, and to actively protect, promote and improve existing food systems to ensure food and nutrition security. It also provided a preliminary analysis of the agriculture–food–nutrition nexus from a variety of perspectives [5]. Around 2013, academics gradually began to discuss the concept of nutrition-sensitive agriculture, and several scholars have extensively explored its definition, objectives and connotations from a food system perspective [6–9]. In 2017, The Food and Agriculture Organization of the United Nations (FAO) defined nutrition-sensitive agriculture as a new agricultural paradigm or program that meets the dietary needs of the population in a sustainable manner, aiming to ensure the production of a wide range of foods that are adequate in quantity and quality, affordable, nutritious, culturally appropriate and safe, with nutrition and health as the ultimate goals and measurements. Nutrition-sensitive agriculture provides an important entry point for exploring the relationship between agriculture, nutrition and health and improving the nutritional status and health of the population [1]. It provides an important direction for the transformation of China's agricultural development and supply side structural reform, as well as for dealing with the new demand for food consumption in China's economic and social development today [10]. Developing nutrition-sensitive agriculture is an important initiative to promote the nutritional transformation of the food system, support the optimization of the population's dietary structure and combat malnutrition [11]. Therefore, it is important to construct an evaluation index system suitable for use in China, to measure the development level of nutrition-sensitive agriculture and to investigate regional differences, and dynamic evolution and convergence in each region, which is of great significance when promoting the transition of China's agricultural development from yield-sensitive to nutrition-sensitive, and also provides a reference for the global promotion of nutrition-sensitive agriculture.

Numerous scholars have recognized nutrition-sensitive agriculture as a multidimensional, multifaceted, multifactorial and complex system. Dury et al. argued that agricultural development affects individual nutrition through food, health and care practices, while proposing six categories of risks: income, price, type of production, women's social status, workload, health environment and inequality [12]. Berti et al. argued that nutrition-sensitive agriculture not only considers agriculture as an economic activity, but also focuses on the broader relationship between food production and the health of farmers and their families [13]. Herforth et al. reviewed studies on agricultural nutrition and concluded that agriculture can affect nutrition through various pathways. They also constructed a conceptual framework for agricultural interventions to influence nutrition [14]. In the 2016 publication "Compendium of Indicators for Nutrition-Sensitive Agriculture by the

Food and Agriculture Organization of the United Nations (FAO)", it is further argued that six domains influence the development of nutrition-sensitive agriculture: availability and diversity, the food environment within markets, income, women's empowerment, nutrition knowledge and norms and the health and sanitation environment [15]. Wesana et al. argue that agriculture is part of the whole food system (farm-to-table) and can have an impact on nutritional outcomes [16]. Currently, most academics focus on evaluating the level of high-quality development in Chinese agriculture, with little research on the level of nutrition-sensitive agricultural development in China. Yu Ting et al. [17], Liu Tao et al. [18] and Gao Xue et al. [19] constructed an indicator system from five aspects of innovation, coordination, openness, greenness and sharing, and measured and analyzed the level of high-quality development of Chinese agriculture in terms of regional differences. Yang Nian et al. developed a comprehensive evaluation index system for high-quality agricultural growth based on four criteria: agricultural development, environmental circumstances, resource availability and economic conditions [20]. Xin Ling et al. constructed an evaluation system for high-quality agricultural development, focusing on green development leadership, supply quality and efficiency, large-scale production and industrial diversification integration [21]. Zhang Xiaoyun et al. assessed China's food security using five criteria: supply capacity, supply structure, green development, economic efficiency and basic support [22]. On this basis, scholars further analyzed the convergence of agricultural development. Xiang Yun et al. concluded that there is significant σ convergence, absolute β convergence and conditional β convergence in the high-quality development of China's agricultural economy [23]. According to Li Yaonan et al., there is a substantial conditional β convergence trend but there are no clear σ convergence or absolute β convergence characteristics in China's agricultural green growth level [24]. Xu Xiaoxin et al. demonstrated that the high-quality development of agriculture in China's principal grain-producing regions exhibits typical σ convergence and β convergence characteristics [25]. Yang Chuanxi et al. concluded that there is no obvious σ convergence or absolute β convergence characteristics of agricultural high-quality development under the conditions of agro-ecological zoning, and that there is more significant conditional β convergence [26].

In summary, it can be seen that existing studies have made useful explorations into the measurement, regional differences, dynamic evolution and convergence of the development of nutrition-sensitive agriculture, laying the foundation for this study, but there is still room for further research. Firstly, existing research has explored the concept and influencing factors of nutrition-sensitive agriculture from multiple perspectives. However, there is no consensus on how to measure the development of nutrition-sensitive agriculture, and there is a need to further develop a systematic and structured evaluation index system. Secondly, existing studies have focused on analyzing high-quality development in agriculture, with weak analyses of regional differences, dynamic evolution and convergence in the development of nutrition-sensitive agriculture. In view of this, this study selects panel data from 31 provinces in China from between 2000 and 2022, constructs an evaluation index system for assessing nutrition-sensitive agricultural development in China and employs the entropy method to quantify the progress of nutrition-sensitive agriculture. Furthermore, this study examines regional differences and the dynamic evolution of nutrition-sensitive agriculture, utilizes the Dagum Gini coefficient to reveal the size and source of differences in each region and uses Kernel density estimation to further clarify its spatial non-equilibrium pattern and its dynamic evolution characteristics. Additionally, multiple convergence analyses are conducted to investigate the convergent characteristics of nutrition-sensitive agricultural development. This study aims to provide references for narrowing regional differences in the development of nutrition-sensitive agriculture in China, thereby driving the nutritional transformation of the food system and improving national nutrition and health.

This study also aims to reduce regional gaps in the development of nutrition-sensitive agriculture in China, to facilitate a nutritional shift in the food system and to enhance national nutrition and health outcomes.

2. Materials and Methods

2.1. Materials

2.1.1. Construction of Evaluation Indicator System for Nutrition-Sensitive Agriculture

According to a previous review of research on nutrition-sensitive agriculture, it is evident that nutrition-sensitive agriculture is a complex system with multiple dimensions, levels and elements, which should be presented as a systematic and structured organic whole. Figure 1 shows the development of nutrition-sensitive agriculture. Based on the characteristics and requirements of the new development stage, based on the reality of China's national conditions, agricultural conditions and grain conditions, and taking into account the structure of agricultural resource endowment and environmental constraints, the nutrition-sensitive agricultural development system can be divided into the five following subsystems: agricultural production, distribution control, international trade, health and sustainability and nutritional demand adaptation. The input of production factors into the nutrition-sensitive agricultural production system creates output, which is stabilized by the circulation regulation system of the domestic agricultural products market, which ensures that the agricultural products can reach the people. Under the joint action of the agricultural product international trade system and the health and sustainability system, a nutrition-sensitive food supply is formed, which adapts to the nutritional needs of consumers. The nutrition-sensitive agricultural development system exists in a feedback loop that can enhance these subsystems through different nutrition-sensitive agricultural interventions, which in turn promote further nutrition-sensitive agricultural development.

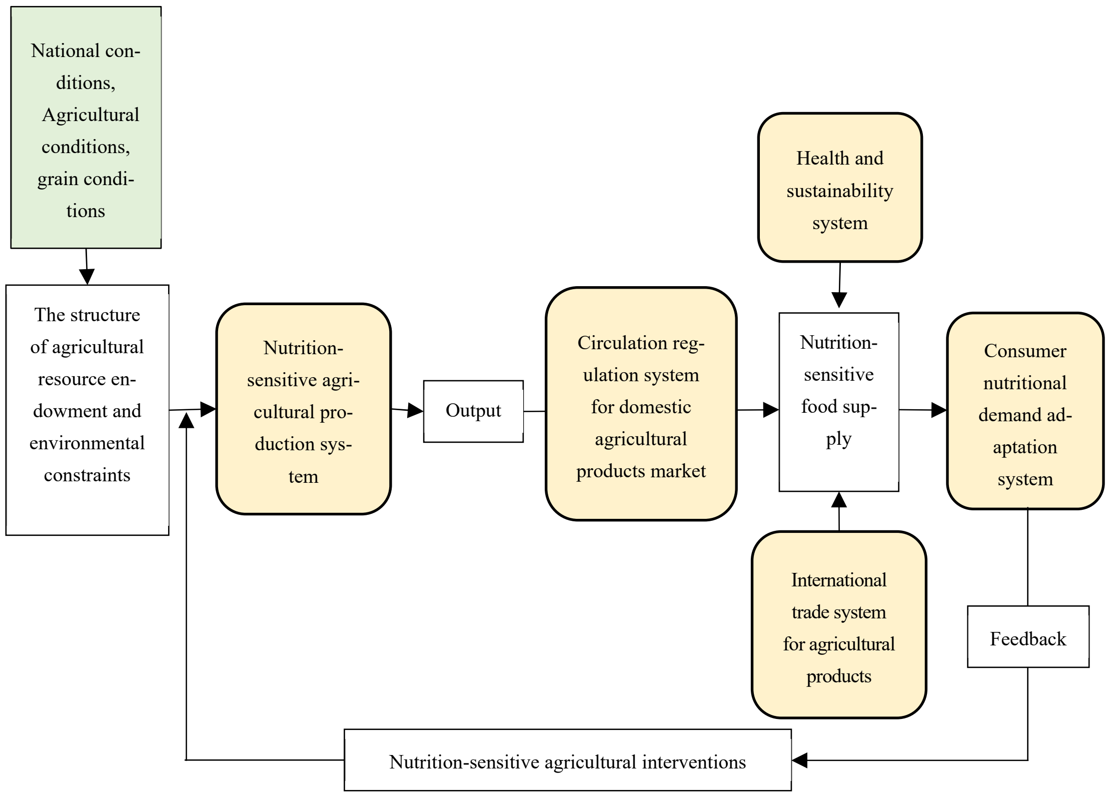

Figure 1. Nutrition-sensitive agricultural development system.

The nutrition-sensitive agricultural production system is the cornerstone of the nutrition-sensitive agricultural development system, with its core criteria being usability and accessibility. Usability is defined by the key elements of the agricultural primary products, including their comprehensive production capacity and post-harvest handling and processing capacity, while accessibility is characterized by the capacity for a diversified food supply. The circulation regulation system for the domestic agricultural products market is the hub of the nutrition-sensitive agricultural development system, with its core criteria being reachability and controllability, which correspond, respectively, to its capacities for modern distribution and storage, as well as regulation. The agricultural products international trade system provides security to the nutrition-sensitive agricultural development system, with its core criterion being substitutability, corresponding to its capacity for international market regulation. The health and sustainability system acts as the driver of the nutrition-sensitive agricultural development system, with its core criterion being sustainability; this corresponds to its capacities for health and environmental protection, women's empowerment, income security and nutrition awareness. The consumer nutritional demand adaptation system guides the nutrition-sensitive agricultural development system, with its core criterion being adaptability, corresponding to its capacity for nutritional demand adaptation. Therefore, the evaluation indicator system contains 5 subsystems: the nutrition-sensitive agricultural production system, the circulation regulation system for the domestic agricultural products market, the international trade system for agricultural products, the health and sustainability system and the consumer nutritional demand adaptation system. The evaluation indicator system will consist of 7 criteria, 11 elements and 43 basic indicators (Table 1).

