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Spatiotemporal Dynamics of Agricultural Sustainability Assessment: A Study across 30 Chinese Provinces

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Abstract: Agricultural sustainability is crucial for ensuring food security, promoting economic development, maintaining ecological balance, and achieving sustainable development goals. In this study, based on relevant theories of agricultural sustainability, an analytical framework is constructed for agricultural sustainability encompassing economic, resource, environmental, and social dimensions. The Analytic Network Process (ANP) method is employed to determine indicator weights and assess the spatiotemporal changes in agricultural sustainability levels across Chinese provinces. The findings reveal that environmental quality is the primary dimension for assessing agricultural sustainability, and the significance of the rural social development dimension is continuously increasing. Although the sustainability levels have significantly improved in various regions of China, there remain issues of development imbalance and instability. In conclusion, this paper offers a comprehensive understanding of the spatiotemporal changes in agricultural sustainability across Chinese provinces, providing valuable insights for policymakers and researchers.

Keywords: sustainable agriculture; spatiotemporal analysis; analytic network process; China

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1. Introduction

Agriculture is a fundamental pillar of human civilization, shaping the way societies have evolved and interacted throughout history. In the contemporary world, agricultural sustainability development has emerged as a crucial aspect of global progress, significantly impacting food security, economic growth, and ecological balance [1]. As the global population continues to rise and the ramifications of climate change become increasingly evident, the intensified demand for agriculture leads to mounting pressures on natural resources and ecosystems [2]. Consequently, achieving sustainability in global agriculture is essential to meet current human development needs and ensure long-term sustainable growth [3].

Sustainable agriculture refers to a mode of production that aims to meet current and future human needs while increasing resource efficiency, protecting natural resources and ecosystems, and promoting socio-economic well-being [4]. On a macro level, sustainable agriculture contributes to global food security and poverty eradication [5]. Moreover, sustainable agricultural practices can help mitigate climate change by reducing greenhouse gas emissions, enhancing carbon sequestration, and promoting biodiversity and ecosystem protection [6,7]. As a result, improving agricultural sustainability can directly advance several targets of the United Nations' 2030 Sustainable Development Goals (SDGs), primarily involving SDG1 "No Poverty", SDG2 "Zero Hunger", SDG4 "Quality Education", SDG5 "Gender Equality", SDG8 "Decent Work and Economic Growth", SDG12 "Responsible Consumption and Production", SDG13 "Climate Action", SDG14 "Life Below Water", and SDG15 "Life on Land" [8]. Given the multifaceted nature of agricultural sustainability and its intersection with ecological, environmental, social, and resource aspects, a comprehensive evaluation of agricultural sustainability is paramount for informing policy decisions and promoting sustainable development worldwide.

Over the past few decades, various efforts have been made to assess agricultural sustainability, ranging from simplistic indicator-based approaches to intricate integrated assessment models [9–12]. On the indicator level, initial evaluations of agricultural sustainability focus primarily on the ecological impacts of agricultural production [13], gradually expanding to encompass economic, environmental, and social aspects [14,15], with some studies emphasizing the role of resource utilization [16]. At the model level, numerous assessment models have been developed for gauging agricultural sustainability, such as the Sustainability Assessment of Farming and the Environment (SAFE) [17], Sustainability Assessment (MOTIFS) [18], Sustainability Assessment for Food and Agriculture (SAFA) system [19], Agricultural Environmental Indicators (AEI) [20], the Multi-Criteria Decision Analysis (MCDA)-based method [21,22] and some complex assessment models based on the generalized combination rule [22] and deep learning [23].

In the literature, indicators or models for agricultural sustainability assessment may differ due to variations in time, space, and theoretical considerations, with most involving the standardization of indicator data and weight calculation [6,24–27]. Previous studies have mostly employed evaluation methods such as the Entropy weight method [28], Principal Component Analysis (PCA) [29], Dematel [30], and Analytic Hierarchy Process (AHP) [31] for calculating indicator weights in agricultural sustainability assessments. While these studies have significantly contributed to understanding agricultural sustainability, many of these approaches fail to capture the full complexity and interconnectedness, ignoring the interactions among ecological, resource, environmental, and social factors [32,33]. Addressing these limitations, this study constructs a comprehensive agricultural sustainability evaluation system using the Analytic Network Process (ANP) methodology. By acknowledging the interconnected nature of agricultural systems, this approach provides a more integrated and detailed understanding of agricultural sustainability, offering a more robust framework for its assessment.

The Analytic Network Process (ANP) is a multi-criteria decision making method developed by Saaty based on the foundation of the Analytic Hierarchy Process (AHP), allowing for the comprehensive evaluation of complex systems with multiple interdependent dimensions [34]. The primary feature of ANP lies in providing a framework that considers the interrelationships among all evaluation indicators (criteria) within and across clusters [32]. ANP has been employed by numerous researchers to address various decision-making problems, proving its suitability for constructing models with evaluation criteria and dimensions encompassing intricate interactions [35]. Consequently, it has been widely applied in risk assessment [36], environmental management [37], and various evaluation problems [38]. This study uses the ANP method to thoroughly explore the interplay among economic, resource, environmental, and social dimensions while evaluating agricultural sustainability levels.

By integrating the ANP methodology, this study seeks to develop a holistic agricultural sustainability assessment framework that captures the complexity and interconnections among various dimensions of agricultural sustainability, offering a more robust and comprehensive evaluation tool for policymakers and researchers. Using China as a case study, we investigate the spatiotemporal dynamics of agricultural sustainability, providing valuable insights for those seeking to advance sustainable agriculture worldwide. Our findings contribute to a broader understanding of agricultural sustainability assessment and management, emphasizing the importance of a holistic approach that considers the interactions among economic, resource, environmental, and social dimensions.

The remainder of this study is organized as follows. The next section describes the methods, starting with the research area and data sources, then the construction of the evaluation index system, determination of index weights using the ANP method, and calculation of agricultural sustainability levels. In Section 3, we analyze the results, examining index weights and conducting temporal and spatial comparative analyses of agricultural sustainability. Section 4 focuses on the discussion, comparing our findings with previous studies, exploring the implications of our results for agricultural policy and planning, and identifying limitations and potential improvements for future research. The conclusion summarizes our findings and offers policy recommendations for enhancing agricultural sustainability within sustainable development goals and global ecological, environmental, and resource management.

2. Materials and Methods

2.1. Research Area and Data Source

Situated in East Asia, China spans from 73°40′ to 135°2′ east longitude and 3°52′ to 53°33′ north latitude, encompassing a diverse array of climates and abundant natural resources (Figure 1). China's agriculture provides a supply of staple foods for approximately 22% of the global population, establishing itself as one of the world's largest food producers and consumers [39]. Investigating agricultural sustainability in China offers valuable insights that contribute to advancing research and practice in global sustainable agriculture.

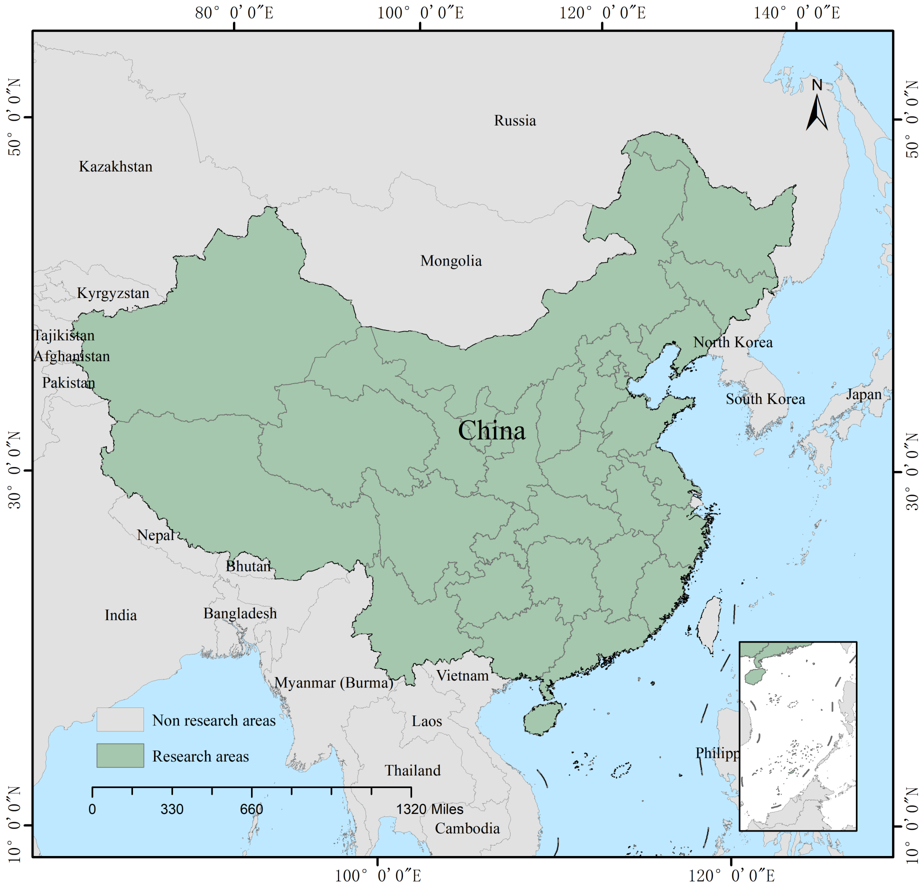


Figure 1. The spatial distribution features of China's three regions.

