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Research on the Evolution of the Spatial Association Network Structure and Driving Factors of China's Agricultural Green Development

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Abstract: Against the backdrop of global environmental challenges and sustainable development goals, this paper pioneers the application of social network analysis to the study of spatial associations in China's agricultural green development. It not only enhances the understanding of the spatial interconnectivity and network structural characteristics of agricultural green developments, but also captures the complex dependencies and interactions among provinces through a network lens, offering a fresh perspective on regional agricultural cooperation and competition. The study reveals: (1) The spatial network of China's agricultural green development displays strong overall connectivity and enhanced stability, with regional green development trends becoming increasingly interlinked and interdependent. (2) The network exhibits a clear hierarchical and core-periphery structure which, over time, shows signs of diminishing, indicating a narrowing of developmental disparities among regions. (3) Significant shifts in the roles and positions of provinces within the network occur due to the relocation of industrial focal points and adjustments in development strategies, highlighting the complexity of dynamic changes among regions. (4) The spatial association network can be divided into four main clusters: Net spillover block, Bidirectional spillover block, Net beneficial block, and Broker block, with significant gradient characteristics in the relationships between these clusters, suggesting directional and differential flows and exchanges of resources and information among regions. (5) Geographic proximity, economic development level, informatization, and agricultural technological advancement significantly influenced the development and structural evolution of the network.

Keywords: agricultural green development; modified gravity model; spatial association network; dynamic evolution; driving factors

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1. Introduction

As economic and social development has progressed, the environmental challenges posed by human economic activities. such as climate change, air pollution, water contamination, and land degradation have emerged as formidable obstacles to global sustainability. These issues are pervasive worldwide, affecting every nation, from the most developed to the developing, with the pressures of ecological deterioration and the quest for sustainable growth. Consequently, these concerns have become focal points of international attention [1]. In response, the concept of green development, which advocates for the harmonious progress of both society and the natural environment, has gained traction. Green development promotes economic growth while safeguarding ecological balance, aiming for sustainability across economic, social, and environmental spheres through efficient resource use, reduced chemical consumption, and enhanced biodiversity. This philosophy has received widespread recognition and adoption internationally [2]. In the realm of agricultural production, which is fundamental to human survival and societal advancement, the stakes involve food security and ecological equilibrium. With the global population on the rise and escalating food demands, agriculture faces heightened challenges. Traditional farming methods, heavily reliant on the extensive use of fertilizers and pesticides, have led to significant environmental issues such as soil degradation, water pollution, and a reduction in biodiversity. Thus, promoting a shift towards agricultural green development has become an imperative choice in global agricultural reform and a critical strategy to ensure food security and achieve sustainability goals [3].

To propel agricultural green development, the European Union has implemented a series of environmental policies for agriculture. These include measures to promote eco-friendly farming practices through agricultural environmental actions and organic farming initiatives, encouraging farmers to adopt sustainable methods [4]. In the United States, the focus has been on fostering innovative agricultural technologies through the Sustainable Agriculture Research and Education program, aimed at enhancing both the environmental and economic efficiency of farming [5]. Meanwhile, Japan has concentrated on developing precision and smart agriculture technologies to reduce resource wastage and increase production efficiency [6]. In China, amid rapid economic growth and population expansion, agricultural green development has become a critical focus for policymakers and academics alike. The socio-economic conditions of a large population and limited per capita resources mandate a green development path for Chinese agriculture [7]. The Chinese government has established numerous policies and measures to support this green transformation, including the "Zero Growth" action plan for chemical fertilizer and pesticide use, and the promotion of integrated water and fertilizer management, green pest control, and ecological breeding techniques [8].These initiatives aim to diminish the environmental impact of agricultural production, improve efficiency and product quality, and achieve a harmonious coexistence between agriculture and environmental conservation.

Agricultural green development is an integral part of China's strategy to build a strong agricultural nation and has garnered extensive attention from the academic community. Current research on this topic mainly focuses on three areas: firstly, exploring the essence and connotations of agricultural green development [9–11]; secondly, constructing and refining the evaluation systems for this development [12–14]; and thirdly, analyzing the factors influencing agricultural green development [15–17]. With advances in spatial econometric tools, the spatial distribution and dynamic changes in agricultural green development have increasingly become a focal point of study. Scholars are beginning to use spatial econometric models to explore the heterogeneity and spatiotemporal evolution of agricultural green development [18–22]. In the context of China's deepening unified market strategy, the flow of technology, labor, and capital across regions is accelerating, which makes the spatial relationships between economic development and agricultural activities less constrained by geography and more complex and networked across regions. Although existing studies have revealed the significant spatial effects of agricultural green development, there are several limitations: Firstly, most studies rely on spatial econometric models to explore spatial effects between specific regions, neglecting the spatial network effects at a national scale and lacking a holistic and systematic research perspective. Secondly, these studies are primarily based on attribute data, failing to analyze the internal structure characteristics of the spatial network in agricultural green development, which prevents a comprehensive portrayal of the spatial network features of China's agricultural development. Lastly, research on agricultural spatial networks often relies on cross-sectional data from a single time point, which does not adequately reveal how spatial network characteristics evolve over time. This limitation hinders a deeper understanding of the dynamic properties of the agricultural green development spatial network, thereby affecting the effective advancement of related policies and practices.

Therefore, this study employs relational data and network analysis methods to deeply explore and elucidate the spatial network characteristics and their dynamic changes in China's agricultural green development. Initially, an enhanced gravity model is introduced to quantify and interpret the interaction strengths among various regions in China more precisely. Additionally, utilizing social network analysis, the aim is to reveal the spatial network structure, evolutionary trends, and regional clustering characteristics of China's agricultural green development, and to discuss the roles and impacts of various provinces within this network in depth. Moreover, the study incorporates the Quadratic Assignment Procedure (QAP) analytical method to further examine the factors driving the formation of the agricultural green development spatial network, offering new perspectives and empirical evidence for exploring resource flows and promoting coordinated regional agricultural development. The principal contributions of this research are manifold: from a research perspective, it integrates global network analysis and relational data, providing a novel viewpoint for examining the spatial connections in China's agricultural green development; methodologically, this paper is the first to apply the modified gravity model, social network analysis, and QAP method to analyze the spatial network characteristics of agricultural green development and its influencing factors, demonstrating the effectiveness of these methods in exploring spatial network structures and dynamics; from the scale of the study, based on data from all 31 provinces in China, it comprehensively analyzes the spatiotemporal evolution and driving forces behind the agricultural green development spatial network. The structure of this article is organized as follows: the second part systematically reviews the related literature; the third part details the research methodologies and data sources; the fourth part delves into the structural characteristics and dynamic changes in China's agricultural green development spatial network; the fifth part discusses the driving factors behind the formation of this spatial network; the sixth part systematically summarizes the findings and proposes relevant policy recommendations and directions for future research and improvement.

2. Literature Review

Agricultural green development underscores the importance of sustainable agricultural practices, aiming to strike a balance between agricultural production and the natural environment to fulfill the present and future demands for agricultural products while safeguarding the ecological environment. The concept of agricultural green development mirrors contemporary society's new recognition and requirements for sustainable agricultural advancement, eliciting widespread interest from the academic community upon its introduction. Research within the academic realm concerning agricultural green development predominantly concentrates on the following four areas.

2.1. Definition of the Essence of Agricultural Green Development

The essence of defining the connotation of agricultural green development is fundamental to research in this field. It aids in delineating the scope of study and establishing a shared understanding. According to Kansanga (2019), agricultural green development was defined as a process that respects the laws of nature, utilizing advanced scientific techniques to explore the sustainability of agricultural development [23]. Jaung W (2016) posited that agricultural green development is a fundamentally new developmental concept, demanding a commitment to sustainable development with green institutional construction and innovative mechanisms as safeguards [24]. Alsanius et al. (2021) asserted, after researching the Norwegian agricultural and fisheries sectors, that agricultural green development involves addressing agricultural environmental issues through innovative technologies and maximizing the use of locally sustainable resources [25]. Gargano et al. (2021) contended that agricultural green development involves applying various professional skills to clean production in the agricultural sector, facilitating the transformation of agricultural ecological development [26]. Huang T et al. (2022) viewed agricultural green development as an extension and practice of the green development concept in the agricultural domain [9]. Liu Y et al. (2022) characterized agricultural green development as a systemic undertaking encompassing the entire process of greening in six aspects: agricultural production layout, resource utilization, technological means, industrial systems, agricultural product supply, and consumption [10]. Zhou F et al. (2023) perceived agricultural green development as a comprehensive endeavor, including resource conservation, ecological stability, clean production, supply security, and enhanced benefits [11].