2.1.2. Data Sources and Explanation

Regarding the evaluation index system of nutrition-sensitive agricultural development level, the following three points are now explained. Firstly, the average number of years of education of the rural labor force is measured by the proportion of the rural educated population to the total rural population, and this paper defines the number of years of education for each education level as follows: below elementary school is 0 years, elementary school is 6 years, junior high school is 9 years, senior high school is 12 years and junior college and above is 16 years [27]. Secondly, the standardized amounts of each food group in the diet were adopted from the data in the weight tower charts of each food group recommended by the Dietary Guidelines for Chinese Residents (2022), and the recommended food groups and weights met the dietary energy and nutritional requirements for members of the population aged 2 years and older, according to the 2000 kcal energy requirement level [28]. Thirdly, building on existing studies, this article introduces the per capita production and supply deviation of vegetable, fruits, animal food, milk and beans, in order to comprehensively measure the diversified food supply capacity. At the same time, it uses supply and demand coupling, supply and demand coordination and supply and demand matching to measure the nutrition demand adaptation capacity, which is a new attempt to measure the level of nutrition-sensitive agricultural development. Fourthly, this study measures the degrees of coupling, coordination and matching between the level of the nutrition-sensitive food supply (LS) and the level of consumer nutritional demand (LD), in order to examine the capacity for nutrition demand adaptation [29,30]. The level of nutrition-sensitive food supply (LS) is calculated using the entropy method with the indicators of four subsystems, namely, the nutrition-sensitive agricultural production system, the circulation regulation system for the domestic agricultural products market, the international trade system for agricultural products and the health and sustainability system. The level of consumer nutritional demand (LD) is evaluated by referencing the research of Yu Guansheng [31], Wen Xue et al. [32] and Peng Jizeng et al. [33], selecting indicators related to the number of consumption groups, purchasing power of consumption and intensity of consumption, and using the entropy method to evaluate them. The number of consumption groups is represented by population density, the purchasing power of consumption is represented by the per capita consumption expenditure of all residents and the intensity of consumption is represented by the total retail sales of consumer goods. The rest of the indicators are calculated according to the formulas in the explanations of the underlying indicators and are not presented here in detail due to space limitations.

Table 1. Evaluation index system for nutrition-sensitive agricultural development level.

System Layer	Criterion Layer	Element Layer	Index Layer	Basic Index Interpretation	Indicator Attributes	Data Sources
Nutrition-sensitive agricultural production system	Usability	Capacity for comprehensive production of agricultural primary products	Cultivated land resources	Cultivated land area/resident population at year-end	Positive	Database of the National Bureau of Statistics, etc.
			Forestry resources	Rate of forest cover	Positive	Database of the National Bureau of Statistics, etc.
			Water resources	Effective irrigated area/total cultivated area	Positive	Database of the National Bureau of Statistics, etc.
			Labor input	Number of persons employed in primary sector/number of persons employed in society as a whole	Positive	China Statistical Yearbook, etc.
			Financial support for agriculture	Expenditure on agriculture, forestry and water affairs/total fiscal expenditure	Positive	Database of the National Bureau of Statistics
			Scientific and technological investment	Science and technology expenditure/total fiscal expenditure	Positive	Database of the National Bureau of Statistics
			Land productivity	Gross agricultural output/area sown for crops	Positive	Database of the National Bureau of Statistics
			Labor productivity	Gross output value of agriculture, forestry, animal husbandry and fishery/number of persons employed in the primary sector	Positive	Database of the National Bureau of Statistics
		Post-harvest handling and processing capacity	Number of agro-processing enterprises	Stock of enterprises in agro-processing industry	Positive	China Academy for Rural Development—Qiyan China Agri-Research Database (CCAD)
			Agricultural processing conversion rate	Main business income from agro-processing/gross output value of agriculture, forestry, animal husbandry and fisheries	Positive	Yearbook of China's agricultural products processing industries, etc.

Table 1. *Cont.*

System Layer	Criterion Layer	Element Layer	Index Layer	Basic Index Interpretation	Indicator Attributes	Data Sources
Nutrition-sensitive agricultural production system	Accessibility	Diversified food supply capacity	Grain production per capita	Grain production/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Vegetable production per capita	Vegetable production/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Fruit production per capita	Fruit production/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Animal food production per capita	(Meat production + fish production + egg production)/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Milk production per capita	Milk production/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Bean production per capita	Bean production/resident population at year-end	Positive	Database of the National Bureau of Statistics
			Quality of specialty agricultural products	Number of geographical indications for agricultural products	Positive	Ministry of Agriculture and Rural Affairs of the People's Republic of China
			Agricultural industry structural adjustment index	Agricultural output/gross output of agriculture, forestry, livestock and fisheries	Positive	Database of the National Bureau of Statistics
			Grain supply deviation	(Per capita grain production − grain dietary standards)/grain dietary standards	Positive	Database of the National Bureau of Statistics
			Vegetable supply deviation	(Vegetable production per capita − vegetable dietary standards)/vegetable dietary standards	Positive	Database of the National Bureau of Statistics
			Fruit supply deviation	(Per capita fruit production − fruit dietary standards)/fruit dietary standards	Positive	Database of the National Bureau of Statistics
			Animal food supply deviation	(Per capita production of animal food − dietary standards for animal food)/dietary standards for animal food	Positive	Database of the National Bureau of Statistics

Table 1. *Cont.*

System Layer	Criterion Layer	Element Layer	Index Layer	Basic Index Interpretation	Indicator Attributes	Data Sources
Nutrition-sensitive agricultural production system	Accessibility	Diversified food supply capacity	Milk and milk products supply deviation	(Per capita production of milk and milk products − dietary standards for milk and milk products)/dietary standards for milk and milk products	Positive	Database of the National Bureau of Statistics
			Bean supply deviation	(Per capita production of beans − dietary standards for beans)/dietary standards for beans	Positive	Database of the National Bureau of Statistics
Circulation regulation system for domestic agricultural products market	Reachability	Modern distribution capacity	Number of employees in the transportation sector	Number of employees in transportation and postal services	Positive	Database of the National Bureau of Statistics
			Density of hierarchical road network	Miles of graded roads/area of provinces and municipalities	Positive	Database of the National Bureau of Statistics
	Controllability	Storage and regulation capacity	Stabilization of food retail prices	(Absolute value of (retail price index for food commodities − 100)	Negative	Database of the National Bureau of Statistics
			Stabilization of consumer food prices	Absolute value of (food consumer price index − 100)	Negative	Database of the National Bureau of Statistics
International trade system for agricultural products	Substitutability	International market regulation capacity	Scale of agricultural imports	Agricultural imports/gross agricultural product	Positive	The Ministry of Commerce of China, etc.
			Scale of agricultural exports	Agricultural exports/gross agricultural product	Positive	The Ministry of Commerce of China, etc.
			Dependence of agriculture on foreign trade	Total agricultural imports and exports/value added in primary sector	Positive	The Ministry of Commerce of China, etc.

Table 1. *Cont.*

System Layer	Criterion Layer	Element Layer	Index Layer	Basic Index Interpretation	Indicator Attributes	Data Sources
Health and sustainability system	Sustainability	Capacity for health and environmental protection	Level of rural health personnel	Average village health center staff per village	Positive	National Health Commission, etc.
			Fertilizer application intensity	Fertilizer application/area sown for crops	Negative	Database of the National Bureau of Statistics, etc.
			Intensity of pesticide use	Pesticide use/area sown for crops	Negative	Database of the National Bureau of Statistics, etc.
		Capacity for women's empowerment	Proportion of female employee representatives in trade unions	Proportion of female representatives in the workers' conference	Positive	Database of the National Bureau of Statistics, etc.
			Percentage of rural women in politics	Proportion of women on the village committee	Positive	Economy Prediction System (EPS)
		Capacity for income security	Disposable income of rural residents	Disposable income per rural household	Positive	China Rural Statistical Yearbook
			Quality of life of rural residents	Engel's coefficient for rural households	Negative	China Statistical Yearbook
		Capacity for nutrition awareness	Educational level of rural labor force	Average years of schooling of the rural labor force	Positive	China Population and Employment Statistics Yearbook
			Level of healthcare consumption	The proportion of rural residents' healthcare expenditure in their consumption expenditure	Positive	Database of the National Bureau of Statistics, etc.
Consumer nutritional demand adaptation system	Adaptability	Nutrition demand adaptation capacity	Supply and demand coupling	Quantitative modeling of coupling	Positive	Database of the National Bureau of Statistics, etc.
			Supply and demand coordination	Quantitative modeling of coordination	Positive	Database of the National Bureau of Statistics, etc.
			Supply and demand matching	Quantitative modeling of matching	Positive	Database of the National Bureau of Statistics, etc.

Regarding the control variables affecting nutrition-sensitive agriculture, with reference to the studies of Cao Jie et al. [34], Gu Liangjun [35] and Wang Xingguo et al. [36], this article selects the following seven control variables: economic development level, industrialization level, informatization level, tax burden level, financial development level, industrial structure and government intervention level, as shown in Table 2. Among these, economic development level is measured by GDP per capita; industrialization level is measured by the proportion of industrial added value in the regional GDP; informatization level is measured by the ratio of total postal and telecommunication business to GDP; tax burden level is measured by the ratio of tax revenue to GDP; financial development level is measured by the ratio of loan balances of financial institutions to GDP; industrial structure is measured by the share of added value of the tertiary industry in the regional GDP; and government intervention level is measured by the ratio of local general budget expenditure to GDP.

Table 2. Descriptive statistics of control variables.

Variables	Obs	Mean	Std. Dev.	Min	Max
Nutrition-sensitive agricultural development level	713	0.1377	0.0575	0.0571	0.4703
Economic development level	713	3.8575	3.1398	0.2759	19.0313
Industrialization level	713	0.3449	0.0972	0.0705	0.5738
Informatization level	713	0.0620	0.0413	0.0151	0.2901
Tax burden level	713	0.0782	0.0260	0.0339	0.1882
Financial development level	713	1.2775	0.4452	0.5499	2.9959
Industrial structure	713	0.4639	0.0916	0.2964	0.8386
Government intervention level	713	0.2446	0.1824	0.0691	1.3537

Considering the availability of data, this study selects panel data from 31 provinces in China from between 2000 and 2022; the data for the relevant indicators come from the China Statistical Yearbook, the China Agricultural Yearbook, the China Rural Statistical Yearbook, the China Agricultural Products Processing Industry Yearbook and the China Population and Employment Statistical Yearbook. There are also some relevant indicator data from the official databases of China's National Bureau of Grain and Material Reserves, provincial statistical yearbooks, China's Ministry of Agriculture and Rural Affairs announcements, China's Ministry of Commerce Trade Department, the National Health and Family Planning Commission, the State Administration of Traditional Chinese Medicine, China's Ministry of Human Resources and Social Security, China's Ministry of Civil Affairs and other official databases. All data for the underlying price-related indicators have been deflated using price indices with a base period of 2000, and individual missing data have been supplemented by methods such as average estimation and index smoothing. At the same time, according to the rules of the National Bureau of Statistics for the division of economic zones, the 31 provinces are divided into four major regions, including the eastern region, the central region, the western region and the northeastern region.

2.2. Methods

Based on the indicators selected in the previous section, firstly, the entropy method is applied to measure the level of nutrition-sensitive food supply (LS) and the level of consumer nutritional demand (LD), respectively; secondly, the coupling, coordination and matching degrees of the level of nutrition-sensitive food supply (LS) and the level of consumers' nutritional demand (LD) are calculated using the supply and demand fit evaluation model, in order to be used as the evaluation indicators of the consumer nutritional demand adaptation system. On this basis, the entropy method is applied to measure the level of nutrition-sensitive agricultural development using the indicators of the five subsystems. Then, the Dagum Gini coefficient is used to analyze the magnitude and sources of regional differences in the development level of nutrition-sensitive agriculture in the whole country and in the four regions, and the kernel density estimation method is used to characterize the dynamic evolution of the level of nutrition-sensitive agriculture development in different regions. Finally, the convergence model is used to explore the characteristics of σ convergence and β convergence.