The primary data used in this paper are the agricultural and rural-related data of 30 provinces, autonomous regions, and municipalities in mainland China from 2005 to 2020. Due to data availability and completeness, this study does not include Shanghai, Taiwan, Macau, and Hong Kong. All data are from the China Statistical Yearbook and the China Rural Statistical Yearbook released by the National and Local Bureau of Statistics of China. All the data are carried out at the provincial level because all indicators at the provincial level are the complete data, which can ensure this paper's scientific and comprehensive results.

2.2. Construction of Evaluation Index System

In order to construct a comprehensive agricultural sustainability evaluation system, we integrated the multiple connotations of agricultural sustainability into different discourses.

Globally, politics prioritize sustainable agriculture techniques and economic growth [40], while academia examines resource use and environmental preservation [41]. Notably, social welfare is increasingly recognized in both domains [42]. Based on the above-mentioned theoretical analysis, this study synthesizes the focal points of both domains, developing a comprehensive agricultural sustainability assessment framework encompassing four dimensions: agricultural economy, resource utilization, environmental quality, and rural society. The details are as follows.

In the agricultural economy dimension, specifically, five key indicators are considered: per labor gross agricultural value (e1), per labor grain output (e2), agricultural mechanization level (e3), agricultural electrification level (e4), and land productivity (e5) [43,44]. These indicators reflect the agricultural sector's overall economic vitality and directly influence the potential for sustainable growth. Higher values in these indicators suggest a more robust agricultural economy conducive to long-term sustainability. Enhanced agricultural electrification (e4), for example, fosters the adoption of advanced machinery and irrigation systems, catalyzing production efficiency, economic growth, and, consequently, agricultural sustainability [45].

Transitioning to the resource utilization dimension, we focus on four indicators: per capita arable land area (e6), per capita water resource availability (e7), rural power supply level (e8), and effective irrigation rate (e9) [43,46]. Efficient resource utilization efficiency is the basis for achieving sustainable agricultural development, reducing resource depletion and achieving environmental protection. Higher scores in these indicators denote more sustainable resource use and bolster agricultural activities without compromising the needs of future generations.

For the environmental quality dimension, we examine five indicators: fertilizer use intensity (e10), pesticide use intensity (e11), forest coverage rate (e12), air quality index (e13), and soil and water conservation area (e14) [6,46]. These indicators illustrate the ecological impact of agricultural practices and underscore the necessity of environmentally friendly approaches. Reduced values in e10 and e11 and increased values in e12, e13, and e14 imply enhanced environmental quality—an indispensable component for the long-term viability of agriculture and rural ecosystems.

Finally, the rural society dimension incorporates four indicators: per capita disposable income of rural residents (e15), Engel's coefficient of rural residents (e16), rural healthcare level (e17), and education level of rural residents (e18) [44,47]. These epitomize the overall welfare of the rural populace, integral to sustainable agriculture. High disposable income and education levels in rural areas foster investment in and comprehension of sustainable agricultural practice, while robust rural healthcare sustains a capable workforce [26]. A lower Engel coefficient indicates improved rural living standards and a transition toward sustainable lifestyles. Collectively, these indicators buttress the long-term sustainability of agriculture.

Based on the above analysis and guided by systematicity, scientificity, and data availability principles, this paper constructs a comprehensive agricultural sustainability evaluation system with 18 secondary indicators covering the four dimensions of the economic, resource, environmental, and social aspects of sustainable agricultural development, as shown in Table 1.

Table 1. Agricultural sustainability evaluation index system.

Dimensions	Indexes	Description	Units	Direction	References
Agricultural Economy	e1: Per labor agricultural gross value	Agricultural, forestry, animal husbandry, and fishery output value/rural population	Yuan/rural labor	+	[15,44]
Agricultural Economy	e2: Per labor grain output	Total grain output/rural labor	kg/person	+	[15]
	e3: Agricultural mechanization level	Total agricultural machinery power/cultivated land area	kW/hm^2	+	[15]
	e4: Agricultural electrification level	Rural electricity consumption/rural population	kW·h/person	+	[43,45]
	e5: Land productivity	Total grain output/cultivated land area	kg/hm^2	+	[18]
Resource Utilization	e6: Per capita arable land area	Total arable land area at year-end/total population at year-end	hm^2/person	+	[46]
	e7: Per capita water resource availability	Total water resources availability/total population	m^3/person	+	[44]
	e8: Rural power supply level	Total rural power supply generation/rural population	%	+	[26]
	e9: Effective irrigation rate	Effective irrigation area/sown area	%	+	[12,26]
Environmental Quality	e10: Fertilizer use intensity	Fertilizer consumption/sown area	kg/hm^2	-	[15,43]
	e11: Pesticide use intensity	Pesticide consumption/sown area	kg/hm^2	-	[12,31]
	e12: Forest coverage rate	Forest area/land area	%	+	[12,15]
	e13: Air quality index	Days of good air quality/365	/	+	[18]
	e14: Soil and water conservation area	Soil and water conservation area	khm^2	+	[6]

Table 1. *Cont.*

Dimensions	Indexes	Description	Units	Direction	References
Rural Society	e15: Per capita disposable income	Per capita disposable income of rural residents	Yuan/person	+	[18,26]
	e16: Engel's coefficient of rural residents	Food expenditure cost/total rural resident consumption expenditure	/	-	[44]
	e17: Rural healthcare level	Average health personnel per thousand rural population	/	+	[15]
	e18: Education level of rural residents	Average years of education	years	+	[24,26]

2.3. Index Weights Determination Using ANP

In order to take into account the complex interactions between the dimensions of the agricultural sustainability evaluation indicators, this study uses the Analytic Network Process (ANP) method to evaluate indicator weights. The calculation process and basic steps are as follows.

2.3.1. Network Model Construction

The ANP network structure is divided into control and network layers. The control layer determines the system's general objective and the corresponding criterion, while the construction of the relationship between the network layer elements is the core of the ANP method. In this study, the control layer has only one element, agricultural sustainability, and thus was omitted. The network layer is constructed using the previous agricultural sustainability evaluation index system. The clusters in the network layer and the nodes under each cluster correspond to the four dimensions and indicators of the agricultural economy, resource use, environmental quality, and rural society in the evaluation system (Table 1), respectively.

In the network layer, the nodes are interdependent and dominated by each other, and the nodes and clusters are not internally independent, forming a network structure of mutual influence [48]. The dependency relationships may not also occur between nodes from different clusters but between those included in the same cluster. Within the agricultural sustainability evaluation system, for example, the node "e1 (Gross agricultural product of rural population)" from the "Agricultural Economy" cluster is both affected by "e4 (Agricultural electrification level)" from the same cluster and "e9 (Effective irrigation rate)" from the "Resource utilization" cluster, and so on.

Based on the above analysis, a network model of agricultural sustainability evaluation was constructed in this study, as shown in Figure 2. In this network model, the influence relationships between different nodes are indicated by arrows: arrows pointing to other clusters indicate that there are nodes under the original cluster that influence the nodes of other clusters, and arrows pointing to their self-clusters indicate that there are nodes under the same cluster that influence each other.

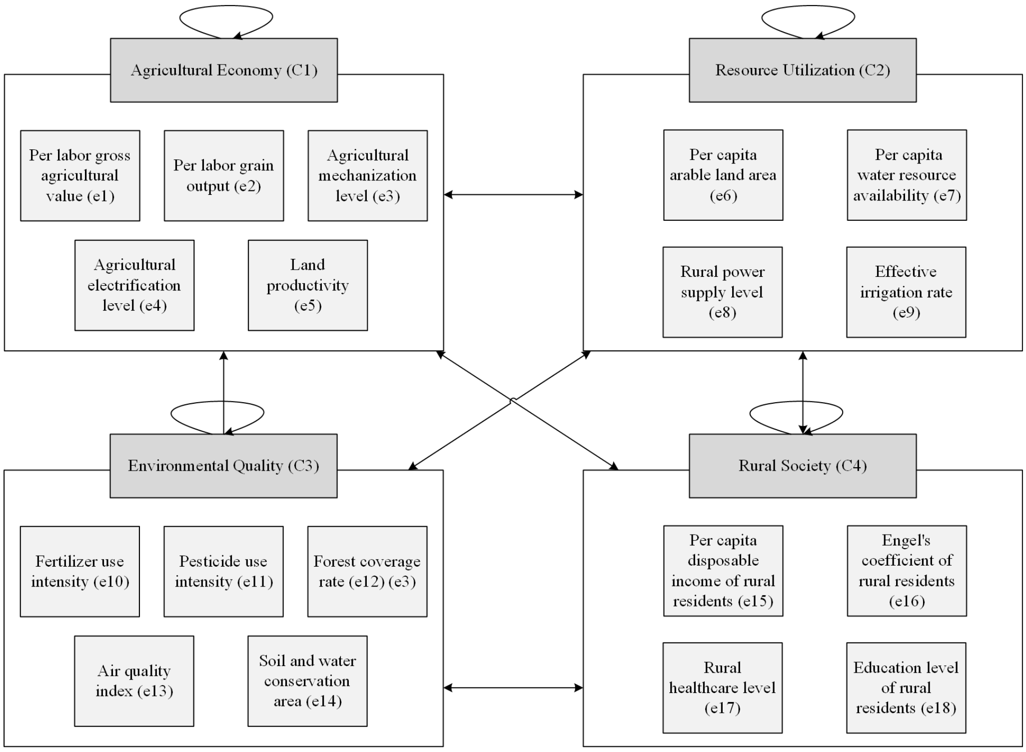


Figure 2. Network model of agricultural sustainability.