2.2. Measurement and Evaluation of Agricultural Green Development

Currently, the academic community employs two primary approaches to measure the level of agricultural green development. The first involves measurement through individual indicators, primarily encompassing the comprehensive calculation of agricultural green total factor productivity and agricultural carbon emissions [27]. Agricultural green total factor productivity is determined by identifying input and output elements in the agricultural production process, comprehensively assessing the level of agricultural green development from the dimensions of production efficiency and resource consumption. A higher numerical value of agricultural green total factor productivity indicates a faster pace of agricultural green development [22,27–32]. Conversely, agricultural carbon emissions are measured by the release of carbon dioxide (CO_2) and other greenhouse gases into the atmosphere during agricultural activities in the production and operation processes, gauging the degree of agricultural greening. A lower agricultural carbon emission quantity and intensity indicates a higher level of agricultural green development [33–38]. The second approach involves constructing composite indices for measurement from multiple perspectives. Due to the complexity of agricultural green development as a systemic undertaking, and its involvement in various aspects, a single indicator quickly falls short of reflecting its entirety. Therefore, constructing a comprehensive evaluation index system can encompass more abundant information, making the agricultural green development comprehensive evaluation index relatively more convincing [11–14].

2.3. Spatiotemporal Distribution Characteristics of Agricultural Green Development

As spatial econometric tools and methods advance, the introduction of spatial econometric models propels scholars to delve deeper into the spatial relationships of agricultural green development. Therefore, some researchers utilize the Theil index, Moran index, and spatial Durbin model to analyze the spatial pattern evolution characteristics of agricultural green development [39–41]. Deng et al. (2022) found significant regional imbalances in the level of agricultural green development in China, with inter-regional disparities continuously widening, indicating a pronounced spatial correlation in agricultural green development [19]. Liu et al. (2023) discovered significant spatial agglomeration characteristics in the efficiency of agricultural green development in China, with the progression of time posing spatial dispersion risks [20]. Zhou F et al. (2023) employed methods such as kernel density estimation, Moran's I index, and Markov chain to analyze regional differences and spatial evolution of agricultural green development in China [11]. Zhu et al. (2022) investigated the spatiotemporal convergence of agricultural green development in China through sigma convergence, absolute beta convergence, conditional beta convergence, and dynamic spatial convergence [22]. Yu et al. (2022) demonstrated a significant spatial correlation among the agricultural green development of various provinces in China, without exhibiting absolute α convergence and absolute β convergence characteristics [21].

2.4. Factors Influencing Agricultural Green Development

Regarding research on factors influencing agricultural green development, in terms of economic factors, Wang et al. (2023) found that industrial agglomeration has a positive promoting effect on agricultural green production efficiency. Under different scales of land transfer, the impact of industrial agglomeration on agricultural green production efficiency exhibits heterogeneity [42]. Ge et al. (2023) discovered that urbanization, as a measure to facilitate the migration of rural populations, effectively promotes the transformation of agricultural green development [43]. In terms of policy factors, Deng et al. (2023) found that financial support for agriculture can significantly influence agricultural green development by strengthening rural infrastructure [15]. Sun et al. (2022) found that when the level of regional economic development is low, environmental regulations have limited impact on agricultural green development [16]. In the realm of financial service factors, Wang et al. (2023) discovered that agricultural credit input significantly enhances the total factor productivity of local agricultural green development [17]. Fang et al. (2021) found that agricultural insurance has a significant positive impact on the total factor productivity of agricultural green development [44]. However, Hou et al. (2022) reached the opposite research conclusion, finding that agricultural insurance has an inhibitory effect on agricultural green development [3]. Gao et al. (2022) found that digital inclusive finance promotes agricultural green development by improving green technological levels [45]. Regarding technological factors, Jiang et al. (2022) found that the digital economy significantly enhances the level of green development in Chinese agriculture [46].

Amidst the global environmental challenges and the objectives of sustainable agricultural development, the academic community has extensively studied the spatial effects of China's agricultural green development, yielding a wealth of research findings. However, these studies have certain limitations. Firstly, while many studies have identified significant spatial spillover effects in China's agricultural green development, most have employed tools like Moran's I index and spatial econometric panel models. While these attribute data-based analytical methods can reveal trends and patterns in spatial distribution to a certain extent, they fail to delve into the complex interactions and network structures between regions. The analysis of attribute data is constrained by the characteristics of the data itself, making it difficult to capture dynamic relationships between regions and the structural features of the overall network. Secondly, when discussing the spatial clustering characteristics of agricultural green development, the existing literature often fails to consider all 31 provinces as an interconnected network system, instead performing analysis based on geographic "adjacency" effects alone. This approach overlooks the cross-geographical influences and potential spatial connections between non-adjacent provinces, thus failing to comprehensively reveal the spatial correlation network and overall structure of China's agricultural green development. Lastly, although traditional spatial econometric methods have certain advantages in analyzing geographic spatial factors, they have not fully considered the structural forms, spatial clustering patterns, and their underlying operational mechanisms of agricultural green development. As a result, these methods fall short of thoroughly depicting and reflecting the intrinsic connections and impact mechanisms between regions in agricultural green development.

In light of these deficiencies, this paper makes concerted efforts in several areas to address the shortcomings of the existing research. Firstly, by introducing complex network analysis methods and constructing a spatial correlation network of agricultural green development, this paper overcomes the limitations inherent in analyses based solely on "attribute data". This method allows for a comprehensive consideration of both the direct and indirect connections between regions, offering a more detailed depiction of the spatial correlation network structure of agricultural green development across China, and capturing the complex interactions between regions. Secondly, by viewing China's 31 provinces as a tightly connected network, this study transcends simple geographic "adjacency" or "neighboring" effects. Utilizing a network perspective and methodology, it delves into the nationwide spatial clustering characteristics and their evolutionary processes. This approach enables a holistic understanding of the spatial relational structure of China's agricultural green development, identifying the interrelationships and key nodes within the complex network structure, and providing a fresh perspective for understanding spatial clustering characteristics.

Moreover, unlike traditional methods that focus solely on geographic spatial factors, this paper further explores the structural forms, clustering patterns, and evolutionary trends of the agricultural green development spatial correlation network. Utilizing tools such as modular and centrality analyses from social network analysis, the paper not only reveals the overall structure and group clustering patterns of China's Agricultural green development spatial relations but also analyzes the underlying mechanisms and operational dynamics behind these network structures and clustering modes. Finally, this paper does not merely focus on a static description of the spatial correlation network, it also explores the dynamic processes and driving factors behind the evolution of the agricultural green development spatial correlation network structure. By integrating multi-dimensional factors, including economic, social, and environmental aspects, it reveals the factors influencing the evolution of the agricultural green development spatial correlation network, providing theoretical foundations and practical guidance for policy formulation.