2.2.1. Methodology for Measuring Development of Nutrition-Sensitive Agriculture

The current academic indicator system construction approaches are mainly divided into two categories, namely the subjective weighting approach and the objective weighting approach [37]. The subjective weighting approach determines weights based on the evaluator's subjective emphasis on each indicator [38], including methods such as the Delphi method, the analytic hierarchy process (AHP) and the expert scoring method. On the other hand, the objective weighting approach determines indicator weights based on the information content and variation in magnitude of indicator values for different evaluation objects [39], including methods such as the entropy method [18,21], data envelopment analysis (DEA) [40] and gray relational analysis. The number of indicators for the design of nutrition-sensitive agricultural development systems is large, and the subjective weighting approach makes it difficult to comprehensively, accurately and objectively grasp the actual degree of importance of each indicator, thus increasing or decreasing the weight of each indicator. In the objective weighting approach, the entropy method calculates the corresponding weights for each indicator by leveraging the tool of information entropy, based on the degree of variation in each indicator, and has a strong mathematical basis. At the same time, the entropy method is very suitable for nutrition-sensitive agriculture, as this kind of systematic research can obtain a more objective result; therefore, the use of the entropy method to establish the weight of each indicator in order to measure the development of China's nutrition-sensitive agriculture is particularly suitable. The specific steps are as follows:

Construct the initial matrix as follows, assuming that there are n samples to be evaluated and m evaluation indicators, x_{ij} (i = 1, 2, 3. . . . . ., n; j = 1, 2, 3. . . . . ., m) is the raw indicator value of the jth indicator of evaluation object i.

$$x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Standardize the indicators. The positive and negative indicators in the evaluation indicator system are found to be dimensionless and isotropic using the extreme value method [41]. The specific treatment of positive and negative indicators in the indicator system for the level of nutrition-sensitive agricultural development is as follows:

$$\text{Positive indicators: } X_{ij} = \frac{x_{ij} - \min\{x_{1j}, \cdots, x_{nj}\}}{\max\{x_{1j}, \cdots, x_{nj}\} - \min\{x_{1j}, \cdots, x_{nj}\}} \tag{2}$$

$$\text{Negative indicators: } X_{ij} = \frac{\max\{x_{1j}, \cdots, x_{nj}\} - x_{ij}}{\max\{x_{1j}, \cdots, x_{nj}\} - \min\{x_{1j}, \cdots, x_{nj}\}} \tag{3}$$

In the equations, X_{ij} is the value of the indicator after standardization. max(x_{ij}) and min(x_{ij}) represent the maximum and minimum values of the jth indicator in the evaluation index system, respectively. The normalization matrix is obtained using the following calculation: $X = (X_{ij})_{n \times m}$.

Calculate the weighting matrix. Calculate the weighting p_{ij} of the jth nutrition-sensitive agricultural development level evaluation indicator x for the ith evaluation object, from which the weighting matrix $p = (p_{ij})_{n\times m}$ can be obtained as follows:

$$p_{ij} = \frac{X_{ij}}{\sum\limits_{i=1}^{n} X_{ij}}, j = (1, 2, \cdots, m) \quad (4)$$

Calculate the entropy of the jth indicator e_j as follows:

$$e_j = -k\sum_{i=1}^{n} (p_{ij} \ln p_{ij}), j = (1, 2, \cdots m) \quad (5)$$

In the equation, let $k = 1/\ln(n)$ and $0 \le e_j \le 1$.

Calculate the coefficient of variation in the jth indicator d_j. For the jth indicator, the greater the variation in the indicator value, the greater the impact on the evaluation result and the smaller the entropy value. The calculation formula is as follows:

$$d_j = 1 - e_j, j = (1, 2, \cdots m) \quad (6)$$

Calculate the weight value W_j for the jth indicator using the following formula:

$$W_j = \frac{d_j}{\sum\limits_{j=1}^{m} d_j}, j = (1, 2, \cdots m) \quad (7)$$

Calculate the composite score for each sample as follows:

$$S_i = \sum_{j=1}^{m} W_i \times X_{ij} \quad (8)$$

In the equation, S_i is the nutrition-sensitive agricultural development level score of the ith province. The larger S_i is, the better the nutrition-sensitive agricultural development level of the province is, and the smaller S_i is, the worse the nutrition-sensitive agricultural development level of the province is.

2.2.2. Supply and Demand Fit Evaluation Model

In this paper, we construct a nutrition-sensitive food supply and demand fitness evaluation model from three dimensions, namely the degrees of coupling, coordination and matching. The degree of coupling refers to the dynamic interrelationship of coordinated development achieved through the interaction and influence between two or more systems. It reflects the degree of mutual dependence and restraint among systems. A high coupling degree indicates strong connections between systems, while a low coupling degree signifies loose connections between systems. However, the coupling degree can only reflect the strength of interactions between systems and cannot indicate the degree of coordination between them [42]. The degree of coordination refers to whether the relationships among systems are reasonable and harmonious. A high coordination degree indicates tight and harmonious relationships between systems, while a low coordination degree suggests loose and uncoordinated relationships. The degree of matching refers to the symmetrical relationship between systems [29]. A high matching degree indicates a high level of congruence between systems, whereas a low matching degree suggests significant differences among systems.

(1) The quantitative modeling of coupling is carried out as follows:

$$C_v = \frac{s}{\frac{1}{2}(LS + LD)} = \sqrt{2\left[1 - \frac{LS \times LD}{\left(\frac{LS+LD}{2}\right)^2}\right]} \tag{9}$$

C_v is the coefficient of divergence between the level of nutrition-sensitive food supply (LS) and the level of consumer nutritional demand (LD); s is the standard deviation. To make C_v as small as possible, C' is as large as possible; C' is calculated as follows:

$$C' = \frac{LS \times LD}{\left(\frac{LS+LD}{2}\right)^2} \tag{10}$$

According to the above formula, a quantitative coupling model is constructed to assess the interaction and influence between nutrition-sensitive food supply and consumer nutrition demand levels. The coupling degree C ranges from [0, 1], with values closer to 1 indicating better coupling and values closer to 0 indicating poorer coupling. The specific calculation formula is as follows:

$$C = \left[\frac{LS \times LD}{\left(\frac{LS+LD}{2}\right)^2}\right]^{\frac{1}{2}} \tag{11}$$

(2) The quantitative modeling of coordination is carried out as follows:

$$T = \alpha \times LS + \beta \times LD \tag{12}$$

$$D = \sqrt{C \times T} \tag{13}$$

D is the degree of coordination between the level of nutrition-sensitive food supply and consumer nutritional demand, with a value range of [0, 1]. The closer to 1, the better the coordination, and the closer to 0, the worse the coordination; C is the degree of coupling; $\alpha = \beta = 0.5$; T is the reconciliation index.

(3) The quantitative modeling of matching is carried out as follows:

$$M_j = 1 - \frac{|LS_j - LD_j|}{U - 1}, (j = 1, 2, \cdots, U) \tag{14}$$

M_j is the matching degree in year j and the value range is [0, 1]. The closer to 1, the better the matching, whereas the closer to 0, the worse the matching. LS_j and LD_j are ranked in ascending order as the ordinal values of nutrition-sensitive food supply level and consumer nutrition demand level, respectively. U is the number of the research system.

2.2.3. Dagum Gini Coefficient and Its Decomposition

Due to the assumption of homoscedasticity and normal distribution in traditional measurement indicators like the Gini coefficient and the Theil index, the stringent assumptions do not reflect the overlapping parts between grouped samples. In 1997, Dagum addressed these shortcomings by proposing the Dagum Gini coefficient [43], which further decomposes overall sample differences. This method has been widely applied since then. This article uses the Dagum Gini coefficient for subgroup decomposition to analyze the spatial differentiation of nutrition-sensitive agricultural development levels, with the calculation formula as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{i=1}^{k}\sum_{h=1}^{n_j}\sum_{r=1}^{n_i}\left|y_{jh} - y_{ir}\right|}{2n^2\overline{y}} \tag{15}$$

In Formula (15), y_{jh} and y_{ir} represent the nutrition-sensitive agricultural development level of a province in regions j and i, respectively, with $\overline{y}$ indicating the average nutrition-sensitive agricultural development level of each province. Here, k denotes the number of regions, n represents the number of provinces and n_j and n_i are the number of provinces in regions j and i, respectively. It is worth noting that, during decomposition, the regions should be sorted based on the average nutrition-sensitive agricultural development level, as shown in Formula (16) below:

$$\overline{y_i} \leq \cdots \overline{y_j} \cdots \leq \overline{y_k} \tag{16}$$

Furthermore, the Dagum Gini coefficient can be decomposed into the contribution of intra-regional variance (G_w), the net contribution of inter-regional variance (G_{nb}) and the contribution of inter-regional hypervariance density (G_t), i.e., $G = G_w + G_{nb} + G_t$.

The intra-regional Gini coefficient (G_{jj}) measures the differences in the development of nutrition-sensitive agriculture within different regions and is calculated using the following formula:

$$G_{jj} = \frac{\sum_{h=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{jh} - y_{jr}\right|}{2n_j^2\overline{y_j}} \tag{17}$$

The inter-regional Gini coefficient (G_{ji}) measures the differences in the development of nutrition-sensitive agriculture between regions and is calculated using the following formula:

$$G_{ji} = \frac{\sum_{h=1}^{nj}\sum_{r=1}^{ni}\left|y_{jh} - y_{ir}\right|}{n_j n_i(\overline{y_j} + \overline{y_i})} \tag{18}$$

The formulae for the contribution of intra-regional variance (G_w), the net contribution of inter-regional variance (G_{nb}) and the contribution of inter-regional hypervariable density (G_t) are given below:

$$G_w = \sum_{j=1}^{k} G_{jj}P_jS_j \tag{19}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{i=1}^{j-1} G_{ji}(P_jS_i + P_iS_j)D_{ji} \tag{20}$$

$$G_t = \sum_{j=2}^{k}\sum_{i=1}^{j-1} G_{ji}(P_jS_i + P_iS_j)(1 - D_{ji}) \tag{21}$$

In the above equation, $P_j = n_j/n$ is the number of provinces in region j as a proportion of the country, $S_j = \overline{y_j}/n\overline{y}$ and j = 1, 2, . . ., k.

D_{ji} is defined as the relative impact of the level of nutrition-sensitive agricultural development between regions j and i. The calculation formula is as follows:

$$D_{ji} = \frac{d_{ji} - p_{ji}}{d_{ji} + p_{ji}} \tag{22}$$

where d_{ji} represents the difference between regions in the development of nutrition-sensitive agriculture, i.e., the expectation of the sum of all the sample values of $y_{jh} -> 0$ in regions j and i and P_{ji} represents the hypervariable first-order moments. The formulas for d_{ji} and P_{ji} are as follows:

$$d_{ji} = \int_0^{\infty} dF_j(y)\int_0^{y}(y - x)dF_i(x) \tag{23}$$

$$P_{ji} = \int_0^{\infty} dF_i(y) \int_0^{y} (y - x) dF_j(x) \tag{24}$$

where F_j and F_i are cumulative density distribution functions for regions j and i.

2.2.4. Kernel Density Estimation

Kernel density estimation is a non-parametric estimation method that is often used to describe the distribution dynamics of random variables in the time dimension and is able to characterize the distribution of the level of nutrition-sensitive agricultural development using continuous density curves. In an individual period, the position of the kernel density curve can indicate the level of nutrition-sensitive agricultural development, the height and width of the peaks of the kernel density curve can represent the degree of aggregation of the level of nutrition-sensitive agricultural development, the number of peaks can represent the degree of polarization, the distribution of the extensibility can represent the distance between the highest and the lowest level of nutrition-sensitive agricultural development and the distance from other provinces, and a more serious trailing tail indicates a higher degree of variation within the sample area. The more severe the tailing, the higher the degree of difference within the sample area [44]. Assuming that the density function of the random variable x is $f(x)$, the Gaussian kernel function is used to estimate the distributional dynamics and evolutionary trends of the development of nutrition-sensitive agriculture, using the following formula:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{25}$$

$$K(x) = (1/2\pi) e^{(-x^2/2)} \tag{26}$$

where n denotes the number of samples, h is the window width, x_i is the number of observations, x is the mean of the observations and $K(x)$ denotes the Gaussian kernel function.

2.2.5. Convergence Model

(1) σ convergence

σ convergence refers to a tendency for the degree of dispersion to decrease over time; if the σ convergence coefficient decreases gradually over time, then there is σ convergence. Referring to the studies of Gu et al. [45] and Xiang Yun et al. [23], in this paper, the coefficient of variation is used to measure the σ convergence of the development of nutrition-sensitive agriculture, and the calculation formula for this is as follows:

$$\sigma_t = \frac{\sqrt{\sum_{n=1}^{N} \left(NSA_{n,t} - \overline{NSA_t}\right)^2 / N}}{\overline{NSA_t}} \tag{27}$$

where $NSA_{n,t}$ denotes the level of nutrition-sensitive agricultural development in the nth region in period t; $\overline{NSA_t}$ denotes the average level of development in nutrition-sensitive agriculture across all provinces during period t; and n is the number of provinces in the sample.