2.3.2. Calculation of Weights

Due to the complex relationship between the elements and the excessive calculation of ANP method, this paper uses Superdecisions software to calculate the weights in the agricultural sustainability evaluation index system. The specific process and principles are as follows.

- step 1: conduct the pairwise comparisons.
  Expert opinions were sought to perform pairwise comparisons of the indicators within each cluster and between clusters, reflecting their relative importance in determining agricultural sustainability. The pairwise comparisons were quantified using a nine-point scale, where 1 represented equal importance and 9 indicated extreme importance. Inverses of these values were assigned for reciprocal comparisons [32,49]. These values were subsequently input into the SuperDecisions software for further computations.
- step 2: calculate the unweighted supermatrix.
  Based on the scoring results in step 1, firstly, the maximum eigenvalues are calculated, and then the eigenvectors are normalized. 2. Please carefully check variable formatting (italic, bold, subscript, uppercase, etc.) throughout the manuscript to ensure the formatting is consistent and revise if needed.

$$
\begin{array}{c|cccc|c}
\mathcal{R}_{jl} & \mathcal{R}_{i1} & \mathcal{R}_{i2} & \dots & \mathcal{R}_{in} & \text{Normalized Eigenvector} \\
\hline
\mathcal{R}_{i1} & e_{11} & e_{12} & \dots & e_{1n} & \Omega_{i1}^{jl} \\
\mathcal{R}_{i2} & e_{21} & e_{22} & \dots & e_{2n} & \Omega_{i2}^{jl} \\
\vdots & & \dots & & & \vdots \\
\mathcal{R}_{in} & e_{n1} & e_{n2} & \dots & e_{nn} & \Omega_{in}^{jl}
\end{array}
\quad (1)
$$

Then, using the eigenvalue method, calculate the ranking vector $(\Omega_{i1}^{jl}, \Omega_{i2}^{jl}, \dots, \Omega_{in}^{jl})$ and complete the consistency check. W_{ij} is denoted as:

$$W_{ij} = \begin{bmatrix} \Omega_{i1}^{j1} & \Omega_{i1}^{j2} & \dots & \Omega_{i1}^{jn} \\ \Omega_{i2}^{j1} & \Omega_{i2}^{j2} & \dots & \Omega_{i2}^{jn} \\ \dots & \dots & \dots & \dots \\ \Omega_{in}^{j1} & \Omega_{in}^{j2} & \dots & \Omega_{in}^{jn} \end{bmatrix} \tag{2}$$

The column vector W_{ij} represents the influence ranking of element $\mathcal{R}_{ini}$ in system $\mathcal{R}_i$ on element $\mathcal{R}_{jj}$ in system $\mathcal{R}_j$. If the elements in $\mathcal{R}_i$ have no influence on the elements in $\mathcal{R}_j$, then $\Omega_{ij} = 0$ $(i = 1, 2, \dots, N; j = 1, 2, \dots, N)$.
Finally, the unweighted supermatrix of elemental interactions under the control level of the total system is obtained.

$$W = \begin{array}{c} \\ \begin{matrix} r_{11} \\ r_{12} \\ \vdots \\ r_{1n} \end{matrix} \\ \begin{matrix} r_{21} \\ r_{22} \\ \vdots \\ r_{2n} \end{matrix} \\ \vdots \\ \begin{matrix} r_{i1} \\ r_{i2} \\ \vdots \\ r_{in} \end{matrix} \\ \vdots \\ \begin{matrix} r_{N1} \\ r_{N2} \\ \vdots \\ r_{NN} \end{matrix} \end{array} \begin{array}{c} \begin{matrix} r_{11}r_{12}\dots r_{1n1} & r_{21}r_{22}\dots r_{2n2} & \dots & r_{j1}r_{j2}\dots r_{jnj} & \dots & r_{n1}r_{n2}\dots r_{NN} \end{matrix} \\ \begin{bmatrix} \Omega_{11} & \Omega_{12} & \dots & \Omega_{1j} & \dots & \Omega_{1N} \\ \Omega_{21} & \Omega_{22} & \dots & \Omega_{2j} & \dots & \Omega_{2N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{i1} & \Omega_{i2} & \dots & \Omega_{ij} & \dots & \Omega_{iN} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \Omega_{N1} & \Omega_{N2} & \dots & \Omega_{Nj} & \dots & \Omega_{NN} \end{bmatrix} \end{array} \tag{3}$$

- step 3: calculate the weighted supermatrix.
  In the above supermatrix, all W_{ij} matrices are based on $\mathcal{R}_{jn}$ as the sub-criterion, and the ranking vectors are obtained by pairwise comparisons of elements in $\mathcal{R}_i$. Although each column in W_{ij} is column-normalized, W is not normalized. Therefore, it is necessary to compare the importance of each element group $\mathcal{R}_i$ $(i = 1, 2, \dots, N)$ under the control layer for the sub-criterion $\mathcal{R}_j$ $(j = 1, 2, \dots, N)$ and pass the consistency check.

$\mathcal{R}_i$	$\mathcal{R}_1$	$\mathcal{R}_2$	$\dots$	$\mathcal{R}_N$	Normalized Eigenvector
$\mathcal{R}_1$	r_{11}	r_{12}	$\dots$	r_{1N}	a_{1j}
$\mathcal{R}_2$	r_{21}	r_{22}	$\dots$	r_{2N}	a_{2j}
$\dots$	$\dots$	$\dots$	$\dots$	$\dots$	$\dots$
$\mathcal{R}_N$	r_{N1}	r_{N2}	$\dots$	r_{NN}	a_{Nj}

(4)

According to the relative weight value $\mathcal{A}$ of $\mathcal{R}_i$, calculate the eigenvector to obtain the following weighted matrix $\mathcal{A}$:

$$\mathcal{A} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1j} & \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2j} & \cdots & \alpha_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{ij} & \cdots & \alpha_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_{N1} & \alpha_{N2} & \cdots & \alpha_{NN} & \cdots & \alpha_{nn} \end{bmatrix} \tag{5}$$

Weight the elements in the supermatrix to obtain $\bar{W} = [\Omega_{ij}]_{n\times n}$, where $\bar{w}_{ij} = a_{ij}\Omega_{ij}$, $(i = 1, 2, \ldots, N; j = 1, 2, \ldots, N)$. W is the weighted supermatrix, and its characteristic is that the sum of the columns is 1.

$$\bar{W} = \begin{bmatrix} a_{11}\Omega_{11} & a_{12}\Omega_{12} & \cdots & a_{1j}\Omega_{1j} & \cdots & a_{1n}\Omega_{1n} \\ a_{21}\Omega_{21} & a_{22}\Omega_{22} & \cdots & a_{2j}\Omega_{2j} & \cdots & a_{2n}\Omega_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{i1}\Omega_{i1} & a_{i2}\Omega_{i2} & \cdots & a_{ij}\Omega_{ij} & \cdots & a_{in}\Omega_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n1}\Omega_{n1} & a_{n2}\Omega_{n2} & \cdots & a_{nj}\Omega_{nj} & \cdots & a_{nn}\Omega_{nn} \end{bmatrix} \tag{6}$$

- step 4: Calculate the weights of the elements
  By using the weighted supermatrix and the idea of normalization, the limit supermatrix W^{∞} is obtained through consecutive multiplication, and its vector is the weight vector W' of the element R_{ini}:

$$W' = (\omega_{11}, \omega_{12}, \ldots, \omega_{nn})^{\Gamma} \tag{7}$$

Here, Γ represents the number of matrix multiplications performed until the convergence criterion is satisfied. Thus, the weight vectors of each element R_{ij} are as follows.

$$W_i' = (\omega_{i1}', \omega_{i2}', \ldots, \omega_{in}')^{\Gamma} \tag{8}$$

2.4. Calculation of the Evaluation Value

2.4.1. Normalization of Indicator Data

Due to our agricultural sustainability evaluation system involving many aspects of economic resources, environment, and society, the indicators are scattered, some of which are negative. In order to eliminate the influence of direction and dimensionality, this paper adopts a normalization method to process the data. Specifically, we postulate the application of our agricultural sustainability indicator framework to assess the sustainability levels of T distinct regions. For the t-th region, the manifestation of agricultural sustainability pertaining to the n-th indicator, denoted as e_n, is represented by A_{tn}, where $t = 1, 2, \ldots, T$, and $n = 1, 2, \ldots, 18$. The specific equations are as follows:

$$X_{tn} = \frac{A_{tn} - \min\{A_{1n}, \ldots, A_{Tn}\}}{\max\{A_{1n}, \ldots, A_{Tn}\} - \min\{A_{1n}, \ldots, A_{Tn}\}} \tag{9}$$

$$X_{tn} = \frac{\max\{A_{1n}, \ldots, A_{Tn}\} - A_{tn}}{\max\{A_{1n}, \ldots, A_{Tn}\} - \min\{A_{1n}, \ldots, A_{Tn}\}} \tag{10}$$