3. Data Sources and Methods

3.1. Methods

3.1.1. Refined Gravity Model

The spatial correlation network of agricultural green development constitutes a set of relationships among various regions. Simultaneously, these regions act as "nodes" within the network, and the connections between regions in agricultural green development form the "links" of the network. The strength of connections between regions represents the degree of correlation in agricultural green development. Following the approach of BAI C [47], the traditional gravity model underwent refinement and improvement in this study. The modified gravity model was employed to construct the spatial correlation matrix for agricultural green development among Chinese provinces, portraying the spatial correlation relationships between them. Subsequently, the obtained gravity matrix underwent the removal of extreme values for each row, and the average value was taken as the threshold. The values in the row above the threshold were set to 1, indicating the presence of a correlation in agricultural green development between the provinces at the intersection of that row and column. Conversely, the values below the threshold were set to 0, signifying the absence of a correlation in agricultural green development between the provinces at the intersection of that row and column. The formulated refined gravity model is as follows:

$$\mathrm{R}_{ij} = \mathrm{L}_{ij}\frac{\sqrt[3]{\mathrm{G}_i P_i H_i}\sqrt[3]{\mathrm{G}_j P_j H_j}}{\left(\frac{\mathrm{D}_{ij}}{g_i - g_j}\right)},\ \mathrm{L}_{ij} = \frac{H_i}{H_i + H_j} \tag{1}$$

In Equation (1), the term R_{ij} denotes the gravitational intensity between province i and province j, while L_{ij} signifies the gravitational coefficient reflecting the proportionate contribution of province i to the connection with province j. H_i and H_j, respectively, stand for the agricultural green development index of provinces i and j, whereas G_i and G_j represent the total agricultural output of provinces i and j. P_i and P_j indicate the rural population of provinces i and j, and g_i and g_j denote the agricultural per capita output of provinces i and j. D_{ij} represents the spatial distance between the provincial capitals, and $\mathrm{D}_{ij}/g_i - g_j$ encapsulates the economic-geographic distance between province i and province j.

3.1.2. Methodology of Social Network Analysis

Social Network Analysis (SNA) is a methodology delving into phenomena such as network structures, organizational relationships, and the flow of resource elements. Employing "relations" as the fundamental unit of analysis, SNA utilizes graph theory tools and algebraic modeling techniques to investigate the patterns of relationships among entities. This approach unveils the interconnections and interactions between entities, and finds broad applications in fields such as economics, management, and sociology [48]. This study employs Social Network Analysis to scrutinize the overall structural characteristics, individual structural features, and clustering characteristics of the interprovincial agricultural green development spatial correlation network in China.

(1) Overall network structural characteristics.

The overall network structural characteristics delineate the relational structure and the strength of associations between regions. Key metrics encompass network density, network connectivity, network degree, and network efficiency [49]. Specifically, network density is the ratio of the actual number of relationships in the network to the theoretically maximum number of relationships. It gauges the tightness of connections among nodes in the spatial correlation network, reflecting the intensity of the associations between nodes [50]. In this context, a higher network density implies a closer connection between provinces in agricultural green development. The calculation formula is given by (2), where N represents the number of nodes, and L represents the number of existing relationships in the network.

$$\mathrm{D} = \frac{\mathrm{L}}{\mathrm{N} \times (\mathrm{N} - 1)} \tag{2}$$

Network connectivity reflects the robustness of the spatial correlation network, emphasizing the impact of the logarithm of unreachable node pairs within the network. A value of 1 indicates the absence of unreachable node pairs in agricultural green development across regions, signifying the robustness of the spatial correlation network [51].The calculation formula is provided by (3), where N represents the number of nodes in the network, and V represents the number of unreachable nodes in the network.

$$C = 1 - \frac{2V}{\mathrm{N} \times (\mathrm{N} - 1)} \tag{3}$$

The network degree signifies the asymmetrical reachability of the spatial correlation network. A high value in network degree indicates that specific nodes assume a "leadership" role in the spatial correlation network, exercising "control" over the flow of internal elements within the network. However, if these "leadership" nodes encounter disruptions, the supporting force contributing to the formation of the spatial correlation network weakens. Hence, a lower network degree implies a reduced dependence of the spatial correlation network on individual or a few nodes, enhancing the stability of the network [52]. The specific calculation formula is given by (4), where D H represents the network degree, K denotes the actual number of symmetrically reachable node pairs in the network, and $\max(K)$ represents the maximum number of possible symmetrically reachable node pairs in the network.

$$H = 1 - \frac{K}{\max(K)} \tag{4}$$

Network efficiency reflects the abundance of network association lines, and a lower network efficiency indicates greater stability in the overall spatial correlation network of agricultural green development [53]. In this study, a higher efficiency in the agricultural green development correlation network implies more redundant connections, indicating lower stability in the spatial correlation network. The specific calculation formula is presented as (5), where E represents network efficiency, M denotes the actual number of redundant connections in the network, and $\max(M)$ signifies the maximum number of redundant connections in the network.

$$E = 1 - \frac{M}{\max(M)} \tag{5}$$

(2) Individual network structural characteristics.

In the context of spatial correlation networks, individual network characteristics refer to the specific attributes and status of nodes within a network. Key measurement indicators include: degree centrality, closeness centrality, and betweenness centrality [54]. A higher degree centrality indicates that a region is closer to the center of the agricultural green development spatial correlation network. When the degree centrality of a node is higher than the mean, it is more likely to influence other nodes in the spatial correlation network of agricultural green development. In a network, a higher degree centrality of a node implies greater control over other members in the network [55]. The calculation is performed using Formula (6), where N represents the total number of nodes in the network; $inDC$ is the in-degree of the node; *outDC* is the out-degree of the node. DC_i is the degree centrality of node i, which is the sum of the in-degree and out-degree of node i.

$$DC_i = \frac{(inDC + outDC)}{2(\mathrm{N} - 1)} \tag{6}$$

Closeness centrality in social network analysis measures the average shortest path length from a node to other nodes. Closeness centrality represents a node's ability to remain unaffected by other nodes' "control" in the network. When a node's closeness centrality is higher than the mean, it indicates that the node is closer to other nodes in the spatial correlation network of agricultural green development. This proximity enhances the advantage of transmitting information and driving the flow of elements [56]. Closeness centrality also reflects the extent to which a node in the network remains unaffected by other nodes. The specific calculation formula is provided as (7), where N is the number of nodes in the network, and d_i is the geodesic distance from node i to other nodes.

$$d_i = \frac{1}{\mathrm{N} - 1}\sum_{j=1}^{N} d_{ij}\ \mathrm{CC_i} = \frac{1}{d_i} \tag{7}$$

Betweenness centrality is a metric in social network analysis that measures the number of times a node serves as an intermediary or bridge in the network [57]. Betweenness centrality reflects the role of a node as an intermediary in the spatial correlation network. When a node lies on the shortcut paths between many node pairs, its betweenness centrality is higher. When the betweenness centrality of a node exceeds the mean, its intermediary role in the spatial correlation network becomes more pronounced, influencing and regulating the agricultural green development in other regions. The specific calculation formula is given by (8), where N is the number of nodes in the network, and $g_{jk}(i)$ represents the number of shortest paths passing through node i between province j and province k, where $j \neq k \neq i$ and $j < k$.

$$\mathrm{BC}_i = \frac{2\sum_{j}^{\mathrm{N}}\sum_{k}^{\mathrm{N}} g_{jk}(i)/g_{jk}}{3\mathrm{N}^2 - 3\mathrm{N} + 2} \tag{8}$$

3.1.3. Clustering Network Structural Characteristics

The analysis of clustering structural characteristics in spatial correlation networks involves characterizing the internal structural state of the correlation network and the roles and statuses of its members through spatial clustering. In this study, following the approach of WANG H [58], the sectors in the agricultural green development spatial correlation network are categorized into four types: "Net beneficial block", "Net spillover block", "Broker block" and "Bidirectional spillover block". The specific criteria for classification involve defining a sector as a "Net beneficial block" when the actual internal relationship proportion is greater than the expected internal relationship proportion, and the receiving relationships are significantly greater than the relationships emitted by that sector. Sectors with a clear balance between receiving and emitting relationships are classified as "Bidirectional spillover blocks". Sectors are labeled as "Net spillover blocks" when the actual internal relationship proportion is less than the expected internal relationship proportion, and the emitted relationships are significantly greater than the received relationships. Sectors with a small difference between emitted and received relationships are designated as "Broker blocks".