(2) β convergence

β convergence refers to the fact that, over time, the gap between the growth rates of nutrition-sensitive agricultural development levels in different regions gradually narrows, and these levels reach a stable growth rate eventually. Β convergence mainly includes absolute β convergence and conditional β convergence. Absolute β convergence refers to the tendency of convergence of the nutrition-sensitive agricultural development level among regions without considering the factors that can have an important influence on the nutrition-sensitive agricultural development level. The formula for calculating absolute β convergence is as follows:

$$\ln(\frac{NSA_{n,t+1}}{NSA_{n,t}}) = \alpha + \beta \ln(NSA_{n,t}) + u_n + \lambda_t + \varepsilon_{n,t} \quad (28)$$

where $NSA_{n,t+1}$ denotes the level of nutrition-sensitive agricultural development in the nth region in period t + 1 and $NSA_{n,t}$ denotes the level of nutrition-sensitive agricultural development in the region n in period t. $\ln\left(\frac{NSA_{n,t+1}}{NSA_{n,t}}\right)$ is the growth rate of the level of nutrition-sensitive agricultural development in province n in period t + 1. β is the coefficient of convergence; if β is significantly negative, it means that there is absolute β convergence in the development of nutrition-sensitive agriculture, and vice versa, suggesting a divergent trend in the development of nutrition-sensitive agriculture. The rate of convergence is calculated using the following formula: $V = -\ln(1 - |\beta|)/T$. u_n, λ_t and $\varepsilon_{n,t}$ are random disturbance terms.

The conditional β convergence model refers to adding control variables affecting the development of nutrition-sensitive agriculture on the basis of the above absolute β convergence model and discussing whether the nutrition-sensitive agricultural development has a convergence trend when a series of factors that have an important influence on the development of nutrition-sensitive agriculture are controlled. The formula for calculating conditional β convergence is as follows:

$$\ln(\frac{NSA_{n,t+1}}{NSA_{n,t}}) = \alpha + \beta \ln(NSA_{n,t}) + \delta X_{n,t+1} + u_n + \lambda_t + \varepsilon_{n,t} \quad (29)$$

where X denotes a set of control variables affecting the development of nutrition-sensitive agriculture and δ is a vector of parameters.

3. Results

3.1. Results of the Measurement of the Development of Nutrition-Sensitive Agriculture

The development of nutrition-sensitive agriculture in 31 provinces was measured using STATA18.0 software. The specific calculation results are shown in Appendix A (Table A1). In order to more directly show the dynamic changes in the spatial and temporal patterns of nutrition-sensitive agriculture in China, according to the relative degree of development of 31 provinces, the development of nutrition-sensitive agriculture is divided into four echelons, namely, high-level (greater than or equal to 0.20), medium–high-level (less than or equal to 0.20 and greater than or equal to 0.15), medium–low-level (less than or equal to 0.15 and greater than or equal to 0.1) and low-level (less than 0.1). As the space herein is limited, this paper selects four temporal cross-sections, in 2000, 2008, 2015 and 2022, and uses ArcGIS10.8 software to analyze the development of nutrition-sensitive agriculture in each province (Figure 2).

The development of nutrition-sensitive agriculture has shown an upward trend year-on-year in China. However, there are significant differences between provinces, exhibiting a clear spatial pattern of "higher in the east and lower in the west". Provinces that have long maintained a relatively high level include Shanghai, Beijing, Heilongjiang, Shandong and Inner Mongolia, while provinces with lower levels include Gansu, Chongqing, Shanxi, Tibet and Qinghai. As shown in Figure 2, in 2000, the development of nutrition-sensitive agriculture across China was generally low, with 30 provinces at a medium–low level or below. Among these, 23 provinces were at a low level, accounting for 74.19%, and only Beijing reached a medium–high level, with no provinces at a high level. By 2008, the number of low-level provinces had decreased significantly to twelve, medium–low-level provinces increased to fourteen, medium–high-level provinces rose to three and high-level provinces increased to two, with Beijing and Inner Mongolia reaching a high level. In 2015, the number of medium–high- and high-level provinces increased to nine and five, respectively, while the number of medium–low-level provinces remained at fourteen and the number of low-level provinces decreased to three. By 2022, the number of medium–high-level provinces surged to seventeen and the number of high-level provinces increased to eight, with the proportion of provinces at a medium–high level and above rising to 80.65%. The number of medium–low-level provinces decreased to five and Qinghai remained the only low-level province.

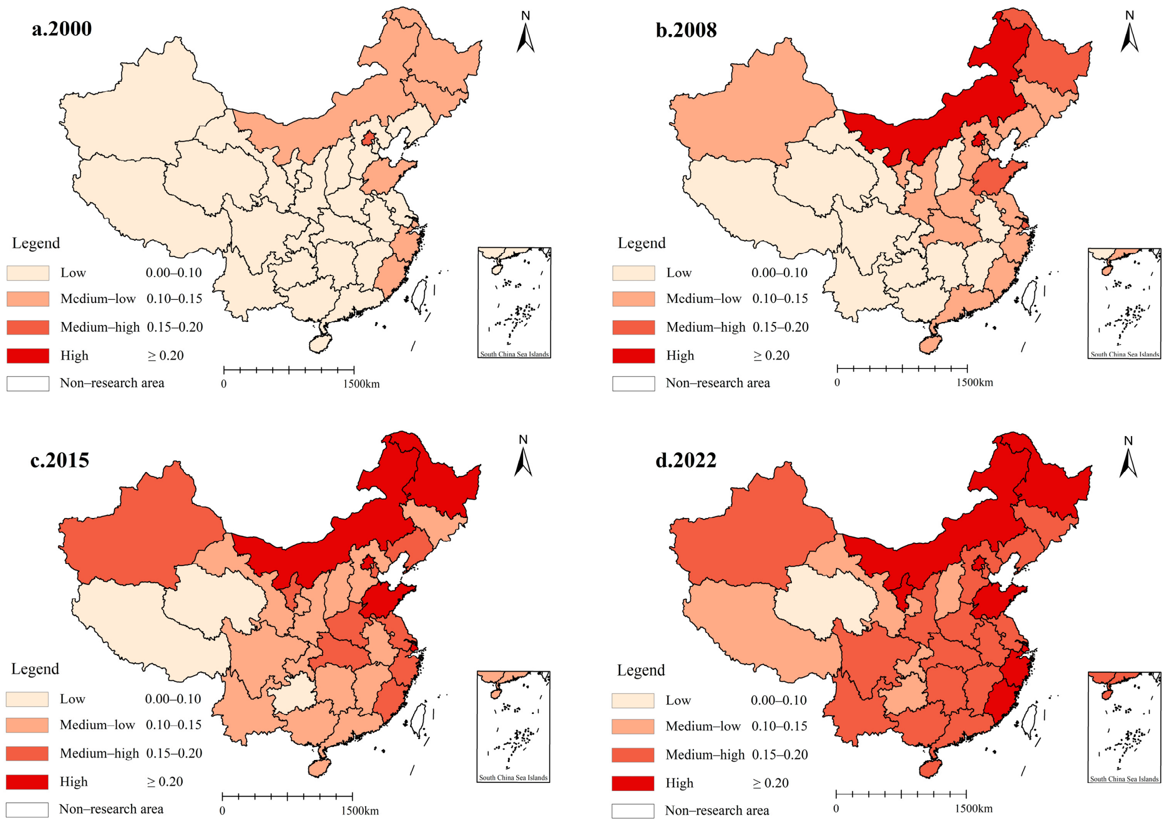

Figure 2. The spatial distribution of the development level of nutrition-sensitive agriculture in China. Note: Produced on the basis of the standard base map of the Standard Map Service System of the State Administration of Surveying, Mapping and Geographic Information (Review No. GS (2023) 2767), with no modifications to the base map.

From the perspective of the four major regions, there is an imbalance in the development of nutrition-sensitive agriculture in China. As shown in Table 3, the ranking of nutrition-sensitive agricultural development levels among the four regions is as follows: eastern region > northeastern region > central region > western region, with corresponding average values of 0.1659, 0.1642, 0.1197 and 0.1167. Notably, before 2012, except for the year 2007, the development of nutrition-sensitive agriculture in the northeastern region was higher than that in the eastern region. However, since 2012, the development of nutrition-sensitive agriculture in the eastern region has gradually surpassed that of the northeastern region. By 2022, the development of nutrition-sensitive agriculture in the eastern region rose to a high of 0.2469, while that of the northeastern region rose to 0.2179. The development of nutrition-sensitive agriculture in the eastern and northeastern regions is relatively close, as is that in the central and western regions. This disparity may reflect differences in economic, technological and infrastructural factors.

Table 3. Level of development of nutrition-sensitive agriculture in four regions from 2000 to 2022.

Year/Region	Eastern Average	Central Average	Western Average	Northeastern Average	National Average
2000	0.1085	0.0806	0.0745	0.1160	0.0907
2001	0.1090	0.0818	0.0770	0.1191	0.0923
2002	0.1111	0.0848	0.0812	0.1292	0.0962
2003	0.1176	0.0834	0.0816	0.1334	0.0986
2004	0.1209	0.0840	0.0853	0.1327	0.1011
2005	0.1303	0.0883	0.0923	0.1421	0.1086
2006	0.1318	0.0918	0.0946	0.1418	0.1106
2007	0.1426	0.0953	0.0969	0.1387	0.1154
2008	0.1457	0.0979	0.1002	0.1499	0.1192
2009	0.1465	0.1062	0.1078	0.1562	0.1247
2010	0.1529	0.1103	0.1100	0.1605	0.1288
2011	0.1596	0.1150	0.1124	0.1657	0.1333
2012	0.1699	0.1221	0.1195	0.1684	0.1410
2013	0.1728	0.1304	0.1235	0.1717	0.1454
2014	0.1774	0.1361	0.1295	0.1769	0.1508
2015	0.1834	0.1392	0.1342	0.1787	0.1554
2016	0.1890	0.1421	0.1377	0.1847	0.1596
2017	0.1986	0.1467	0.1408	0.1900	0.1654
2018	0.2069	0.1518	0.1446	0.1895	0.1704
2019	0.2214	0.1556	0.1496	0.1986	0.1787
2020	0.2284	0.1628	0.1552	0.2072	0.1853
2021	0.2438	0.1718	0.1644	0.2078	0.1957
2022	0.2469	0.1753	0.1704	0.2179	0.2006
Average	0.1659	0.1197	0.1167	0.1642	0.1377

3.2. Analysis of Regional Differences in the Development of Nutrition-Sensitive Agriculture

3.2.1. Overall and Intraregional Differences

The Dagum Gini coefficient was used to measure the degree of intra-group differences in the development of nutrition-sensitive agriculture in 31 provinces and four major regions, and the results are reported year-by-year in Figure 3.