Here, Equation (9) is employed for the normalization of positive indicators, while Equation (10) is utilized for the normalization of negative indicators. It is important to note that the aforementioned normalization equations are exclusively applicable for spatial analysis, which is employed to compare the agricultural sustainability development levels of distinct regions at the same point in time. When comparing temporal differences, we normalize the data for the same region at different points in time. In this case, the new equations can be expressed in Equations (11) and (12), where Y represents the total duration of the data, y denotes the ordinal year with an interval of one year, and other variables remain unchanged. Unless otherwise specified, the following analysis will evaluate agricultural sustainability development levels for different regions from both spatial and temporal perspectives.

$$X_{yn} = \frac{A_{yn} - \min\{A_{1n}, \ldots, A_{Yn}\}}{\max\{A_{1n}, \ldots, A_{Yn}\} - \min\{A_{1n}, \ldots, A_{Yn}\}} \tag{11}$$

$$X_{yn} = \frac{\max\{A_{1n}, \ldots, A_{Yn}\} - A_{yn}}{\max\{A_{1n}, \ldots, A_{Yn}\} - \min\{A_{1n}, \ldots, A_{Yn}\}} \tag{12}$$

2.4.2. Calculation and Processing of Evaluation Value

After standardizing all the collected data and combining the indicator weights and normalized data for each region, the development levels of different dimensions of regional agricultural sustainability (S_t^i) can be obtained, as shown in Equation (14).

$$S_t^i = \sum_{n=1}^{M_i} w_i' \cdot x_{ti}, t = 1, 2, \ldots, T \tag{13}$$

where i represents the four dimensions within the agricultural sustainable development evaluation system, while M denotes the number of component indicators for each dimension. The level of regional integrated agricultural sustainability(S_t) is:

$$S_t = \sum_{i=1}^{4} s_t^i, \tag{14}$$

In order to improve spatiotemporal analysis, the results of agricultural sustainability evaluation are further processed in this paper, and the processing is as follows:

- For the temporal analysis, to comprehensively capture the overall development and internal disparities in agricultural sustainability, we conducted calculations of the mean ($\bar{S_y}$) and coefficient of variation (CV) for the results (as shown in Equations (15) and (16)). The $\bar{S_y}$ represents the central tendency of the data, while the CV quantifies the extent of variability relative to the mean, thereby shedding light on the degree of heterogeneity among the studied objects [50,51].

$$\bar{S_y} = \frac{1}{n} \sum_{i=1}^{n} S_{i,y} \tag{15}$$

$$CV = \frac{\sigma}{\bar{S_y}} \times 100 \tag{16}$$

  where y denotes a specific year, $S_{i,y}$ represents the agricultural sustainability level of region i in a specific year, n signifies the number of observed regions, and σ denotes the standard deviation of the dataset.
  Additionally, this study decomposes the agricultural sustainability level into dimensions to better reflect the changes in each dimension and their contributions to the overall level of agricultural sustainability. By calculating the contribution margin(CR), we can clearly distinguish the strengths and weaknesses of the dimensions that contribute to agricultural sustainability and make targeted improvements [52,53]; the formula is as follows:

$$CR_t^i = S_t^i / S_t, i = 1, 2, \ldots, 4, t = 1, 2, \ldots, T \tag{17}$$

- In the spatial analysis, this study employs the Natural Breaks Classification(NBC) method to further process the agricultural sustainability levels of various regions. This method is based on the distribution characteristics of the data, attempting to group similar data values into the same category while maximizing the differences between different categories [54]. In this study, we classified the level of agricultural sustainability using NBC method according to 5 classification standards in the ecological field: low level, relatively low level, medium level, relatively high level, and high level [55]. The Jenks optimization algorithm is employed to determine the optimal breaking points for the classification [56]. The detailed calculation principle is described below, with Equations (18) and (19) representing the optimization algorithm:

$$SSD_{c,k} = \min_{1 \leq j \leq n-k+1} \left[SSD_{c-1,j-1} + \frac{1}{n-j+1} \sum_{i=j}^{n-k+1} (S_i - \bar{S}_j)^2 \right] \quad (18)$$

$$\bar{S}_j = \frac{1}{n-j+1} \sum_{i=j}^{n} S_i \quad (19)$$

In the above equations, $SSD_{c,k}$ represents the sum of squared deviations between classes for c classes, wherein $c = 5$, and k observations; n denotes the number of observed regions; S_i stands for each individual agricultural sustainability level; and $\bar{S}_j$ is the mean value from j to n.

3. Result

3.1. Index Weights Results

In this paper, the index weights of the agricultural sustainability evaluation system were determined by the ANP method. Following the procedures and formulas delineated in Section 2.2, this study employs the SuperDecisions software to determine the weights of the various elements (Figure 3).

At the indicator level, the weight of an indicator reflects its relative importance compared to all the indicators within the evaluation system. For a given evaluation indicator, the higher the weight, the greater its impact on the final agricultural sustainability assessment value. As illustrated in Figure 3, it is evident that Forest coverage rate (e12, weight: 0.1537), Air quality index (e13, weight: 0.1132), and Per capita disposable income (e15, weight: 0.1305) are the three most crucial indicators. In contrast, the Agricultural electrification level (e4) and Rural healthcare level (e17) are the indicators with the most negligible impact on the agricultural sustainability assessment, with weights of only 0.0104 and 0.0117, respectively. Aside from indicators such as Agricultural mechanization level (e3) and Fertilizer use intensity (e10), which also have relatively low impact weights, most indicator weights lie within a range of 0.3 to 0.7.

At the dimension level, according to Figure 3, the weight of Environmental Quality (C3) is significantly higher than the other three dimensions—at 0.3999—accounting for 40% of the total. The Agricultural Economy dimension follows, with a weight of 0.2138. Resource Utilization and Rural Society exhibit similar weights, at 0.1923 and 0.1939, respectively. This suggests that Environmental quality is the primary evaluation dimension in the agricultural sustainability assessment process, with the other three dimensions having relatively less influence.

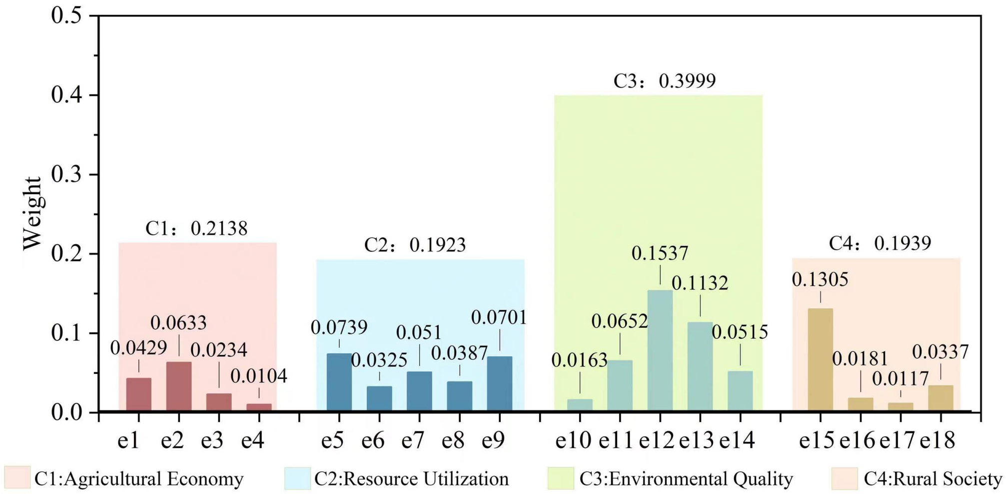


Figure 3. The index weights of agricultural sustainability evaluation system.

3.2. Temporal Analysis of Agricultural Sustainability

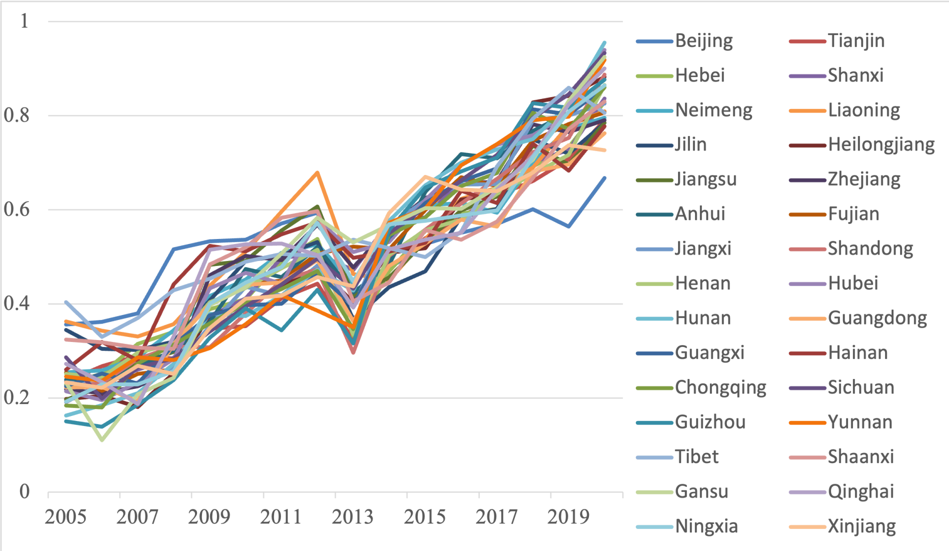
Upon obtaining the index weights, the data are processed using the time normalization method presented in Section 2.3 (Equations (11) and (12)), followed by calculating the agricultural sustainability levels of Chinese provinces from 2005 to 2020 using Equations (13) and (14). Further processing is conducted based on these results (Equations (15)–(17)) and shown in Sections 3.3.1 and 3.3.2. In accordance with the paper's formatting and presentation requirements, the specific results of the agricultural sustainability levels for Chinese provinces are not shown here. For detailed information, refer to Table A1 in the Appendix A.