3.1.4. QAP Analysis Method

The Quadratic Assignment Procedure (QAP) is a non-parametric method suitable for situations where the data structures are complex and the relationships between variables are intertwined. It objectively reflects the correlations and regression relationships between variables. After analyzing the structural characteristics of the agricultural green development spatial correlation network, it is necessary to further examine the factors driving changes in this network. These factors can induce variations in the network, leading to different structural characteristics. Due to the presence of multicollinearity among variables in the spatial correlation network, it can affect the estimation results of regression models. The QAP model, not requiring assumptions of independence and normal distribution, effectively addresses the issue of multicollinearity in relationship data. The application of the QAP model to analyze relationship data yields more robust results [59]. Therefore, this study utilizes the QAP model to analyze the driving factors of the agricultural green development spatial correlation network. The selected influencing factors and their representations are as follows.

(1) Geographical spatial proximity (Distance): represented using an interprovincial adjacency weight matrix, with a value of 1 for adjacent provinces and 0 otherwise. (2) Economic development level (Pgdp): represented by per capita GDP. (3) Environmental regulation level (Envi): represented by the proportion of investment in completed industrial pollution control projects to industrial GDP. (4) Industrial structure (Indus): represented by the proportion of GDP from the tertiary industry to the region's GDP. (5) Agricultural technology investment level (AgriS): represented by the amount of agricultural science and technology R&D investment. (6) Informationization level (Infor): represented by per capita postal and telecommunication business volume. (7) Financial support for agriculture (Fin): represented by the proportion of agricultural expenditure to total fiscal expenditure. (8) Economic openness level (Open): represented by the proportion of import and export trade to GDP. (9) Urbanization level (Urban): represented by the proportion of urban population to total population. (10) Human capital level (Human): represented by the average years of education for the population. Based on this analysis, a quantification model for the driving factors of the agricultural green development spatial correlation network is established (Formula (9)).

$$\mathrm{Agd}_{ij} = f(\mathrm{Distance}_{ij}, \mathrm{Pgdp}_{ij}, \mathrm{Indus}_{ij}, \mathrm{AgriS}_{ij}, \mathrm{Infor}_{ij}, \mathrm{Envi}_{ij}, \mathrm{Fin}_{ij}, \mathrm{Open}_{ij}, \mathrm{Urban}_{ij}, \mathrm{Human}_{ij}) \quad (9)$$

In Formula (9), Agd_{ij} represents the matrix of the agricultural green development spatial correlation network, and Pgdp_{ij}, Envi_{ij}, Indus_{ij}, AgriS_{ij}, Infor_{ij}, Fin_{ij}, Open_{ij}, Urban_{ij}, and Human_{ij} are the standardized difference matrices for each respective factor. $\mathrm{Distance}_{ij}$ is the adjacency weight matrix.

3.2. Data Sources

Based on the availability of data, this study focuses on the 31 provinces and municipalities within Mainland China, excluding Taiwan, Hong Kong, and Macau regions. This study selects all 31 provinces of China as its research subjects, encompassing over 95% of the country's territory. Consequently, the sample provinces can, to a considerable extent, represent the state of agricultural green development in China. The research timeline spans from 2003 to 2020. Data regarding the evaluation indicators for China's agricultural green development, gravity model calculation data, and variables for driving factors are sourced from the corresponding annual volumes of the "China Statistical Yearbook", "China Environment Statistical Yearbook", "China Rural Statistical Yearbook", "China Population and Employment Statistics Yearbook", and "China Agricultural Statistical Data", along with provincial statistical yearbooks and the provincial annual statistical data from the National Bureau of Statistics of China's website. The map data for China's provincial administrative boundaries are obtained from the National Geomatics Center of China. For instances where certain regional variables are missing data, a linear interpolation method is employed for supplementation.

3.3. The Measurement of Agricultural Green Development Levels

Agricultural green development is characterized by harnessing the initiative of agricultural producers to harmonize the economic, social, and ecological benefits of agricultural development. It emphasizes an all-encompassing and comprehensive approach to greening, fundamentally integrating "green" practices throughout the entire process and all aspects of agricultural production, distribution, and consumption. This sustainable method of agriculture aims to minimize the environmental impact while simultaneously enhancing the agricultural productivity and economic benefits. As a systemic project, agricultural green development encompasses a rich variety of content. Drawing upon the scholarly work of Zhou (2023) on the construction and measurement of an evaluation index system for green agricultural development, this paper develops an assessment framework for agricultural green development from five dimensions: resource conservation, ecological stability, clean production, secure supply, and enhanced efficiency [11], as illustrated in Table 1.

Table 1. Comprehensive evaluation index system for agricultural green development.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Measurement Method	Weight Value
Resource Conservation	Conservation of cultivated land resources	Cultivated land retention rate (%)	(The current year's arable land area divided by the arable land area of the previous year) × 100%	0.0370
		Per capita cultivated area (hm^2)	(The arable land area divided by the rural population) × 100%	0.0391
	Conservation of water resources	Proportion of water-saving irrigation area (%)	(The area under water-efficient irrigation divided by the total irrigated area) × 100%	0.0382
		Agricultural water accounted for the proportion of total water use (%)	(The agricultural water consumption divided by the total water usage) × 100%	0.0397
Ecological Stability	Ecological conservation	The proportion of forest in the land area (%)	(The forested area in proportion to the total land area) × 100%	0.0417
		Proportion of wetland in land area (%)	(The wetland area relative to the national land area) × 100%	0.0394
	Ecological restoration	Ecological afforestation country area proportion (%)	(The afforested area for ecological purposes in relation to the national land area) × 100%	0.0371
		Annual growth rate of soil erosion control area (%)	(The difference between the current year's soil and water conservation area and the previous year's soil and water conservation area, divided by the soil and water conservation area of the previous year) × 100%	0.0386
Clean Production	Energy factor consumption	Diesel oil application rate (kg/CNY 10,000)	The agricultural diesel consumption in relation to the total agricultural output value	0.0377
		Electricity efficiency (kW·h/CNY 10,000)	The rural electricity consumption relative to the total agricultural output value	0.0405
	Chemical factor consumption	Fertilizer application rate (kg/CNY 10,000)	The fertilizer application rate in relation to the total agricultural output value	0.0395
		Agricultural film application rate (kg/CNY 10,000)	The quantity of agricultural film usage in proportion to the total agricultural output value	0.0410
		Rate of pesticide application (kg/CNY 10,000)	he amount of pesticide application in relation to the total agricultural output value	0.0408

Table 1. *Cont.*

Primary Indicator	Secondary Indicator	Tertiary Indicator	Measurement Method	Weight Value
Supply Security	Numerical security	Per capita grain production (kg)	Statistical yearbook data.	0.0377
		Meat production per capita (kg)	Statistical yearbook data.	0.0387
		Total grain production (10,000 t)	Statistical yearbook data.	0.0388
		Total meat production (10,000 t)	Statistical yearbook data.	0.0393
	Quality assurance	Number of certified green food products	Statistical yearbook data.	0.0381
		Number of green food enterprises	Statistical yearbook data.	0.0371
		Quality and safety of agricultural products routine inspection pass rate (%)	Data from the Market Supervision Administration.	0.0371
Efficiency Enhancement	Economic benefits	Labor productivity (CNY 10,000)	The total agricultural output value divided by the number of people employed in the primary sector	0.0372
		Land yield rate (CNY 10,000/hm^2)	The total agricultural output value divided by the cultivated crop area	0.0370
		Disposable income of rural residents (CNY)	Data from the National Bureau of Statistics.	0.0373
	Social benefits	Urban-rural income gap	Urban residents' disposable income divided by rural residents' disposable income	0.0371
		Engel coefficient of rural household (%)	Statistical yearbook data.	0.0372
		Agricultural carbon emission intensity (t/CNY 10,000)	Agricultural carbon emissions divided by the total agricultural output value	0.0370

4. Results and Analysis

4.1. Analysis of the Overall Network Characteristics

Table 2 and Figure 1 revealed that the connectivity degree of the spatial correlation network for agricultural green development in China was consistently registered at one, maintaining a stable condition throughout the study period. The research indicates that no province was isolated in China's green agricultural progression during this time; each maintained direct or indirect connections with others, ensuring robust network connectivity. The network density fluctuated between 0.2978 and 0.3473, showing a slight downward trend, yet remaining relatively stable. This reflects that, despite provinces maintaining some level of agricultural green development ties, the closeness of these connections weakened slightly. The primary reason for this is the rapid economic development and industrial restructuring in China, with some provinces prioritizing industrial and service sectors, potentially leading to reduced focus and investment in green agricultural initiatives, thus diminishing inter-provincial collaboration in this area.