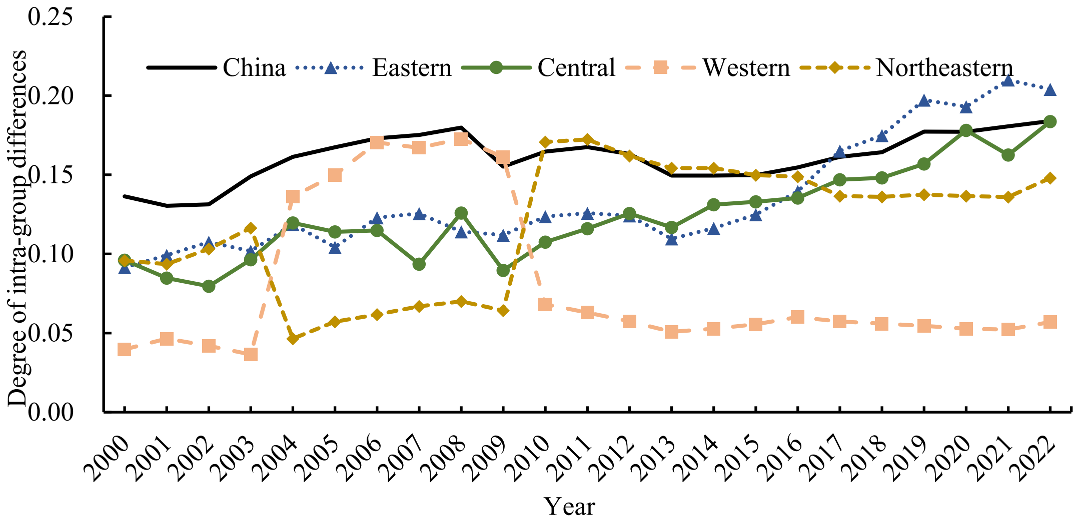

Figure 3. National and regional differentiation degree.

From a national perspective, the overall Gini coefficient showed a fluctuating upward trend between 2000 and 2022, ranging from 0.1305 to 0.1840, with an average of 0.1610. This indicates a significant imbalance in the development of nutrition-sensitive agriculture across China's provinces, and this imbalance is deepening. Specifically, the overall national disparity in nutrition-sensitive agricultural development was 0.1364 in

2000, which increased to 0.1798 in 2008, decreased to 0.1552 in 2009, rose to 0.1675 in 2011, dropped to 0.1495 in 2013 and reached a peak of 0.1840 in 2022. Currently, the development of nutrition-sensitive agriculture in China is still in its initial stages [1], as agriculture is transitioning from a yield-sensitive to a nutrition-sensitive focus. Moreover, the lack of systematic promotion measures makes it a challenging task to reduce regional disparities in nutrition-sensitive agricultural development.

From a regional perspective, except for a few years where the Gini coefficient exceeded the national level, the Gini coefficients of most regions were lower than the overall national Gini coefficient. This indicates that the internal imbalance within the four major regions is relatively low, compared to the national level. Among these, the eastern region exhibits the greatest internal disparity, with an average Gini coefficient of 0.1350 during the sample period. A possible reason for this is that the nutrition-sensitive agricultural development levels in Shanghai and Beijing are significantly higher than in other areas, resulting in a larger regional disparity. The central region follows, with an average Gini coefficient of 0.1242 during the sample period. The northeastern region ranks third, with an average Gini coefficient of 0.1182. The western region exhibits relatively smaller internal variance, with an average Gini coefficient of 0.0808 during the sample period. In terms of trends, the regional disparities in the development of nutrition-sensitive agriculture in all four major regions show a fluctuating upward trend. The disparity in the eastern region is increasing relatively quickly, followed by the central region, with the northeastern and western regions experiencing relatively slower increases. The average annual growth rates are 3.71%, 2.99%, 2.00% and 1.66%, respectively. Comparing the evolutionary trends in the internal disparities of nutrition-sensitive agricultural development levels across the four major regions, it can be observed that the Gini coefficients in all regions exhibit a fluctuating upward trend. Between 2000 and 2016, the Gini coefficients of the eastern and central regions surpassed each other. However, from 2017 to 2022, the growth rate of the Gini coefficient in the eastern region accelerated, gradually widening the gap with the central region. From 2003 to 2010, the Gini coefficients in the western and northeastern regions experienced significant changes, likely related to the "The development of the western region in China" and "Revitalizing the old industrial base in Northeast China" policies.

3.2.2. Inter-Regional Differences

The inter-regional differences in the development of nutrition-sensitive agriculture are shown in Table 4. As illustrated, taking the eastern region–central region comparison as an example, the inter-regional differences in nutrition-sensitive agricultural development levels exhibit a fluctuating upward trend. From 2000 to 2013, the Gini coefficient increased relatively slowly, gradually rising from 0.1035 in 2000 to 0.1162 in 2013. The growth rate accelerated in 2014, reaching 0.2164 by 2022. Other inter-regional differences also show a fluctuating upward trend, characterized by "increase–decrease–increase" patterns, though the overall increase is relatively smaller. In terms of the growth rate of inter-regional Gini coefficients, the eastern–central and western–northeastern regional comparisons have relatively faster growth, with average annual increases of 3.41% and 1.57%, respectively. In contrast, the eastern–northeastern and eastern–western inter-regional Gini coefficients grew more slowly, with average annual increases of 0.18% and 0.17%, respectively.

Comparing the Gini coefficients between different regions, it can be observed that the eastern–northeastern regions exhibit the largest inter-regional differences in nutrition-sensitive agricultural development, with an average Gini coefficient of 0.2153. This disparity may be attributed to various factors such as differences in economic development, technological advancement and social environment between the eastern and northeastern regions, collectively contributing to a significant gap in nutrition-sensitive agricultural development. The eastern region has relatively favorable climatic conditions suitable for the growth of diverse crops, which benefits agricultural output and quality. Additionally, its economic development is more advanced, with a concentration of agricultural research institutions and higher education institutions leading in agricultural technology development and dissemination. The rural infrastructure and public service levels are higher, fostering the robust development of nutrition-sensitive agriculture in areas like Beijing and Shanghai. Conversely, the northeastern region faces delayed economic transformation and primarily focuses on staple grain production, lacking diversified and high-value-added agricultural products. This leads to relatively underdeveloped nutrition-sensitive agriculture in provinces like Liaoning and Jilin, resulting in significant regional disparities. In contrast, the western–northeastern regions show the smallest inter-regional differences in nutrition-sensitive agricultural development, with an average Gini coefficient of 0.1122. The primary reason is that both the northeastern and western regions are at similar stages of economic development, undergoing economic transformation and upgrades. Additionally, there is a certain similarity in terms of policy support and guidance, contributing to more comparable development levels between these regions.

Table 4. Regional Gini coefficients of nutrition-sensitive agriculture development level.

Year/Region	Eastern–Central	Eastern–Western	Eastern–Northeastern	Central–Western	Central–Northeastern	Western–Northeastern
2000	0.1035	0.1803	0.2200	0.1475	0.1899	0.0821
2001	0.1028	0.1859	0.2168	0.1426	0.1756	0.0801
2002	0.1168	0.2073	0.2324	0.1343	0.1656	0.0833
2003	0.1159	0.2305	0.2459	0.1699	0.1930	0.0882
2004	0.1333	0.2390	0.2245	0.2043	0.1802	0.1016
2005	0.1221	0.2421	0.2334	0.2123	0.1923	0.1133
2006	0.1299	0.2441	0.2141	0.2206	0.1817	0.1288
2007	0.1167	0.2318	0.2007	0.2189	0.1856	0.1306
2008	0.1254	0.2396	0.2101	0.2314	0.1987	0.1360
2009	0.1089	0.2205	0.1905	0.1977	0.1604	0.1253
2010	0.1213	0.1883	0.2267	0.1650	0.2095	0.1326
2011	0.1245	0.1848	0.2287	0.1668	0.2154	0.1313
2012	0.1297	0.1678	0.2113	0.1660	0.2093	0.1231
2013	0.1162	0.1438	0.1965	0.1461	0.1967	0.1176
2014	0.1283	0.1398	0.1901	0.1466	0.1945	0.1195
2015	0.1346	0.1454	0.1895	0.1412	0.1855	0.1167
2016	0.1438	0.1515	0.1934	0.1464	0.1883	0.1175
2017	0.1638	0.1635	0.2039	0.1499	0.1899	0.1088
2018	0.1744	0.1683	0.2098	0.1415	0.1826	0.1075
2019	0.1946	0.1871	0.2280	0.1499	0.1900	0.1074
2020	0.2045	0.1826	0.2247	0.1642	0.2004	0.1067
2021	0.2105	0.1907	0.2319	0.1477	0.1814	0.1068
2022	0.2164	0.1870	0.2290	0.1680	0.1994	0.1156
Average	0.1408	0.1922	0.2153	0.1686	0.1898	0.1122

3.2.3. Sources of and Contributions to Regional Differences

The changing trends in contributions to and sources of regional differences in nutrition-sensitive agricultural development levels are shown in Figure 4. Overall, from 2000 to 2022, the main source of regional differences was inter-regional differences, with an average of 56.52%. The contributions of intra-regional differences and hypervariable density were relatively smaller, with averages of 23.47% and 20.01%, respectively. In terms of the evolutionary trend, the contribution rate of inter-regional differences to regional differences showed a fluctuating downward trend, decreasing from 71.89% in 2000 to 48.41% in 2022. The contribution rates of intra-regional differences and hypervariable density showed a fluctuating upward trend. Among them, the contribution rate of hypervariable density increased significantly, rising from 8.91% in 2000 to 25.12% in 2022, comprising an increase of 16.21 percentage points. The growth in the contribution rate of intra-regional differences was relatively smaller, increasing from 19.20% in 2000 to 26.47% in 2022, comprising an increase of 7.27 percentage points. In summary, to promote the coordinated development of nutrition-sensitive agriculture, it is important not only to focus on narrowing inter-regional differences but also to pay attention to the issues of intersection and overlap in nutrition-sensitive agricultural development between regions.

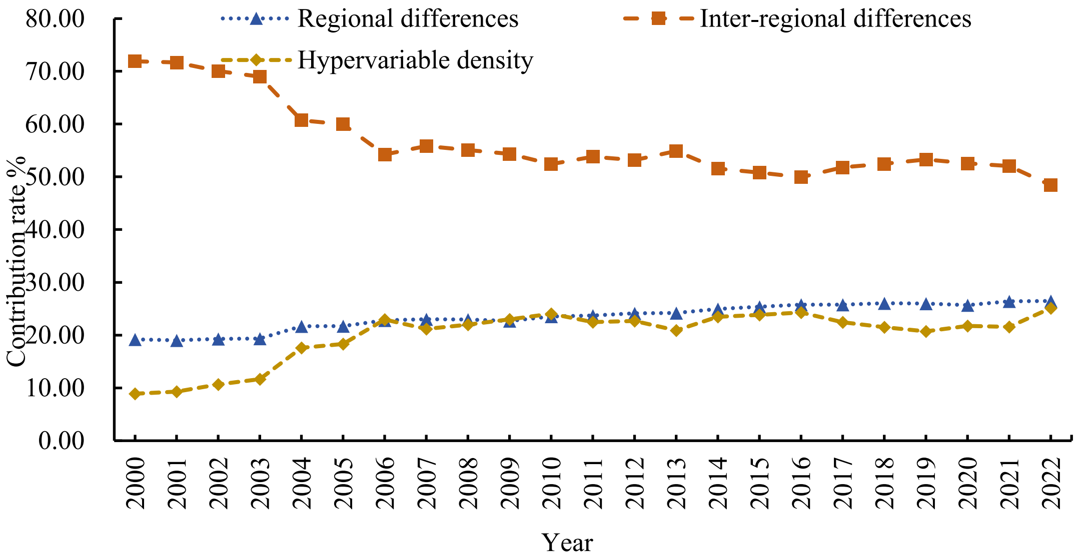

Figure 4. Contribution trend of regional differences in nutrition-sensitive agricultural development level.

3.3. Dynamic Evolution Analysis of Nutrition-Sensitive Agriculture

This study, based on the Dagum Gini coefficient, reveals the size and sources of regional differences in levels of nutrition-sensitive agricultural development in China and identifies the trajectories of relative differences among four major regions. However, it cannot describe the dynamic evolution process of absolute differences in the development of nutrition-sensitive agriculture in each region. Therefore, further analysis was conducted using the Kernel density estimation method, employing three-dimensional graphs to depict the dynamic change characteristics of sample data from the four major regions. This analysis focuses on key attributes such as the position of the corresponding kernel density curve distribution, the distribution shape of the main peak, distribution extensibility and the number of peaks. The corresponding dynamic evolution characteristics are reported in Table 5, while the specific kernel density estimation results are illustrated in Figure 5.

Table 5. Dynamic evolution characteristics of nutrition-sensitive agricultural development level in China and four major regions.