3.2.1. Overall Temporal Variation Analysis

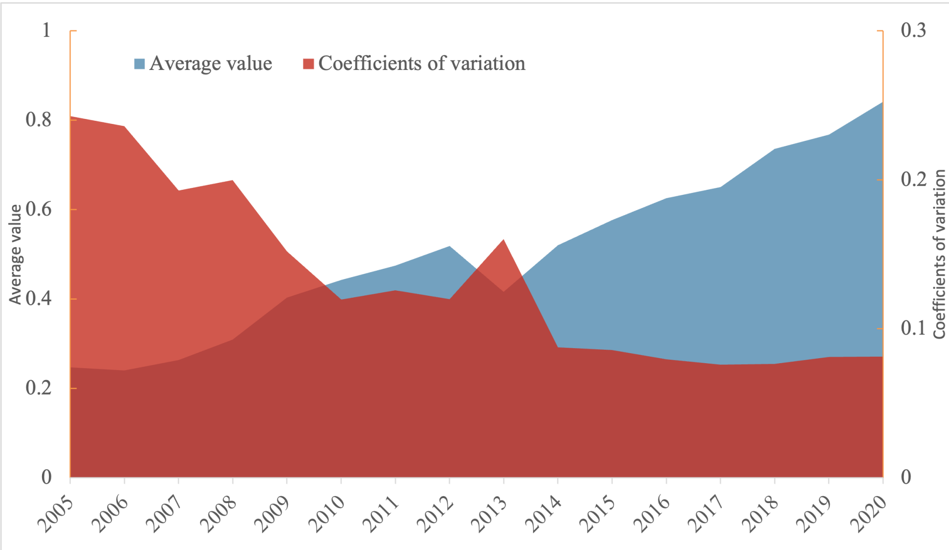
Figure 4 illustrates the overall temporal variation of agricultural sustainability by province in China. From 2005 to 2020, there is a general trend of increasing agricultural sustainability levels in all provinces.

As evident from Figure 4a, the agricultural sustainability levels of various Chinese provinces exhibit similar trends—displaying significant increases except for a substantial decline in 2013. It is important to note that the rate of increase in agricultural sustainability levels varies across provinces. Some provinces experienced relatively steady growth, while others exhibited more fluctuating patterns. For instance, Beijing exhibited a more consistent increase throughout the period, while provinces such as Liaoning and Jilin showed more variation in their trends. Provinces such as Anhui, Hubei, Hunan, and Sichuan demonstrate the most significant increases in agricultural sustainability, with growth rates exceeding 93%.

As indicated by Figure 4b, the average agricultural sustainability levels of Chinese provinces exhibit a rapid growth trend, rising from 0.2464 in 2005 to 0.8407 in 2020. This upward trajectory was interrupted by fluctuations in 2012 and 2013 when the average value declined to 0.416 before rebounding to 0.518. On the other hand, the coefficient of variation displays a more complex pattern. Initially, the values showed a pronounced decrease; however, this trend was disrupted by a notable increase in 2013, with the coefficient reaching its peak at 0.160. Following this apex, the coefficient gradually declined, stabilizing in 2019 and 2020. The trends in mean values and CVs indicate that while the agricultural sustainability capacities of Chinese provinces have been rapidly improving, there is a convergence effect of low-efficiency regions catching up with high-efficiency regions.



(**a**) Regional trends



(**b**) Means and coefficients of variation

Figure 4. Temporal variations in regional agricultural sustainability.

3.2.2. Dimensional Temporal Variation Analysis

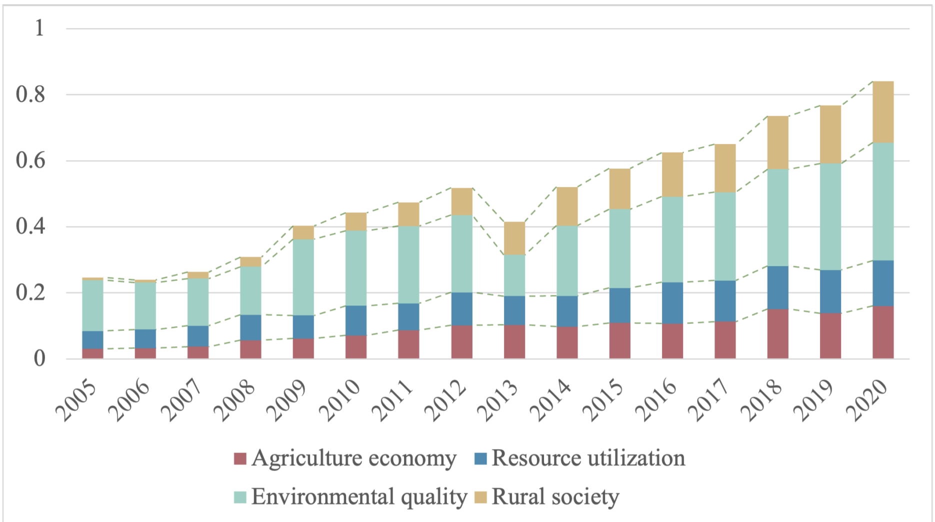
Figure 5 illustrates the temporal changes in the mean values and contribution rates of different dimensions of agricultural sustainability across regions. Between 2005 and 2020, although the scores of each dimension have been continuously increasing, the contribution rates of these dimensions have experienced various changes.

As seen in Figure 5a, the sustainability levels of the four dimensions—agricultural economy, resource utilization, environmental quality, and rural society—all exhibit a continuous upward trend. Among these, the rural society dimension displays the most significant change, increasing more than 20-fold from 0.0077 in 2005 to 0.1856 in 2020. Environmental quality consistently remains the most critical component among the four indicators, with a score of 0.3571 in 2020, significantly higher than the other dimensions. Agricultural economy and resource utilization dimensions demonstrate similar, stable upward trends, rising from 0.0304 and 0.0541 in 2005 to 0.1603 and 0.1377 in 2020, respectively.

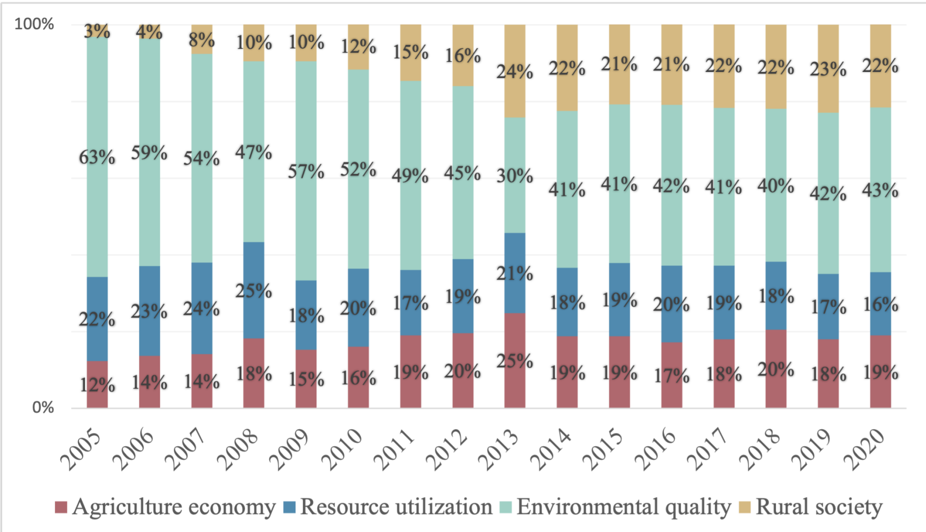
According to Figure 5b, the contribution rates of the four dimensions—Agriculture economy, Resource utilization, Environmental quality, and Rural society—exhibit different changes during the process but ultimately stabilize. Between 2005 and 2020, the proportion of the Agriculture economy dimension of the overall agricultural sustainability demonstrates a generally increasing trend, rising from 12% in 2005 to its peak of 25% in 2013, then stabilizing between 17% and 20%. Conversely, the Resource utilization dimension shows a declining trend, decreasing from its peak of 25% in 2008 to 16% in 2020. Throughout the entire period, the Environmental quality dimension consistently maintains the highest proportion among the four categories, despite experiencing a decline of more than 20%, ultimately remaining between 40% and 42%. Lastly, the contribution of the Rural society dimension to agricultural sustainability significantly increases, rising from 3% in 2005 to eventually stabilizing around 22%.

3.3. Spatial Analysis of Agricultural Sustainability

This section employs the same processing approach as Section 3.3, utilizing the spatial normalization method (Equations (9) and (10)) to process the data. Combined with the index weights from Section 3.2, each province's relative agricultural sustainability scores are calculated using Equations (13) and (14) for each year. Finally, the NBC method is applied for classification and comparison. Similarly, detailed information can be found in Appendix A in Table A2.