The network's hierarchy level oscillated between 0.1250 and 0.3307, indicating a degree of hierarchical structure within the network that generally showed a declining trend. This suggests that, while some provinces held central positions in the network, the prominence of these central positions has gradually lessened. This change is closely linked to the implementation of China's rural revitalization strategy. As the strategy progresses, provinces previously on the periphery of the network have begun to enhance their status, not only through advancements in agricultural green development within these regions, but also due to increased agricultural technology and resource exchanges with central provinces. Thus, the implementation of this strategy is instrumental in balancing development across provinces and promoting a more equitable network of agricultural green development. The network efficiency exhibited a fluctuating upward trend, ranging from 0.5356 to 0.6115, indicating a multi-layered phenomenon of spatial spillover in China's agricultural sector, pointing to a need for further enhancement of the network's stability.

Table 2. Overall characteristic indicator values of the Spatial Connectivity Network.

Year	Density	Connectedness	Hierarchy	Efficiency
2003	0.3215	1	0.3307	0.5540
2004	0.3183	1	0.2921	0.5678
2005	0.3366	1	0.2921	0.5402
2006	0.3366	1	0.2921	0.5425
2007	0.3366	1	0.2876	0.5609
2008	0.3366	1	0.2876	0.5540
2009	0.3452	1	0.2876	0.5425
2010	0.3473	1	0.2861	0.5356
2011	0.3366	1	0.2861	0.5517
2012	0.3312	1	0.2407	0.5609
2013	0.3290	1	0.2407	0.5701
2014	0.3376	1	0.2401	0.5609
2015	0.3269	1	0.2401	0.5701
2016	0.3129	1	0.2381	0.5908
2017	0.3000	1	0.2381	0.6092
2018	0.2978	1	0.1806	0.6115
2019	0.3011	1	0.1806	0.6092
2020	0.3032	1	0.1250	0.6069

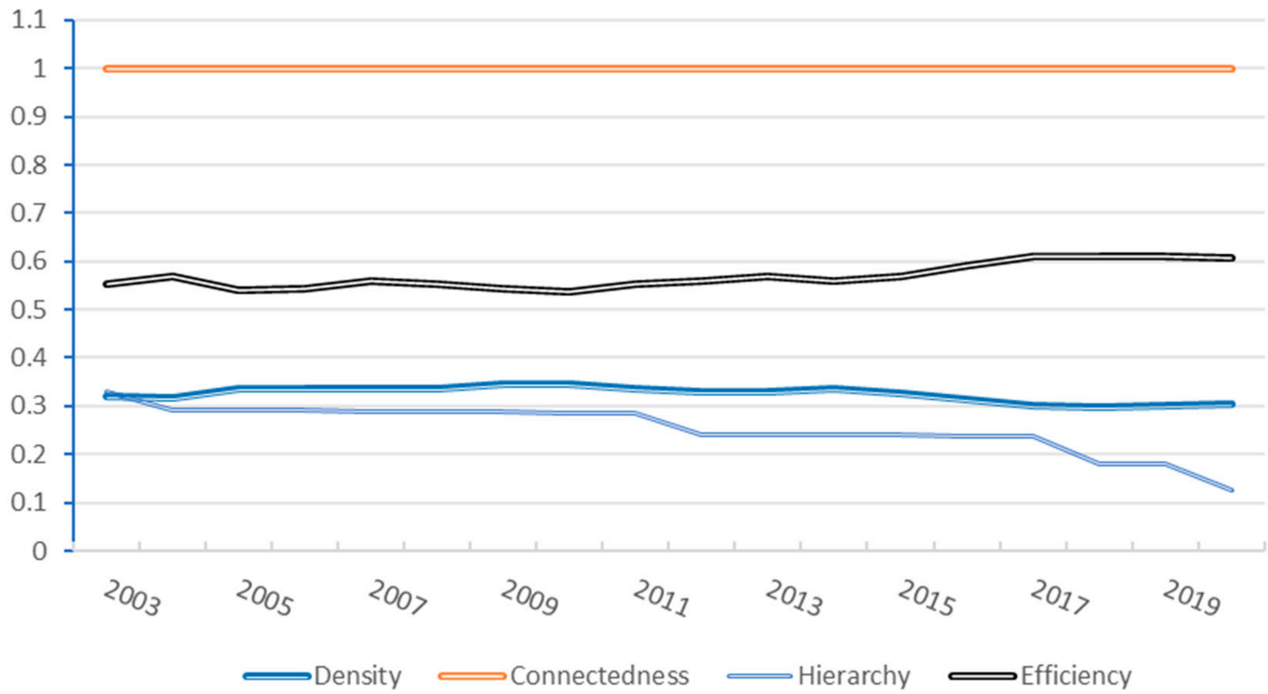

Figure 1. Trends in overall characteristic indicator changes in the Spatial Connectivity Network.

4.2. Analysis of Individual Network Characteristics

4.2.1. Analysis of Network Degree Centrality

This paper selects data from the years 2003, 2010, 2015, and 2020, employing Ucinet 6.0 software to calculate the centrality of the agricultural green development spatial association network. Through a temporal analysis and a comprehensive horizontal comparison among provinces, the study observes the dynamic evolution of the network's degree centrality in agricultural green development, as illustrated in Table 3 and Figure 2.

Table 3. Degree centrality of the spatial association network.

	2003		2010		2015		2020	
Province	**Centrality**	**Ranking**	**Centrality**	**Ranking**	**Centrality**	**Ranking**	**Centrality**	**Ranking**
Beijing	62.5000	1	38.7931	6	27.6498	20	19.9005	26
Tianjin	49.1071	3	21.5517	29	27.6498	21	17.4129	28
Hebei	33.4821	11	38.7931	7	29.9539	17	29.8507	11
Shanxi	17.8571	29	25.8621	22	32.2581	11	49.7512	5
Inner Mongolia	20.0893	27	34.4828	11	27.6498	22	19.9005	27
Liaoning	44.6429	4	43.1034	3	48.3871	3	22.3881	23
Jilin	15.6250	30	25.8621	23	16.1290	31	22.3881	24
Heilongjiang	11.1607	31	28.0172	20	39.1705	6	59.7015	2
Shanghai	58.0357	2	53.8793	1	23.0415	27	14.9254	31
Jiangsu	40.1786	5	45.2586	2	57.6037	1	62.1891	1
Zhejiang	40.1786	6	36.6379	9	43.7788	4	54.7264	3
Anhui	29.0179	18	30.1724	19	32.2581	12	44.7761	7
Fujian	40.1786	7	32.3276	14	39.1705	7	52.2388	4
Jiangxi	20.0893	28	15.0862	31	18.4332	29	17.4129	29
Shandong	33.4821	12	40.9483	5	50.6912	2	29.8507	12
Henan	31.2500	14	36.6379	10	36.8664	8	42.2886	8
Hubei	24.5536	25	32.3276	15	36.8664	9	37.3134	9
Hunan	26.7857	21	23.7069	26	27.6498	23	29.8507	13
Guangdong	37.9464	9	21.5517	30	20.7373	28	27.3632	17
Guangxi	22.3214	26	23.7069	27	18.4332	30	24.8756	21
Hainan	26.7857	22	25.8621	24	25.3456	26	27.3632	18
Chongqing	31.2500	15	32.3276	16	29.9539	18	29.8507	14
Sichuan	33.4821	13	38.7931	8	32.2581	13	29.8507	15
Guizhou	40.1786	8	43.1034	4	34.5622	10	27.3632	19
Yunnan	31.2500	16	34.4828	12	32.2581	14	27.3632	20
Tibet	29.0179	19	28.0172	21	29.9539	19	29.8507	16
Shaanxi	26.7857	23	32.3276	17	32.2581	15	24.8756	22
Gansu	31.2500	17	34.4828	13	41.4747	5	49.7512	6
Qinghai	29.0179	20	25.8621	25	27.6498	24	17.4129	30
Ningxia	26.7857	24	23.7069	28	27.6498	25	22.3881	25
Xinjiang	35.7143	10	32.3276	18	32.2581	16	34.8259	10

Table 3 and Figure 2 revealed that, from 2003 to 2020, the spatial network of China's agricultural green development underwent significant transformations, with profound shifts in the roles and influence of various regions. In the initial stages of development, economically advanced areas such as Beijing, Shanghai, and Tianjin occupied central positions within the network. These regions, boasting higher levels of agricultural economic development and large agricultural product markets, had stringent demands for both the quantity and quality of agricultural goods. Their advantages in attracting talent, capital investments, and resource allocation cemented their central status in the network. However, as urbanization accelerated and the industrial and service sectors became more prominent, the scale of agricultural production in these areas rapidly diminished. The decreasing proportion of agriculture in socio-economic activities led to a significant decline in their roles and impact within the agricultural green development spatial network.