Region	Distribution Position	Main Peak Distribution Shape	Distribution Extensibility	Number of Peaks
National	Shift to the right	Height decreases, width increases	Right tailing, extended dispersion	Single or double peak
Eastern	Shift to the right	Height decreases, width increases	Right tailing, extended dispersion	Single or double peak
Central	Shift to the right	Height decreases, width increases	Right tailing, extended convergence	Single peak
Western	Shift to the right	Height decreases, width increases	Right tailing, extended dispersion	Single or double peak
Northeastern	Shift to the right	Height unchanged, width decreases	Right tailing, extended dispersion	Single or double peak

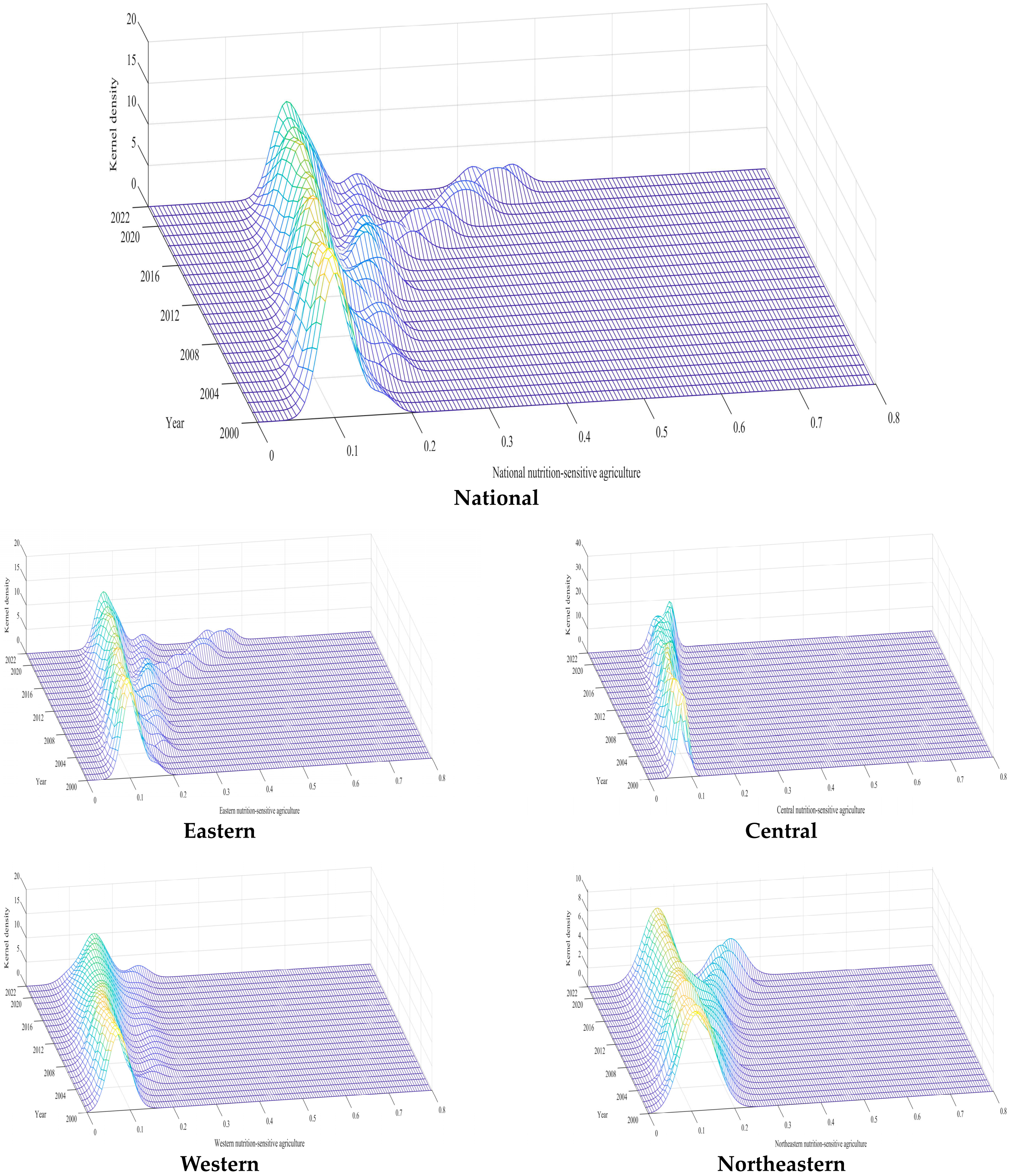

Figure 5. The dynamic evolution of the development level of nutrition-sensitive agriculture. Note: The curve in the figure represents the Kernel density curve, with lighter colors indicating larger Kernel density values.

Firstly, from the perspective of distribution position, on the national level, the Kernel density curve shows an overall rightward shift. This indicates that most provinces in China are on an upward trajectory in terms of their nutrition-sensitive agricultural development, gradually transitioning from yield-sensitive to nutrition-sensitive agriculture. The distribution curves of the four major regions all exhibit varying degrees of a rightward shift, indicating that these regions have achieved some success in nutrition-sensitive agricultural development. Notably, the central and western regions experienced a temporary leftward shift in their curves during the sample period, suggesting some degree of pressure in developing nutrition-sensitive agriculture in these areas, and there are certain challenges in implementing related intervention measures.

Secondly, from the perspective of the main peak distribution shape, on the national level, the Kernel density curve shows a decrease in the height of the main peak and an increase in its width. This implies that, during the sample period, the dispersion of nutrition-sensitive agricultural development levels has been increasing. This is because different regions have varying agricultural resource endowments and environmental constraints, leading to significant differences in the pathways and ease of advancing nutrition-sensitive agriculture. The main peak distribution shapes of the Kernel density curves in the eastern, central and western regions are similar to the national trend, also showing a decrease in peak height and an increase in width, indicating a widening gap in nutrition-sensitive agricultural development levels within these regions. In contrast, the Kernel density curve for the northeastern region shows an unchanged peak height and a decrease in width, suggesting that the absolute differences in nutrition-sensitive agricultural development levels in the northeastern region are gradually narrowing.

Thirdly, in terms of distribution extensibility, on the national level, the Kernel density curve exhibits a right tailing phenomenon. This indicates that, in some provinces within regions, the level of nutrition-sensitive agricultural development is significantly higher than that of other provinces in the same region. The relatively poor convergence of the curve's extension suggests a high likelihood of extreme values in the development levels nationally. The separate nutrition-sensitive agricultural development level distribution curves for the eastern, central, western and northeastern regions also exhibit right tailing. Among them, the eastern, western and northeastern regions show relatively poor convergence of the Kernel density curve extension, indicating a higher likelihood of extreme values. In contrast, the central region shows convergence in the distribution extension, suggesting a decreasing likelihood of extreme values.

Fourthly, during the sample period, the number of peaks at the national level and in the eastern, western and northeastern regions all experienced a bimodal phenomenon. This indicates a polarization in the levels of nutrition-sensitive agricultural development within these regions. In the eastern and northeastern regions, there was a transition from a single peak at the beginning of the sample period to a bimodal distribution by the end, with the distance between the two peaks gradually increasing. This suggests a significant spatial polarization within these regions. In contrast, the central region primarily exhibited a single peak throughout the sample period, indicating a weaker polarization phenomenon and a trend towards reduced differentiation within the region.

3.4. Convergence Analysis of Nutrition-Sensitive Agriculture

3.4.1. σ Convergence Analysis

Figure 6 presents the results of the σ convergence nationwide and across the four major regions. At the national level, the σ value of nutrition-sensitive agricultural development levels shows an upward trend over time. Although there are certain years with slight decreases, the overall trend indicates divergence. Regionally, the northeastern and eastern regions exhibit significant increases in σ values, with growth rates of 2.23 times and 2.11 times, respectively. This suggests an expanding regional disparity in nutrition-sensitive agricultural development levels in these areas, with marked divergence characteristics. In the western and central regions, regional disparities in nutrition-sensitive agricultural development levels also increased, with σ values rising from 0.1722 and 0.0806 in 2000 to 0.2736 and 0.1028 in 2022, respectively. Overall, whether viewed from a national perspective or across the eastern, central, western and northeastern regions, the end-period σ values of nutrition-sensitive agricultural development levels are greater than the initial values, indicating the absence of σ convergence in general. This is consistent with the analysis results of the regional disparity using the Dagum Gini coefficient.

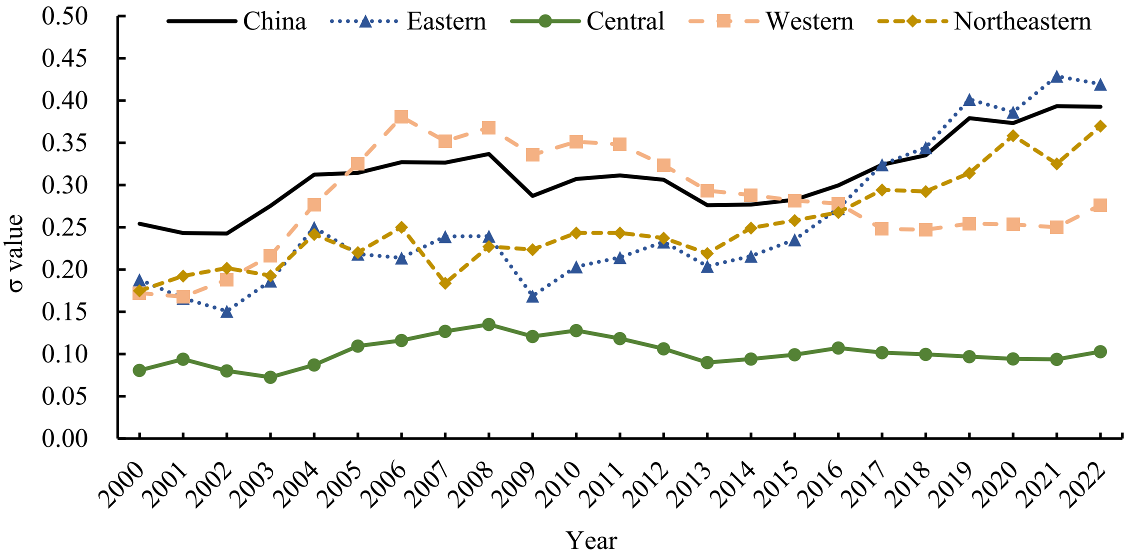

Figure 6. Results of the σ convergence.

3.4.2. Absolute β Convergence Analysis

Table 6 presents the results of the absolute β convergence test for the nation and for the four major regions. The results indicate that, firstly, there is an absolute β convergence characteristic in the nutrition-sensitive agricultural development levels both nationwide and across all four major regions. At the national level, the absolute β convergence coefficient for nutrition-sensitive agricultural development levels in China is −0.0912, which is significant at the 1% statistical level. From a regional perspective, the absolute β convergence coefficients for the central and western regions are significantly negative at the 1% statistical level, while those for the eastern and northeastern regions are significantly negative at the 5% statistical level. This indicates that, in the long term, and without considering a range of economic and social factors affecting nutrition-sensitive agriculture, the development of nutrition-sensitive agriculture across the nation and in the four major regions will converge towards their respective steady-state levels.

Table 6. Absolute β convergence results of nutrition-sensitive agriculture development levels in China and across four major regions therein.