(**a**) Absolute values



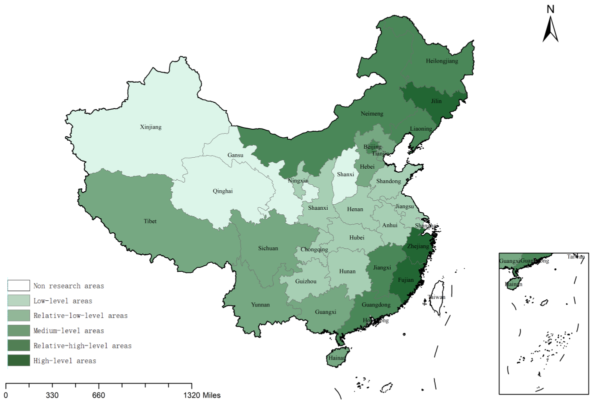
(**b**) Contribution rates

Figure 5. Dimensional temporal variation in agricultural sustainability.

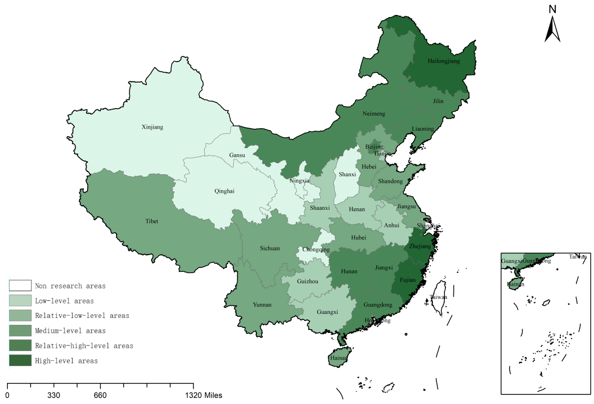
3.3.1. Overall Spatial Variation Analysis

In order to compare more intuitively the spatial differences in the level of agricultural sustainability among different provinces, this study uses ArcGIS software to create maps of agricultural sustainability levels for Chinese provinces in 2005, 2010, 2015, and 2020, with a 5-year interval between each map. The resulting maps are presented in Figure 6.

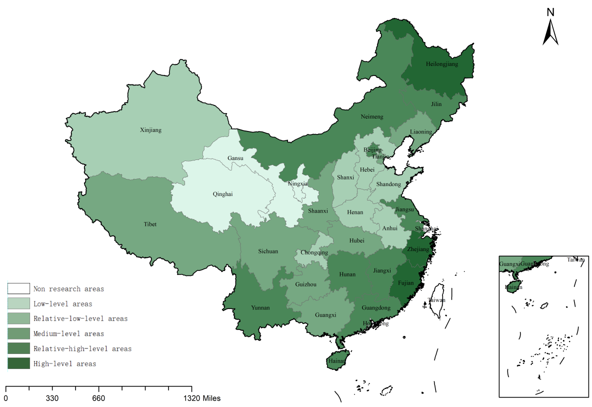
As shown in Figure 6, the differences in agricultural sustainability among many regions remain relatively stable. Between 2005 and 2020, Zhejiang and Fujian's relative agricultural sustainability levels have consistently been higher than those of other regions. Beijing, Jiangxi, and Guangdong maintain stable positions in the second tier. Sichuan and Tibet are among the regions with medium agricultural sustainability levels. Henan and Anhui exhibit relatively low agricultural sustainability, while Gansu and Qinghai rank at the bottom.



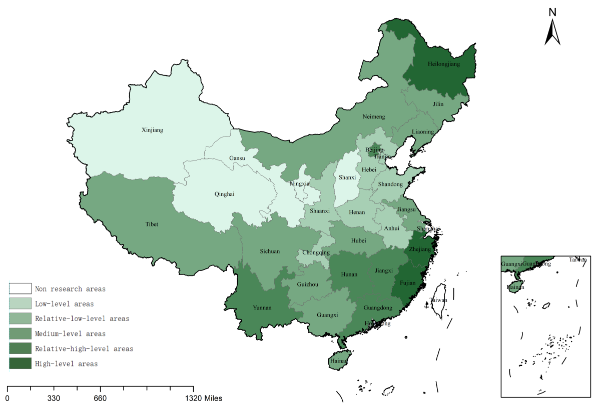
(**a**) 2005



(**b**) 2010



(**c**) 2015



(**d**) 2020

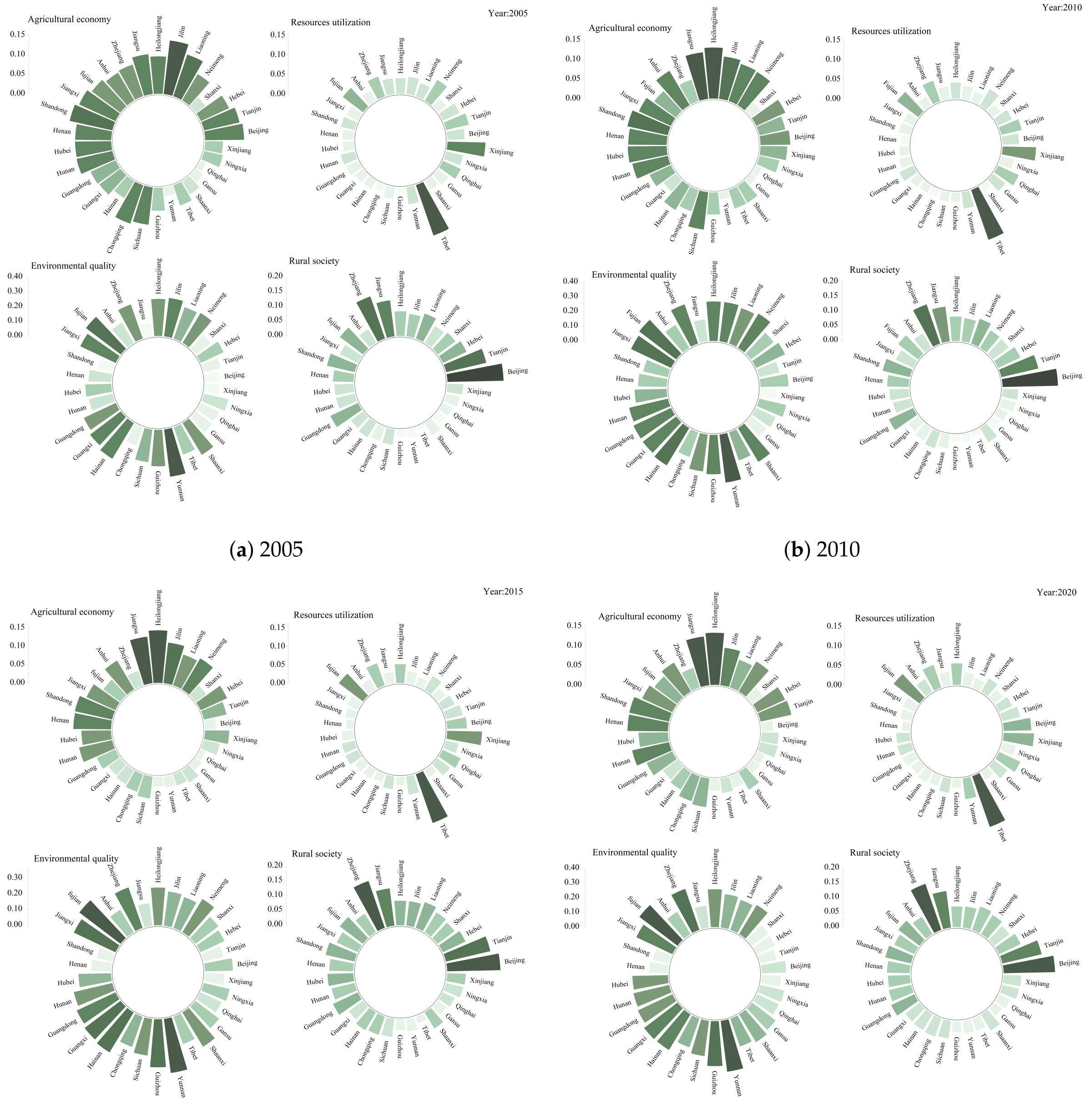
Figure 6. Spatial variations in regional agricultural sustainability.

Apart from these regions, the agricultural sustainability levels of other areas have exhibited varying changes over the 16 years. For example, the relative agricultural sustainability ratings of provinces such as Hebei and Inner Mongolia have displayed different declining trends, with Jilin experiencing the most significant drop (from a high level in 2005 to a medium level in 2020). In contrast, the agricultural sustainability ratings of Heilongjiang, Hunan, and four other provinces have risen. With the exception of Jiangsu, which exhibited relatively large fluctuations in its agricultural sustainability (low level in 2005, medium level in 2010, high level in 2015, and medium level in 2020), nine areas, including Tianjin, Shanxi, and Shandong, have fluctuated between adjacent ratings.

3.3.2. Dimentional Spatial Variation Analysis

Figure 7 displays the spatial differences among various dimensions of agricultural sustainability in 2005, 2010, 2015, and 2020. This table provides an intuitive representation of the comparative advantages and disparities among different dimensions across regions at different time points.

As shown in Figure 7, during the period of 2005–2020, some regions demonstrated remarkable advantages in single dimensions. For example, Beijing's sustainability level in the rural society dimension was significantly higher than other regions, Tibet led substantially in the resources utilization dimension, and Yunnan consistently held an advantage in the environmental quality dimension. In addition, some regions gradually developed their own advantageous dimensions over the 16-year period. For instance, Heilongjiang surpassed Jiangsu and Jilin in the agricultural economy dimension after 2010 and maintained a leading position. Fujian's sustainability level in the resources utilization dimension gradually exceeded Xinjiang and ranked only behind Tibet in 2020.