Simultaneously, the Heilongjiang Province in the Northeast, endowed with abundant arable land, water resources, and favorable climatic conditions, displayed clear advantages in transitioning towards agricultural green development. The province rapidly transformed its agricultural sector by adopting advanced agricultural technologies, promoting large-scale production, and implementing modern farm management models. Heilongjiang led the nation in agricultural scale and mechanization. Coupled with the operation of large state-owned farms and the application of agricultural science and technology, the province progressively assumed a central position within China's agricultural green development spatial correlation network, exerting a strong exemplary influence on other regions.

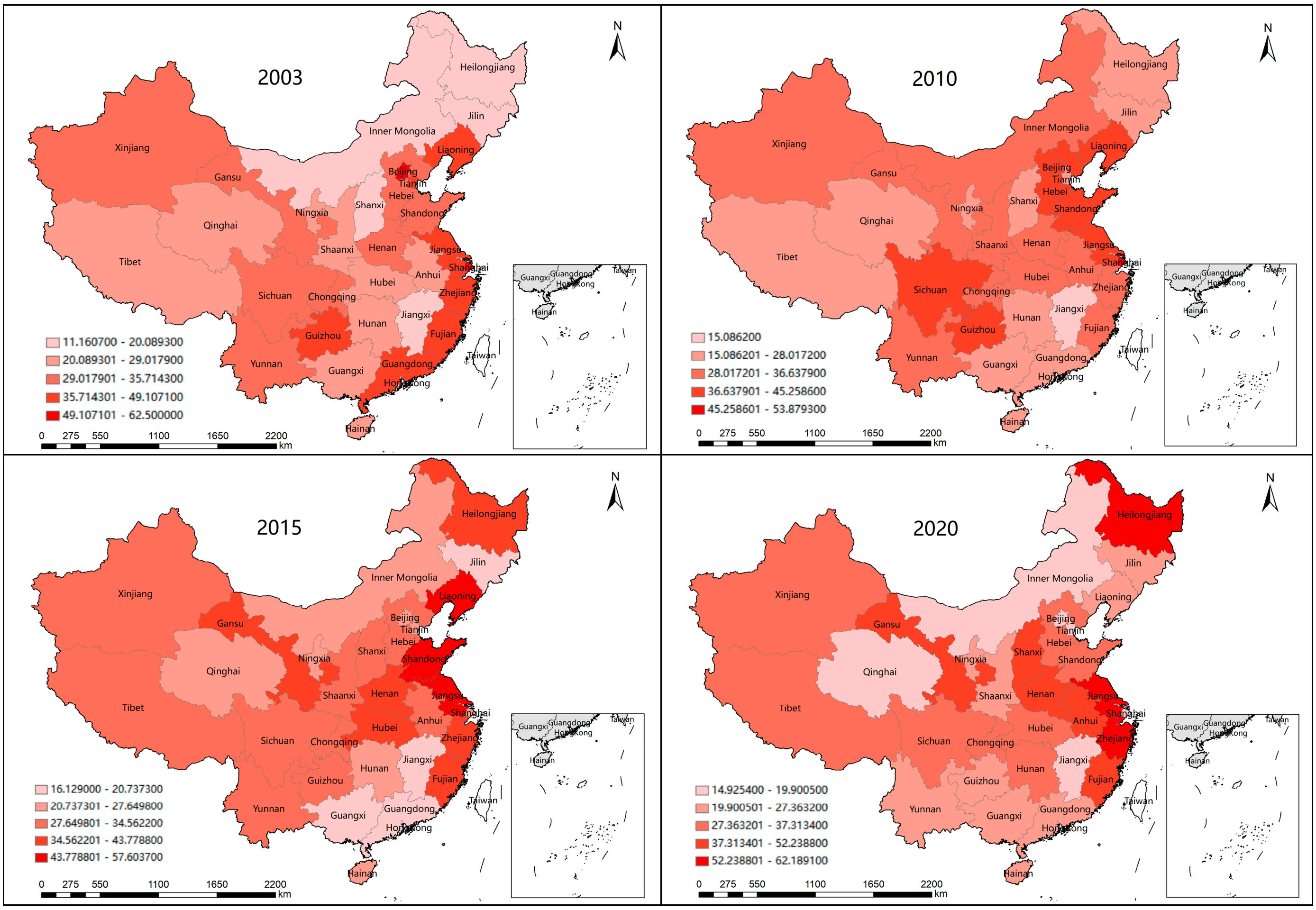

Figure 2. Evolution of degree centrality in the spatial association network.

Moreover, coastal economically developed regions such as Jiangsu, Zhejiang, and Fujian, benefiting from their rich arable lands and advantageous geographical conditions, have consistently maintained core positions within the network. These areas, equipped with advanced agricultural technologies and vast consumer markets, continuously attract substantial agricultural resources. Their superior natural environments and high levels of socio-economic development have enabled them to lead in the network over the long term, significantly influencing the flow of agricultural green development resources in other regions. Conversely, most areas in Northwest China, particularly provinces like Gansu, Xinjiang, and western Tibet, due to environmental and geographical constraints, have remained on the periphery of the agricultural green development spatial correlation network, with relatively weak connections to the network's central regions.

4.2.2. Analysis of Network Closeness Centrality

Utilizing data from the years 2003, 2010, 2015, and 2020, this study employs Ucinet 6.0 software to assess the closeness centrality within the agricultural green development spatial association network. This analysis reveals the dynamic evolution of closeness centrality in China's agricultural green development spatial association network (Table 4 and Figure 3).

Table 4. Closeness centrality in the spatial association network.

	2003		2010		2015		2020	
Province	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**
Beijing	93.7500	1	69.7674	8	61.2245	22	57.6923	26
Tianjin	78.9474	3	57.6923	30	61.2245	23	53.5714	31
Hebei	66.6667	11	71.4286	6	63.8298	16	61.2245	16
Shanxi	56.6038	29	62.5000	22	63.8298	17	75.0000	5
Inner Mongolia	58.8235	26	68.1818	11	62.5000	20	57.6923	27
Liaoning	75.0000	4	75.0000	3	76.9231	3	58.8235	22
Jilin	56.6038	30	62.5000	23	56.6038	30	58.8235	23
Heilongjiang	53.5714	31	63.8298	20	69.7674	6	83.3333	2
Shanghai	88.2353	2	85.7143	1	60.0000	26	55.5556	30
Jiangsu	71.4286	5	76.9231	2	85.7143	1	85.7143	1
Zhejiang	71.4286	6	69.7674	9	73.1707	4	78.9474	3
Anhui	63.8298	18	65.2174	19	65.2174	11	71.4286	7
Fujian	71.4286	7	66.6667	14	69.7674	7	76.9231	4
Jiangxi	58.8235	27	54.5455	31	57.6923	27	56.6038	28
Shandong	66.6667	12	73.1707	5	78.9474	2	62.5000	11
Henan	65.2174	14	69.7674	10	68.1818	8	69.7674	8
Hubei	61.2245	23	66.6667	15	68.1818	9	66.6667	9
Hunan	62.5000	21	61.2245	24	62.5000	21	62.5000	12
Guangdong	69.7674	9	58.8235	29	56.6038	31	61.2245	17
Guangxi	60.0000	25	61.2245	25	57.6923	28	58.8235	24
Hainan	58.8235	28	60.0000	27	57.6923	29	60.0000	18
Chongqing	65.2174	15	66.6667	16	63.8298	18	62.5000	13
Sichuan	66.6667	13	71.4286	7	65.2174	12	62.5000	14
Guizhou	71.4286	8	75.0000	4	66.6667	10	60.0000	19
Yunnan	65.2174	16	68.1818	12	65.2174	13	60.0000	20
Tibet	63.8298	19	63.8298	21	63.8298	19	62.5000	15
Shaanxi	62.5000	22	66.6667	17	65.2174	14	60.0000	21
Gansu	65.2174	17	68.1818	13	71.4286	5	75.0000	6
Qinghai	63.8298	20	61.2245	26	61.2245	24	56.6038	29
Ningxia	61.2245	24	60.0000	28	61.2245	25	58.8235	25
Xinjiang	68.1818	10	66.6667	18	65.2174	15	65.2174	10