Variables	(1) National	(2) Eastern	(3) Central	(4) Western	(5) Northeastern
β	−0.0912 ***	−0.0739 **	−0.1649 ***	−0.0993 ***	−0.1662 **
	(0.0185)	(0.0339)	(0.0532)	(0.0288)	(0.0708)
v	0.0042	0.0033	0.0078	0.0045	0.0079
Time effects	controlled	controlled	controlled	controlled	controlled
Individual effects	controlled	controlled	controlled	controlled	controlled
Constant	−0.2013 ***	−0.1032	−0.3938 ***	−0.2292 ***	−7.5539 *
	(0.0455)	(0.0658)	(0.1326)	(0.0765)	(4.0424)
Observations	682	220	132	264	66
R^2	0.1621	0.2465	0.5756	0.3289	0.1423

Note: The numbers in parentheses () represent standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Secondly, the convergence speeds of nutrition-sensitive agricultural development levels vary across the nation and the four major regions. The national convergence speed is 0.0042. Regions with a convergence speed higher than the national average include the northeastern, central and western regions, while the eastern region is the only area with a convergence speed lower than the national average. Notably, the northeastern region is able to maintain a relatively high convergence speed despite having a relatively high σ value, possibly due to the mutual influence of spatial effects among the provinces within the region. It is important to note that the above analysis of absolute β convergence at the national and regional levels assumes that factors such as economic development, industrialization, informatization, tax burden, financial development, industrial structure and government intervention are at similar levels. However, these factors evidently differ in reality. Therefore, it is necessary to control these variables and further analyze them using the conditional β convergence model.

3.4.3. Conditional β Convergence Analysis

Table 7 provides the results of the conditional β convergence test for the nation and for the four major regions. The results show that, firstly, there is a conditional β convergence characteristic in the nutrition-sensitive agricultural development levels both nationwide and across all four major regions. The conditional β convergence coefficients for the nation and the four regions are significantly negative at the 1% statistical level. This indicates that, even after accounting for factors such as economic development, industrialization, informatization, tax burden, financial development, industrial structure and government intervention, there is still a long-term trend of convergence in nutrition-sensitive agricultural development levels towards their respective steady states at both national and regional levels. Secondly, compared to absolute β convergence, the speed of conditional β convergence has accelerated for the nation and the major regions. The northeastern, western and eastern regions have shown larger increases in convergence speed, with rates rising by 0.0133, 0.0024 and 0.0021, respectively. The central region's increase is relatively smaller, with a convergence rate increase of 0.0004. Moreover, in terms of the model's goodness of fit, after incorporating a set of control variables, the R^2 for all national and regional models in the conditional β convergence model shows a significant increase compared to the absolute β convergence model. This indicates that the selection of control variables is reasonably effective and that these variables have a significantly heterogeneous impact on nutrition-sensitive agricultural development levels across regions.

Table 7. Conditional β convergence results of nutrition-sensitive agriculture development level in China and across four major regions therein.

Variables	(1) National	(2) Eastern	(3) Central	(4) Western	(5) Northeastern
β	−0.1130 ***	−0.1162 ***	−0.1716 ***	−0.1475 ***	−0.3854 ***
	(0.0205)	(0.0398)	(0.0549)	(0.0332)	(0.1279)
Economic development level	0.0549 ***	0.0288	0.0334	0.1048 ***	−0.0939
	(0.0156)	(0.0391)	(0.0442)	(0.0316)	(0.1408)
Industrialization level	−0.0687 ***	−0.0180	−0.1365 **	0.0191	−0.1980
	(0.0238)	(0.0633)	(0.0643)	(0.0473)	(0.1377)
Informationization level	0.0084	0.0107	−0.0006	0.0251	−0.1413
	(0.0108)	(0.0219)	(0.0276)	(0.0176)	(0.0938)
Tax burden level	−0.0105	0.0364	0.0224	−0.0427 **	0.1360
	(0.0145)	(0.0655)	(0.0335)	(0.0193)	(0.0991)
Financial development level	−0.0100	−0.1032 **	0.0429	0.0190	0.0333
	(0.0121)	(0.0420)	(0.0331)	(0.0152)	(0.1001)
Industrial structure	−0.0789 **	−0.1055	−0.1612 **	0.1006	-0.2375
	(0.0355)	(0.0852)	(0.0778)	(0.0666)	(0.1976)
Government intervention level	0.0195	−0.0011	−0.0611	0.0358	0.0382
	(0.0196)	(0.0507)	(0.0691)	(0.0334)	(0.1127)
v	0.0052	0.0054	0.0082	0.0069	0.0212
Time effects	controlled	controlled	controlled	controlled	controlled
Individual effects	controlled	controlled	controlled	controlled	controlled
Constant	−0.3513 ***	−0.1604	−0.7607 ***	−0.1460	−1.3273 **
	(0.0880)	(0.1684)	(0.2244)	(0.1670)	(0.6487)
Observations	682	220	132	264	66
R^2	0.1859	0.2914	0.6178	0.3994	0.6332

Note: The numbers in parentheses () represent standard errors. ** and *** indicate significance at the 5% and 1% levels, respectively.

4. Conclusions and Policy Implications

4.1. Conclusions

This paper measures the nutrition-sensitive agricultural development levels of 31 provinces in China from 2000 to 2022 using the entropy method. It analyzes regional differences in these levels across the nation and four major regions using the Dagum Gini coefficient. To further clarify the distribution characteristics and dynamic evolution trends, this study employs Kernel density estimation. Additionally, it analyzes the convergence trends using σ convergence and β convergence models. The study concludes the following:

Firstly, in terms of regional differences, the ranking of nutrition-sensitive agricultural development levels in the four major regions is as follows: eastern region > northeastern region > central region > western region, showing a "higher in the east, lower in the west" spatial pattern. There is an imbalance in the regional development of nutrition-sensitive agriculture in China, and this imbalance is deepening. The level of imbalance within the four major regions is relatively lower than the national level, with the degree of differentiation ranked as eastern region > central region > northeastern region > western region. Additionally, the differentiation in the eastern region is increasing at a relatively faster pace. The inter-regional differences among the four major regions exhibit a fluctuating upward trend, with a pattern of "increase–decrease–increase". The largest inter-regional difference is between the eastern and northeastern regions, while the smallest is between the western and northeastern regions. The main source of regional differences is inter-regional disparities, contributing an average of 56.52%. However, the contribution rate shows a fluctuating downward trend.

Secondly, from the perspective of dynamic evolution characteristics, the Kernel density curves for the nation and the four major regions generally show a rightward shift, indicating that most provinces in China are on an upward trajectory in this regard. The Kernel density curves for the nation and for the eastern, central and western regions show a decrease in the height of the main peak and an increase in width, suggesting an increasing degree of dispersion in nutrition-sensitive agricultural development levels. In contrast, the northeastern region's Kernel density curve displays a constant peak height and a decrease in width, indicating that the absolute differences in this region are gradually narrowing. There is a higher likelihood of extreme values in nutrition-sensitive agricultural development levels nationwide and in the eastern, western and northeastern regions, suggesting a polarization phenomenon, while the central region exhibits a weaker polarization effect.

Thirdly, regarding convergence characteristics, there is no σ convergence in the nutrition-sensitive agricultural development levels at the national level or within the four major regions, but there is both absolute β convergence and conditional β convergence. For σ convergence, the σ values for the nation and all four major regions show an upward trend, with the northeastern and eastern regions experiencing a relatively large increase, indicating a clearer σ divergence. In terms of absolute β convergence, the northeastern and central regions exhibit faster convergence and a stronger "catch-up effect", while the eastern region has a relatively slower convergence speed with a less pronounced "catch-up effect". In the conditional β convergence, when control variables are included, the convergence speed increases across the nation and all four major regions, with the northeastern, western and eastern regions showing a larger increase. Factors such as the level of economic development, industrialization, informatization, tax burden, financial development, industrial structure and the degree of government intervention significantly influence nutrition-sensitive agricultural development with notable heterogeneity.

4.2. Policy Implications

First, we recommend establishing a systematic perspective and adopting a holistic, systematic strategic approach by simultaneously "expanding resources" and "conserving resources" to enhance the development level of nutrition-sensitive agriculture. Nutrition-sensitive agriculture is a complex system that spans multiple dimensions, levels and elements, involving agricultural production, circulation regulation, international trade, health and sustainability and nutrition demand adaptation. Therefore, it requires starting from resource endowments, being guided by the concept of nutrition orientation and aiming for health and sustainability, in order to reconstruct the agricultural industrial chain and the food value chain. It is necessary to expedite the formulation of agricultural product nutrition standards, promote the construction of nutrition-sensitive food production and processing systems, actively advance structural reform on the supply side of agriculture, establish a modern logistics system, improve the food reserve system, implement a diversification strategy for imports and build a nutrition-sensitive consumption system.

Second, we recommend advancing regional coordinated development strategies to promote the balanced development of nutrition-sensitive agriculture across regions. It is essential to manage the differences in nutrition-sensitive agricultural development levels among different areas, while also ensuring the coordination of development speeds. This requires implementing differentiated policies tailored to local conditions. According to the national "Construction Plan Outline for Distinctive Agricultural Product Advantage Areas", efforts should be made to tap into the agricultural unique resources in regions with lower levels of nutrition-sensitive agriculture and to develop a complete industry chain for distinctive nutrition-sensitive agriculture. This involves fostering new business forms and models to raise the level of development in these regions, thus narrowing the absolute and relative gaps with higher-level regions. Furthermore, it is important to establish cross-regional collaborative innovation platforms for nutrition-sensitive agriculture, leveraging the influence and driving role of advanced regions. Emphasis should be placed on balanced development within the provinces of the eastern and central regions, as well as between the eastern and northeastern regions. Developing a platform for the development, sharing and service of nutrition-sensitive agricultural technological resources can help continuously reduce the polarization between high-level and low-level regions. This approach aims to swiftly address the uneven spatial distribution of nutrition-sensitive agricultural development in China.

Third, we recommend analyzing the convergence trend of nutrition-sensitive agricultural development and achieving regional coordinated development through upgrading and transformation. The levels of nutrition-sensitive agricultural development vary widely across provinces and the four major regions of the country. The eastern and northeastern regions have significantly higher development levels compared to the central and western regions. Although regional disparities show a trend of β convergence, it is still necessary to coordinate the development differences among regions. For areas with relatively high self-development levels and favorable conditions in neighboring provinces, it is essential to leverage their established advantages, to vigorously cultivate and attract scientific and technological talent in the fields of agriculture and food nutrition and to focus on strengthening agricultural technological innovation. This includes accelerating the research and development of new nutrition-sensitive planting and breeding regulation technologies, aiming to transition towards higher levels. For regions that have long been at a low level both within themselves and within their neighboring areas, it is important to prevent them from becoming "trapped" in a low-level state. This involves integrating nutrition orientation into various related policies, strengthening agricultural infrastructure, facilitating the rational flow of agricultural production factors between regions and promoting the faster convergence of nutrition-sensitive agricultural development among different regions and provinces. This approach aims to enable a leap from low-level to high-level development.

Existing research predominantly focuses on defining nutrition-sensitive agriculture and discussing and analyzing the results of specific interventions. There is limited research on measuring the development levels of nutrition-sensitive agriculture at the national and regional levels. This article is the first to systematically and structurally construct an evaluation index system for the development level of nutrition-sensitive agriculture. It calculates the levels of nutrition-sensitive agricultural development in 31 provinces and four major regions in China and analyzes regional differences, dynamic evolution and convergence, aiming to provide references for the global promotion of nutrition-sensitive agriculture.

However, currently, only data from 43 relevant basic indicators at the provincial level in China can be collected, with significant missing data at the municipal and county levels. Therefore, to some extent, it is impossible to conduct in-depth analysis of the differences in the level of nutrition-sensitive agricultural development at the municipal and county levels. Moreover, it is unknown whether other countries can obtain relevant data, which poses an important limitation to the global study of nutrition-sensitive agriculture. Therefore, as government departments and researchers gradually form a unified understanding at both the theoretical and practical levels, a unified and comprehensive database of indicators for the level of nutrition-sensitive agricultural development should be established to track and compare the levels of nutrition-sensitive agricultural development in different regions and take corresponding intervention measures. Additionally, in the future, it will also be possible to conduct in-depth research on the driving mechanisms and enhancement pathways for nutrition-sensitive agricultural development, analyze the impact mechanism of nutrition-sensitive agriculture on residents' health levels and assess the effects of interventions such as women's empowerment and agricultural production diversity on the development of nutrition-sensitive agriculture.