(**a**) 2005 (**b**) 2010

(**c**) 2015 (**d**) 2020

Figure 7. Dimensional spatial variation in agricultural sustainability.

Furthermore, Figure 7 also reveals the unbalanced development of agricultural sustainability across various regions in China. Generally, development in the environmental quality dimension is the most balanced among all provinces, with universally high sustainability levels and relatively small gaps. In the resources utilization dimension, by contrast, most regions exhibit the lowest sustainability scores among the four dimensions, with only a few exceptions such as Tibet, Xinjiang, and Fujian. A similar phenomenon is observed in the rural society dimension. Lastly, the agricultural economy dimension is the most distinctive, showing a divergent trend. It evolves from initially high scores across most regions to a gradual concentration in advantageous areas such as Heilongjiang, Jiangsu, Shandong, and Henan, with relative declines in other regions such as Zhejiang and Fujian.

4. Discussion

In this study, we employ the ANP method to determine index weights for an agricultural sustainability evaluation system and assess the spatiotemporal changes in agricultural sustainability levels across Chinese provinces from 2005 to 2020. Our findings are generally consistent with previous research but also show some differences. Based on these findings, we offer new insights into the constituent factors, development levels, and future policy recommendations for agricultural sustainability in China.

Considering the index weight results, our analysis emphasizes the importance of environmental quality in driving agricultural sustainability outcomes, which diverges from existing studies focusing more on the agricultural economic dimension [15,28]. The potential reasons for this difference may be attributed to our consideration of the interrelationships among different dimensions and indicators when calculating weights and variations in experts' subjective judgments. Moreover, although the per capita disposable income in rural areas is significantly higher than other dimension indicators at the index level, the overall weight of the social dimension does not show a significant difference compared to the agricultural economy and resource utilization dimensions. This insight suggests that, while prioritizing environmental protection in promoting sustainable agricultural development, it is essential to pay attention to the coordinated development of the agricultural economy, resource utilization, and rural society [57].

In terms of temporal trends, our analysis first reconfirms the findings of Liu et al. (2019) [58] and Hu et al. (2022) [59] that the level of agricultural sustainability has significantly improved in all regions of China, indicating that China's agricultural policies and practices are effective in promoting sustainable agriculture. However, the considerable decline in agricultural sustainability observed in various provinces in 2013 may suggest the impact of external factors, such as the peak severity of adverse weather conditions such as smog that year [60]. This implies that while maintaining agricultural sustainability growth, regions should focus on enhancing their response to external shocks and improving the stability of agricultural sustainability growth. Secondly, our study confirms the convergence effect of low-efficiency regions catching up with high-efficiency regions in terms of agricultural sustainability across China [61], highlighting the importance of targeted policies and interventions in addressing regional disparities. Lastly, the analysis of the temporal changes in each dimension reveals that the increasing importance of the rural social dimension reflects the significant role of rural development in enhancing agricultural sustainability [62]. Simultaneously, the persistent high contribution of the environmental quality dimension reiterates the necessity of prioritizing environmental protection in agricultural policies and practices [63].

Regarding spatial disparity, overall, some regions, such as Zhejiang and Fujian, consistently exhibit higher levels of agricultural sustainability, while others, such as Gansu and Qinghai, perform poorly, and some regions show considerable fluctuations in rankings. This indicates that agricultural sustainability levels in China still present specific imbalances and instabilities in development [64,65]. It is worth noting that regions such as Shandong and Henan, which are considered areas with high agricultural sustainability in some studies [65], are only ranked as moderate or even relatively low in our findings. This could be due to our evaluation process placing greater emphasis on the environmental quality dimension and using many per capita indicators in constructing the index system, which weakens these regions' overall leading advantages in economic, resource, and social dimensions. At the dimension level, some regions demonstrate distinct advantages in specific dimensions, such as Beijing in the rural social dimension, Tibet in resource utilization, and Yunnan in environmental quality. The dimensional advantages of regions such as Heilongjiang and Fujian have gradually been established. These findings emphasize the importance of leveraging regional strengths and addressing weaknesses to promote balanced and sustainable agricultural development [66]. In policy formulation and agricultural practices, it is crucial to recognize these differences and strive for balanced development across all aspects. By capitalizing on the strengths of advantageous dimensions and addressing the shortcomings of weaker ones, we can work towards achieving sustainable, resilient, and inclusive agricultural systems that contribute to the well-being of both humanity and our planet.

5. Conclusions

In conclusion, our study contributes to a broad understanding of agricultural sustainability assessment and management by providing a comprehensive and detailed evaluation system based on the ANP methodology, which examines the spatial and temporal variation in agricultural sustainability across regions in China over the last 16 years. Our findings provide valuable insights and policy recommendations for improving agricultural sustainability in China, and they can serve as a valuable reference for other countries seeking to advance sustainable agricultural development.

The main contributions of this study can be summarized as follows. First, by considering the various dimensions and indicators of agricultural sustainability as an interacting whole, our analysis provides a more comprehensive and accurate assessment of China's agricultural sustainability. Second, our examination of the different dimensions reveals the necessity for adopting a sustainable development model centered on environmental protection, with coordinated growth in agriculture, resource utilization, and social aspects after reaching a specific scale of economic development. Third, our analysis of the spatiotemporal differences across China's regions offers a theoretical basis for targeted policymaking and interventions in specific areas.

However, due to data limitations, this study omits the evaluation of a few regions and cannot incorporate all relevant evaluation indicators. Furthermore, the assessment method employed in this research is based on subjective and relative perspectives and does not delve deeply into the influencing factors. Therefore, objectively measuring agricultural sustainability and investigating the external impact factors, internal driving forces, and the effectiveness of policies and measures affecting agricultural sustainability are directions for our future research.

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Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found here: http://www.stats.gov.cn/sj/ (accessed on 30 March 2023).

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

Appendix A. Tables of Results

Table A1. Temporal evolution of agricultural sustainability levels (2005–2020).

Region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	0.3560	0.3614	0.3797	0.5161	0.5331	0.5361	0.5710	0.5937	0.4108	0.4756	0.5269	0.5506	0.5695	0.6007	0.5642	0.6677
Tianjin	0.2348	0.2678	0.2895	0.2838	0.3470	0.3528	0.4119	0.4430	0.3222	0.4741	0.5394	0.5836	0.6306	0.6604	0.7078	0.7903
Hebei	0.2284	0.2518	0.3152	0.3402	0.3884	0.4104	0.4900	0.5376	0.3325	0.4688	0.5553	0.5919	0.6015	0.6920	0.7327	0.8286
Shanxi	0.1913	0.2312	0.2604	0.2858	0.3733	0.4118	0.4975	0.5059	0.4717	0.5734	0.5839	0.6635	0.6558	0.7013	0.7274	0.8363
Neimeng	0.2548	0.2582	0.2867	0.3439	0.4164	0.4519	0.5082	0.5267	0.4431	0.5635	0.6089	0.6143	0.5939	0.7014	0.7724	0.7950
Liaoning	0.3622	0.3431	0.3304	0.3566	0.4387	0.5109	0.5964	0.6792	0.4633	0.4501	0.5372	0.6230	0.6470	0.6893	0.7793	0.8088
Jilin	0.3443	0.3048	0.3022	0.3203	0.4073	0.4909	0.5025	0.5312	0.3673	0.4355	0.4689	0.5850	0.6014	0.7495	0.7187	0.7847
Heilongjiang	0.1978	0.2047	0.1805	0.2529	0.3768	0.3975	0.4371	0.4774	0.4036	0.5082	0.5182	0.6217	0.6332	0.8279	0.8419	0.8821
Jiangsu	0.1967	0.2238	0.2733	0.2977	0.4827	0.4915	0.5555	0.6066	0.4163	0.4561	0.5323	0.5985	0.6284	0.7364	0.6957	0.7845
Xinjiang	0.2330	0.2217	0.2684	0.2514	0.3486	0.4108	0.4178	0.4572	0.4367	0.5925	0.6698	0.6430	0.6398	0.6785	0.7368	0.7263
Zhejiang	0.2181	0.2105	0.2252	0.2594	0.4606	0.5015	0.4926	0.5679	0.4771	0.5619	0.6247	0.6522	0.6612	0.7810	0.7646	0.7906
Anhui	0.2391	0.2388	0.2649	0.3008	0.3619	0.4738	0.4569	0.5208	0.4237	0.4832	0.6379	0.7179	0.7089	0.7674	0.8062	0.9397
Fujian	0.2538	0.2153	0.2510	0.2606	0.3977	0.4402	0.4493	0.5068	0.5213	0.5156	0.5990	0.6687	0.6503	0.7468	0.7822	0.8068
Jiangxi	0.2329	0.2294	0.2326	0.2633	0.3524	0.4366	0.4175	0.4811	0.3919	0.5666	0.6197	0.6535	0.6541	0.7898	0.8002	0.8255
Shandong	0.2243	0.2314	0.2831	0.3089	0.3076	0.3801	0.4495	0.4731	0.2965	0.5021	0.5576	0.6133	0.6657	0.7222	0.7524	0.8867
Henan	0.2514	0.2441	0.2964	0.3148	0.4039	0.4340	0.4754	0.5151	0.3357	0.5043	0.5566	0.5792	0.6334	0.6754	0.7163	0.8645
Hubei	0.2142	0.1955	0.2330	0.2832	0.4327	0.4659	0.4426	0.5791	0.5101	0.5311	0.6206	0.6941	0.7381	0.7583	0.8031	0.9395
Hunan	0.1628	0.1851	0.2098	0.2724	0.3791	0.3743	0.4172	0.4723	0.4284	0.5766	0.6517	0.6999	0.7278	0.7501	0.8249	0.9548
Guangdong	0.2226	0.2236	0.1931	0.3145	0.3990	0.4404	0.4456	0.4930	0.3634	0.4803	0.5276	0.5790	0.5643	0.6811	0.6957	0.7623
Guangxi	0.2247	0.2515	0.2303	0.3126	0.3760	0.3969	0.4005	0.4645	0.3967	0.5410	0.6137	0.6605	0.6877	0.8133	0.8024	0.8600
Hainan	0.2598	0.3189	0.2800	0.4412	0.5234	0.5119	0.5480	0.5732	0.4976	0.5105	0.5295	0.6405	0.6142	0.7405	0.6828	0.7770
Chongqing	0.1836	0.1799	0.2731	0.3135	0.3586	0.4022	0.4316	0.4702	0.3463	0.5459	0.5840	0.6504	0.6777	0.8058	0.7716	0.8597
Sichuan	0.2863	0.1991	0.2652	0.2838	0.3409	0.3943	0.4409	0.4963	0.4324	0.5500	0.6055	0.6621	0.7168	0.7955	0.8454	0.9329
Guizhou	0.1505	0.1389	0.1854	0.2377	0.3285	0.3908	0.3434	0.4299	0.3156	0.5567	0.6473	0.6815	0.7108	0.8263	0.8163	0.8760
Yunnan	0.2450	0.2365	0.2860	0.2806	0.3061	0.3565	0.4184	0.3853	0.3503	0.5721	0.6023	0.6944	0.7392	0.7904	0.7975	0.9180
Tibet	0.4038	0.3302	0.3696	0.4291	0.4532	0.4899	0.5055	0.5015	0.5362	0.5182	0.4997	0.5538	0.6921	0.7936	0.8594	0.8062
Shaanxi	0.3239	0.3182	0.3070	0.3044	0.4841	0.5195	0.5827	0.5966	0.4052	0.4454	0.5566	0.5362	0.5745	0.6674	0.7717	0.8296
Gansu	0.2319	0.1106	0.2081	0.2428	0.3966	0.4358	0.5071	0.5831	0.5307	0.5676	0.6037	0.6021	0.6474	0.7059	0.8312	0.9244
Qinghai	0.2725	0.2342	0.1868	0.3307	0.5151	0.5263	0.5282	0.5036	0.3916	0.5155	0.5362	0.5511	0.6427	0.7138	0.8240	0.8998
Ningxia	0.1925	0.2290	0.2288	0.2569	0.4003	0.4454	0.4779	0.5719	0.4476	0.5692	0.5764	0.5875	0.5987	0.7119	0.8080	0.8643
Xinjiang	0.2330	0.2217	0.2684	0.2514	0.3486	0.4108	0.4178	0.4572	0.4367	0.5925	0.6698	0.6430	0.6398	0.6785	0.7368	0.7263