According to Table 4 and Figure 3, in the initial stages of agricultural green development, the eastern coastal provinces established close ties with other regions by absorbing key resources such as labor and agricultural products from the central and western areas, along with external investments and technology exports. This strategy not only advanced the local agricultural sustainability, but also enhanced the provinces' network closeness centrality through interaction and resource sharing within the network. However, provinces like Jiangxi, Hainan, Shanxi, and Jilin, burdened by their relatively undeveloped agricultural economies, unfavorable geographical positions, and transportation constraints, maintained peripheral ties with other provinces, positioning them on the margins of the agricultural green development spatial association network. This reveals that, in the early phases, resource flow and information exchange within the network tended to concentrate around economically developed provinces, seldom reaching those with lower economic development levels.

As China's economy rapidly expanded and underwent significant industrial restructuring, major economic activities in regions like Shanghai, Beijing, and Tianjin increasingly focused on non-agricultural sectors such as industry and services, significantly reducing the scale and input in agricultural production. This shift weakened these areas' agricultural ties with other provinces, gradually marginalizing their positions in the agricultural green development spatial association network. Concurrently, provinces such as Heilongjiang leveraged their advanced agricultural technologies and abundant resources to swiftly enhance their level of agricultural green development. This not only spurred agricultural growth within the province, but also, through close cooperation with other provinces, significantly reduced the developmental distance to other nodes, thereby elevating Heilongjiang's network closeness centrality and establishing it as a pivotal player in agricultural green development. Moreover, provinces like Jiangsu, Zhejiang, and Fujian, with their solid agricultural foundations and strategic locations, have consistently maintained core positions within the agricultural green development network, fostering tight connections and consistently short developmental distances with other regions.

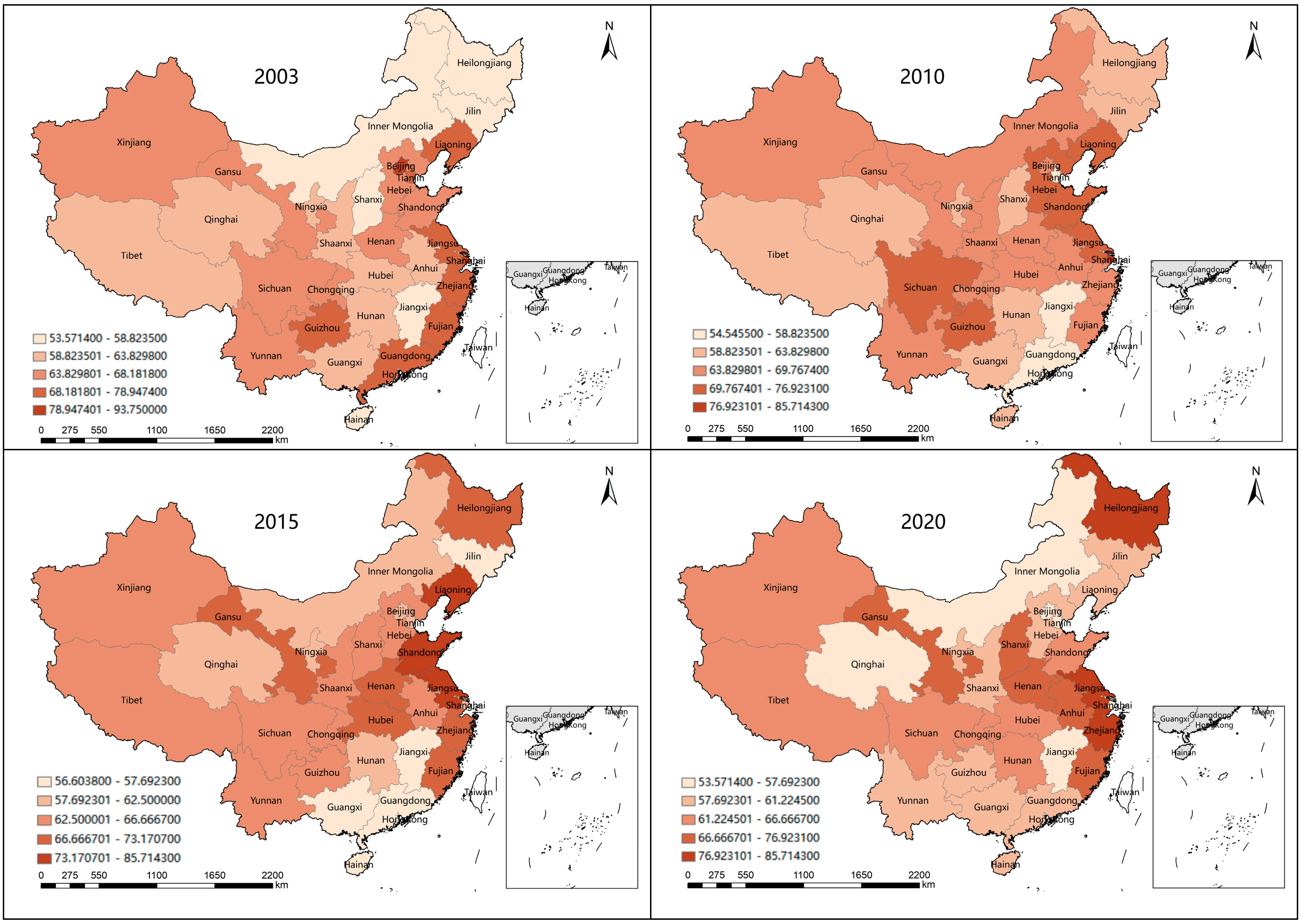

Figure 3. Evolution of closeness centrality in the spatial association network.

4.2.3. Analysis of Network Betweenness Centrality

This study utilizes data from the years 2003, 2010, 2015, and 2020, employing Ucinet 6.0 software to calculate the betweenness centrality of the agricultural green development spatial association network. This analysis aims to reflect the dynamic evolution of betweenness centrality among provinces within China's agricultural green development spatial association network (Table 5 and Figure 4).

Table 5. Betweenness centrality in the spatial association network.