Author Contributions: Conceptualization, Y.G.; methodology, Y.G. and F.L.; software, Y.G. and F.L.; validation, Y.D.; formal analysis, H.Z.; resources, Y.G.; data curation, F.L. and Y.D.; writing—original draft preparation, Y.G.; writing—review and editing, Y.G. and F.L.; visualization, Y.G. and H.Z.; supervision, C.Q.; project administration, C.Q.; funding acquisition, C.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Social Science Fund of China (23BJY155); the China Agriculture Research System (CARS-26-06BY); the Major Consulting Project of Jiangxi Research Institute for the Development Strategy of China Engineering Science and Technology (2022-DFZD-37); and the Fundamental Research Funds for the Central Universities (2662024YJ004).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data presented in this study are available from the first author upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Level of development of nutrition-sensitive agriculture in China from 2000 to 2022.

Region/Year	2000	2001	2002	2003	2004	2005	2006	2007
Beijing	0.1603	0.1549	0.1511	0.1720	0.2026	0.1983	0.1927	0.2155
Tianjin	0.0978	0.1033	0.1072	0.1184	0.1174	0.1284	0.1255	0.1361
Hebei	0.0985	0.1013	0.1057	0.1100	0.1138	0.1218	0.1238	0.1231
Shanxi	0.0669	0.0656	0.0716	0.0711	0.0700	0.0701	0.0729	0.0753
Inner Mongolia	0.1032	0.1052	0.1174	0.1254	0.1523	0.1827	0.2045	0.1962
Liaoning	0.0961	0.0977	0.1016	0.1073	0.1070	0.1197	0.1202	0.1258
Jilin	0.1081	0.1087	0.1219	0.1246	0.1132	0.1202	0.1134	0.1160
Heilongjiang	0.1439	0.1509	0.1641	0.1684	0.1779	0.1863	0.1918	0.1743
Shanghai	0.1176	0.1161	0.1201	0.1340	0.1358	0.1585	0.1663	0.1943
Jiangsu	0.0894	0.0945	0.0963	0.0977	0.0966	0.1028	0.1061	0.1149
Zhejiang	0.1050	0.1060	0.1075	0.1096	0.1099	0.1219	0.1274	0.1376
Anhui	0.0820	0.0841	0.0894	0.0837	0.0859	0.0883	0.0955	0.0988
Fujian	0.1116	0.1079	0.1107	0.1111	0.1111	0.1225	0.1233	0.1278
Jiangxi	0.0801	0.0811	0.0812	0.0832	0.0813	0.0864	0.0908	0.0920
Shandong	0.1218	0.1225	0.1259	0.1294	0.1304	0.1430	0.1499	0.1549
Henan	0.0872	0.0894	0.0914	0.0892	0.0936	0.1028	0.1090	0.1164
Hubei	0.0845	0.0869	0.0896	0.0892	0.0885	0.0917	0.0938	0.0964
Hunan	0.0828	0.0835	0.0858	0.0843	0.0850	0.0906	0.0886	0.0929
Guangdong	0.0955	0.0942	0.0954	0.1001	0.0993	0.1052	0.1063	0.1175

Table A1. *Cont.*

Region/Year	2000	2001	2002	2003	2004	2005	2006	2007
Guangxi	0.0843	0.0854	0.0878	0.0883	0.0856	0.0936	0.0919	0.0954
Hainan	0.0873	0.0889	0.0914	0.0937	0.0924	0.1001	0.0970	0.1048
Chongqing	0.0663	0.0680	0.0717	0.0720	0.0742	0.0793	0.0744	0.0805
Sichuan	0.0808	0.0812	0.0846	0.0849	0.0857	0.0900	0.0877	0.0876
Guizhou	0.0571	0.0579	0.0603	0.0593	0.0583	0.0648	0.0649	0.0680
Yunnan	0.0744	0.0814	0.0833	0.0828	0.0785	0.0851	0.0865	0.0871
Tibet	0.0674	0.0693	0.0710	0.0733	0.0752	0.0775	0.0768	0.0817
Shaanxi	0.0715	0.0743	0.0775	0.0768	0.0850	0.0884	0.0930	0.0953
Gansu	0.0611	0.0635	0.0668	0.0649	0.0668	0.0714	0.0723	0.0693
Qinghai	0.0599	0.0632	0.0657	0.0619	0.0644	0.0666	0.0655	0.0665
Ningxia	0.0819	0.0856	0.0917	0.0896	0.0936	0.0995	0.1058	0.1166
Xinjiang	0.0863	0.0891	0.0962	0.1003	0.1038	0.1092	0.1113	0.1189
National average	0.0907	0.0923	0.0962	0.0986	0.1011	0.1086	0.1106	0.1154
Average annual growth rate	——	1.83%	4.20%	2.49%	2.58%	7.38%	1.86%	4.33%
Region/Year	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Beijing	0.2205	0.1784	0.1989	0.2138	0.2477	0.2228	0.2274	0.2412
Tianjin	0.1425	0.1426	0.1467	0.1592	0.1669	0.1655	0.1716	0.1702
Hebei	0.1250	0.1285	0.1236	0.1267	0.1338	0.1372	0.1434	0.1452
Shanxi	0.0755	0.0833	0.0849	0.0927	0.1012	0.1134	0.1181	0.1186
Inner Mongolia	0.2087	0.2135	0.2216	0.2235	0.2276	0.2175	0.2218	0.2297
Liaoning	0.1312	0.1367	0.1407	0.1478	0.1553	0.1612	0.1610	0.1576
Jilin	0.1208	0.1266	0.1258	0.1278	0.1274	0.1319	0.1327	0.1359
Heilongjiang	0.1977	0.2052	0.2151	0.2216	0.2225	0.2222	0.2371	0.2428
Shanghai	0.1979	0.1997	0.2180	0.2222	0.2281	0.2354	0.2476	0.2675
Jiangsu	0.1195	0.1292	0.1346	0.1393	0.1468	0.1534	0.1566	0.1597
Zhejiang	0.1387	0.1410	0.1448	0.1485	0.1541	0.1599	0.1647	0.1684
Anhui	0.0991	0.1090	0.1155	0.1188	0.1264	0.1337	0.1408	0.1454
Fujian	0.1287	0.1349	0.1404	0.1459	0.1528	0.1612	0.1629	0.1682
Jiangxi	0.0949	0.1024	0.1060	0.1116	0.1175	0.1271	0.1296	0.1327
Shandong	0.1591	0.1646	0.1714	0.1883	0.2031	0.2142	0.2238	0.2292
Henan	0.1208	0.1267	0.1323	0.1387	0.1443	0.1496	0.1518	0.1548
Hubei	0.1007	0.1107	0.1141	0.1178	0.1260	0.1378	0.1512	0.1557
Hunan	0.0963	0.1052	0.1087	0.1107	0.1170	0.1209	0.1252	0.1281
Guangdong	0.1131	0.1265	0.1289	0.1277	0.1351	0.1436	0.1413	0.1485
Guangxi	0.0947	0.1066	0.1109	0.1126	0.1228	0.1299	0.1355	0.1394
Hainan	0.1117	0.1194	0.1220	0.1248	0.1310	0.1350	0.1351	0.1361
Chongqing	0.0860	0.0947	0.0966	0.0982	0.1068	0.1142	0.1172	0.1218
Sichuan	0.0879	0.0960	0.1040	0.1119	0.1211	0.1279	0.1350	0.1378
Guizhou	0.0707	0.0800	0.0788	0.0764	0.0841	0.0869	0.0927	0.0984
Yunnan	0.0911	0.0993	0.0975	0.1049	0.1125	0.1183	0.1260	0.1320
Tibet	0.0832	0.0877	0.0881	0.0869	0.0895	0.0906	0.0925	0.0948
Shaanxi	0.1048	0.1132	0.1140	0.1171	0.1234	0.1261	0.1302	0.1350
Gansu	0.0696	0.0763	0.0780	0.0814	0.0902	0.0947	0.0975	0.1045
Qinghai	0.0674	0.0730	0.0692	0.0690	0.0745	0.0773	0.0834	0.0877
Ningxia	0.1277	0.1313	0.1372	0.1396	0.1469	0.1513	0.1683	0.1699
Xinjiang	0.1105	0.1221	0.1240	0.1272	0.1343	0.1474	0.1535	0.1599
National average	0.1192	0.1247	0.1288	0.1333	0.1410	0.1454	0.1508	0.1554
Average annual growth rate	3.31%	4.56%	3.31%	3.51%	5.76%	3.14%	3.71%	3.02%

Table A1. *Cont.*

Region/Year	2016	2017	2018	2019	2020	2021	2022	Average
Beijing	0.2462	0.2847	0.3193	0.4043	0.3805	0.4301	0.4193	0.2471
Tianjin	0.1661	0.1589	0.1558	0.1676	0.1877	0.1798	0.1773	0.1475
Hebei	0.1472	0.1467	0.1483	0.1530	0.1584	0.1655	0.1696	0.1326
Shanxi	0.1202	0.1260	0.1301	0.1327	0.1386	0.1472	0.1468	0.0997
Inner Mongolia	0.2330	0.2208	0.2271	0.2414	0.2492	0.2508	0.2692	0.2018
Liaoning	0.1589	0.1585	0.1610	0.1635	0.1642	0.1699	0.1713	0.1397
Jilin	0.1413	0.1430	0.1407	0.1460	0.1456	0.1507	0.1512	0.1293
Heilongjiang	0.2538	0.2685	0.2670	0.2862	0.3116	0.3027	0.3313	0.2236
Shanghai	0.3031	0.3410	0.3565	0.3766	0.4099	0.4582	0.4703	0.2467
Jiangsu	0.1617	0.1649	0.1670	0.1698	0.1762	0.1863	0.1889	0.1370
Zhejiang	0.1678	0.1742	0.1813	0.1897	0.1992	0.2101	0.2137	0.1513
Anhui	0.1482	0.1511	0.1575	0.1618	0.1717	0.1828	0.1878	0.1242
Fujian	0.1695	0.1765	0.1848	0.1867	0.1961	0.2073	0.2092	0.1500
Jiangxi	0.1340	0.1384	0.1410	0.1451	0.1493	0.1578	0.1594	0.1140
Shandong	0.2375	0.2430	0.2450	0.2500	0.2581	0.2682	0.2701	0.1914
Henan	0.1589	0.1618	0.1662	0.1709	0.1804	0.1877	0.1927	0.1355
Hubei	0.1614	0.1680	0.1731	0.1753	0.1783	0.1903	0.1953	0.1294
Hunan	0.1298	0.1350	0.1426	0.1476	0.1587	0.1653	0.1700	0.1154
Guangdong	0.1541	0.1582	0.1660	0.1693	0.1662	0.1718	0.1805	0.1324
Guangxi	0.1440	0.1501	0.1569	0.1609	0.1713	0.1826	0.1926	0.1227
Hainan	0.1364	0.1380	0.1449	0.1473	0.1521	0.1609	0.1698	0.1226
Chongqing	0.1243	0.1247	0.1279	0.1315	0.1375	0.1465	0.1483	0.1027
Sichuan	0.1404	0.1433	0.1493	0.1504	0.1562	0.1668	0.1677	0.1165
Guizhou	0.1043	0.1117	0.1185	0.1272	0.1374	0.1449	0.1487	0.0892
Yunnan	0.1359	0.1392	0.1417	0.1429	0.1463	0.1526	0.1569	0.1111
Tibet	0.0941	0.1020	0.1030	0.1074	0.1105	0.1170	0.1179	0.0894
Shaanxi	0.1393	0.1420	0.1445	0.1473	0.1497	0.1569	0.1595	0.1159
Gansu	0.1071	0.1122	0.1172	0.1231	0.1312	0.1416	0.1483	0.0917
Qinghai	0.0906	0.0933	0.0939	0.0958	0.0956	0.1000	0.0986	0.0775
Ningxia	0.1721	0.1813	0.1859	0.1947	0.2016	0.2302	0.2506	0.1458
Xinjiang	0.1680	0.1694	0.1691	0.1724	0.1758	0.1829	0.1863	0.1356
National average	0.1596	0.1654	0.1704	0.1787	0.1853	0.1957	0.2006	0.1377
Average annual growth rate	2.75%	3.58%	3.06%	4.83%	3.73%	5.58%	2.53%	——

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