Table A2. Spatial differences of agricultural sustainability levels (2005–2020).

Region	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	0.4347	0.4660	0.4309	0.4925	0.4990	0.4973	0.4826	0.4475	0.4516	0.4419	0.4429	0.4292	0.4409	0.4219	0.4171	0.4422
Tianjin	0.4093	0.4247	0.4055	0.3793	0.3856	0.3916	0.4073	0.3745	0.3721	0.3829	0.3940	0.3871	0.3830	0.3298	0.3676	0.3755
Hebei	0.3867	0.4102	0.3908	0.4109	0.4175	0.4219	0.4196	0.4064	0.3376	0.3459	0.3685	0.3446	0.3363	0.2827	0.3302	0.3303
Shanxi	0.2589	0.2979	0.2757	0.2932	0.2978	0.3155	0.3134	0.3199	0.3115	0.3196	0.3192	0.3043	0.2732	0.2441	0.2712	0.2658
Neimeng	0.4434	0.4595	0.4644	0.4787	0.4788	0.4869	0.4911	0.4910	0.4609	0.4601	0.4667	0.4550	0.4343	0.4217	0.4564	0.4352
Liaoning	0.4647	0.4729	0.4626	0.4610	0.4625	0.4706	0.4867	0.4745	0.4427	0.4086	0.4130	0.4186	0.4189	0.3820	0.4191	0.3989
Jilin	0.5219	0.5183	0.4894	0.5027	0.4816	0.4906	0.5081	0.4836	0.4694	0.4595	0.4472	0.4658	0.4547	0.4413	0.4466	0.4310
Heilongjiang	0.4712	0.4940	0.4846	0.5031	0.5045	0.5224	0.5343	0.5329	0.5338	0.5366	0.5182	0.5328	0.5251	0.5817	0.5386	0.5169
Jiangsu	0.3583	0.3875	0.3790	0.3869	0.4291	0.4210	0.4352	0.4225	0.4281	0.4241	0.4307	0.4229	0.4355	0.3682	0.4175	0.4351
Zhejiang	0.5365	0.5487	0.5296	0.5348	0.5427	0.5357	0.5492	0.5419	0.5503	0.5449	0.5474	0.5429	0.5493	0.5340	0.5475	0.5741
Anhui	0.3240	0.3435	0.3164	0.3434	0.3434	0.3664	0.3543	0.3694	0.3616	0.3236	0.3630	0.3600	0.3483	0.2891	0.3450	0.3680
Fujian	0.5524	0.5465	0.5448	0.5341	0.5388	0.5386	0.5434	0.5508	0.5758	0.5600	0.5685	0.5724	0.5619	0.5295	0.5654	0.5703
Jiangxi	0.4697	0.4797	0.4849	0.4923	0.4900	0.4842	0.4923	0.4624	0.4594	0.4898	0.4904	0.4770	0.4685	0.4136	0.4595	0.4644
Shandong	0.3524	0.4121	0.3973	0.3862	0.3910	0.4025	0.4102	0.3975	0.3396	0.3430	0.3346	0.3348	0.3448	0.2720	0.3212	0.3376
Henan	0.3438	0.3723	0.3715	0.3809	0.3995	0.3869	0.3815	0.3683	0.3425	0.3428	0.3312	0.3198	0.3259	0.2428	0.3111	0.3299
Hubei	0.3614	0.3712	0.3564	0.3816	0.4139	0.4075	0.3977	0.4355	0.4319	0.4063	0.4091	0.4158	0.4267	0.3695	0.4055	0.4266
Hunan	0.3614	0.3978	0.4039	0.4369	0.4580	0.4518	0.4605	0.4385	0.4360	0.4528	0.4602	0.4517	0.4532	0.3844	0.4417	0.4607
Guangdong	0.4474	0.4673	0.4324	0.4570	0.4663	0.4729	0.4784	0.4742	0.4413	0.4563	0.4593	0.4493	0.4379	0.4032	0.4312	0.4528
Guangxi	0.4073	0.4063	0.3828	0.3908	0.4088	0.3927	0.3984	0.3950	0.3963	0.4052	0.4159	0.4161	0.4120	0.4075	0.4129	0.4194
Hainan	0.4143	0.4326	0.4134	0.4420	0.4425	0.4383	0.4481	0.4512	0.4524	0.4394	0.4385	0.4407	0.4342	0.4209	0.4336	0.4289
Chongqing	0.3040	0.2828	0.2735	0.2850	0.2958	0.3108	0.3204	0.3298	0.3017	0.3244	0.3425	0.3374	0.3346	0.3192	0.3491	0.3653
Sichuan	0.4035	0.3978	0.4120	0.4031	0.4201	0.4207	0.4298	0.3844	0.4097	0.3992	0.3921	0.3830	0.3966	0.3601	0.4142	0.4124
Guizhou	0.3404	0.3302	0.3343	0.3377	0.3193	0.3698	0.3532	0.3707	0.3294	0.3678	0.3907	0.3911	0.3905	0.4011	0.3950	0.3973
Yunnan	0.4199	0.4182	0.4261	0.4139	0.4148	0.4171	0.4440	0.4321	0.4466	0.4720	0.4696	0.4721	0.4743	0.4593	0.4760	0.4827
Tibet	0.3993	0.3915	0.3862	0.3968	0.4015	0.4042	0.4142	0.4105	0.4178	0.3824	0.3810	0.3749	0.4070	0.4001	0.4388	0.4135
Shaanxi	0.3668	0.3765	0.3627	0.3698	0.3814	0.3929	0.3943	0.3809	0.3653	0.3516	0.3799	0.3367	0.3286	0.3118	0.3586	0.3586
Gansu	0.2298	0.2169	0.2395	0.2113	0.2153	0.2155	0.2205	0.2295	0.2882	0.2910	0.2898	0.2680	0.2678	0.2493	0.2992	0.2991
Qinghai	0.2376	0.2322	0.2063	0.2120	0.2227	0.2582	0.2519	0.2356	0.2436	0.2511	0.2609	0.2357	0.2639	0.2567	0.2959	0.2835
Ningxia	0.3108	0.3152	0.3016	0.3061	0.3144	0.3252	0.3214	0.3133	0.3198	0.3166	0.3099	0.2921	0.2820	0.2720	0.3239	0.3057
Xinjiang	0.2909	0.3053	0.2818	0.2757	0.2951	0.3164	0.3104	0.3116	0.3557	0.3481	0.3483	0.3324	0.3235	0.3123	0.3347	0.3108

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