	2003		2010		2015		2020	
Province	**Betweenness**	**Ranking**	**Betweenness**	**Ranking**	**Betweenness**	**Ranking**	**Betweenness**	**Ranking**
Beijing	8.8756	1	2.6894	7	0.9087	20	0.2492	24
Tianjin	6.0172	3	0.4269	29	0.9087	21	0.1731	29
Hebei	1.1923	15	2.0951	9	0.8860	22	1.2212	11
Shanxi	0.2311	28	0.6956	23	1.6602	11	4.2152	7
Inner Mongolia	0.3505	27	1.5141	16	0.7623	26	0.2443	25
Liaoning	3.6892	4	3.8827	3	5.7401	3	0.1983	26
Jilin	0.1411	30	0.6355	25	0.1484	31	0.1983	27
Heilongjiang	0.0198	31	0.6662	24	2.6393	7	8.5752	2
Shanghai	8.2618	2	5.7491	1	0.3921	28	0.0692	31
Jiangsu	2.1939	7	4.1152	2	7.4408	1	8.6693	1
Zhejiang	2.1939	8	2.8035	6	3.9756	4	5.9466	3
Anhui	1.4630	12	1.6413	15	2.2278	9	4.9243	6
Fujian	2.2919	6	1.9650	11	2.9042	5	5.8058	4
Jiangxi	0.1576	29	0.2422	31	0.3826	29	0.1753	28
Shandong	1.2826	13	2.9000	5	5.9753	2	1.0745	13
Henan	1.7636	11	2.4623	8	2.7954	6	3.6522	8
Hubei	0.5843	25	1.7385	14	1.6142	13	1.3684	10
Hunan	0.8027	22	0.6032	27	0.7647	25	0.6123	17
Guangdong	1.9100	9	0.2763	30	0.3089	30	0.4960	21
Guangxi	0.4419	26	0.5913	28	0.4218	27	0.5319	19
Hainan	0.9786	16	1.2706	19	1.2778	18	1.1619	12
Chongqing	0.9011	19	1.3865	17	1.3042	17	0.7819	15
Sichuan	0.9150	18	1.8101	13	1.5298	14	0.6239	16
Guizhou	1.7830	10	3.4390	4	1.6491	12	0.6085	18
Yunnan	0.9011	20	1.9282	12	1.3491	16	0.5287	20
Tibet	0.8724	21	1.1916	20	1.4691	15	0.8442	14
Shaanxi	0.7753	23	1.3834	18	1.0919	19	0.2537	23
Gansu	0.9463	17	1.0367	21	2.2575	8	5.6451	5
Qinghai	1.1952	14	0.8766	22	0.8061	23	0.1324	30
Ningxia	0.6128	24	0.6165	26	0.8061	24	0.3280	22
Xinjiang	2.3468	5	2.0802	10	1.7633	10	2.3005	9

Table 5 and Figure 4 revealed that, during the initial stages of agricultural green development, regions such as Beijing, Shanghai, Tianjin, and Liaoning emerged as key convergence points within the agricultural sector, thanks to their ability to concentrate a vast array of talents, capital, and informational resources. This aggregation not only propelled the green agricultural development of these areas, but also significantly influenced the developmental trajectories of other regions, endowing them with high network betweenness centrality. However, as the economy progressed and industrial focus shifted, these regions saw a diminished influence over the flow of agricultural green development resources. This was due to economic diversification and a focus on high-tech and service industries, which gradually decreased agriculture's proportion relative to other industries, thereby affecting these provinces' mediating role in the agricultural green development spatial network. Meanwhile, economically prosperous coastal provinces such as Jiangsu, Zhejiang, and Fujian, with their robust agricultural bases, advanced agricultural technology, and vast markets, continuously attracted various resources related to agricultural development. These provinces maintained close cooperation in agricultural pursuits with other regions, wielding long-term significant influence on the flow of green development elements, reflected in their high and stable network betweenness centrality.

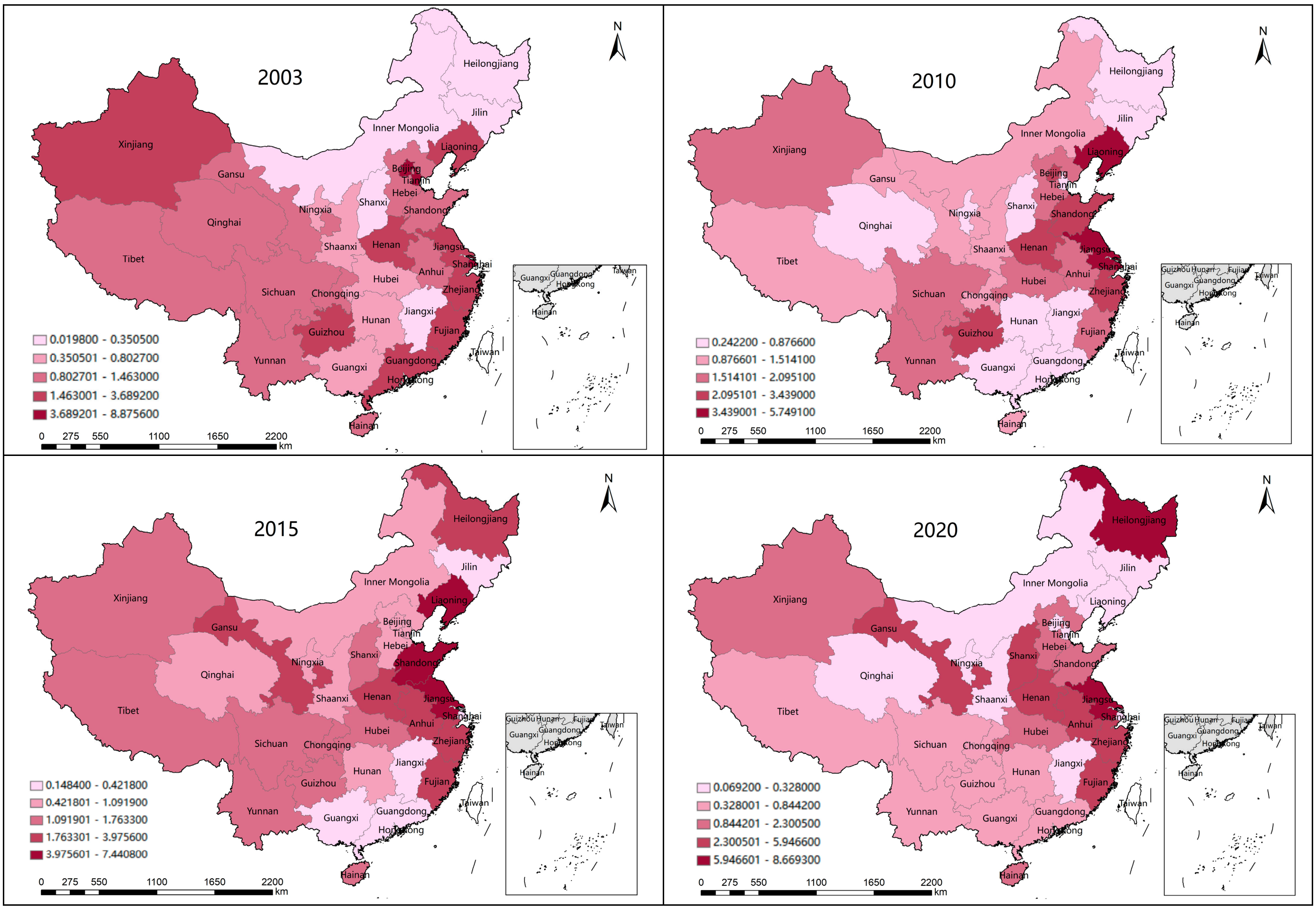

Figure 4. Evolution of betweenness centrality in the spatial association network.

Particularly noteworthy is Heilongjiang Province which, with its abundant arable land and favorable natural conditions, has become one of China's foremost areas in agricultural mechanization and large-scale development. The province, hosting numerous state-owned farms renowned for their advanced technology and standardized management, has become a focal point for capital, information, and technological resources, thereby strengthening its role as a bridge in linking regional agricultural green development. Heilongjiang's role not only fostered its own agricultural progress, but also positively impacted the surrounding areas and the nation's agricultural green development at large. Moreover, it was observed that some provinces in central and western China, such as Gansu and Guizhou, due to their geographical advantages and proximity to multiple provinces, became critical intermediaries in cross-regional collaboration and agricultural resource flow, effectively promoting regional agricultural green development and optimal resource allocation, thus playing a pivotal role in the regional agricultural economic development.

4.3. Cluster Characteristic Analysis of Spatial Association Network

To further unveil the internal structure within China's agricultural green development spatial association network, following the approach of some scholars [58,59] the study utilizes the iterative converging method (CONCOR) provided by Ucinet 6.0 software to analyze the network's clustering characteristics. The maximum module division depth parameter is set to 2, and the convergence criterion parameter to 0.2, dividing the network into four clustering modules. Based on indicators such as the number of incoming and outgoing relationships and the proportion of internal relationships among the modules, the roles of different blocks within the network are identified. The results are used to draw a diagram depicting the clustering block relationships in China's agricultural green development spatial association network (Figure 5).

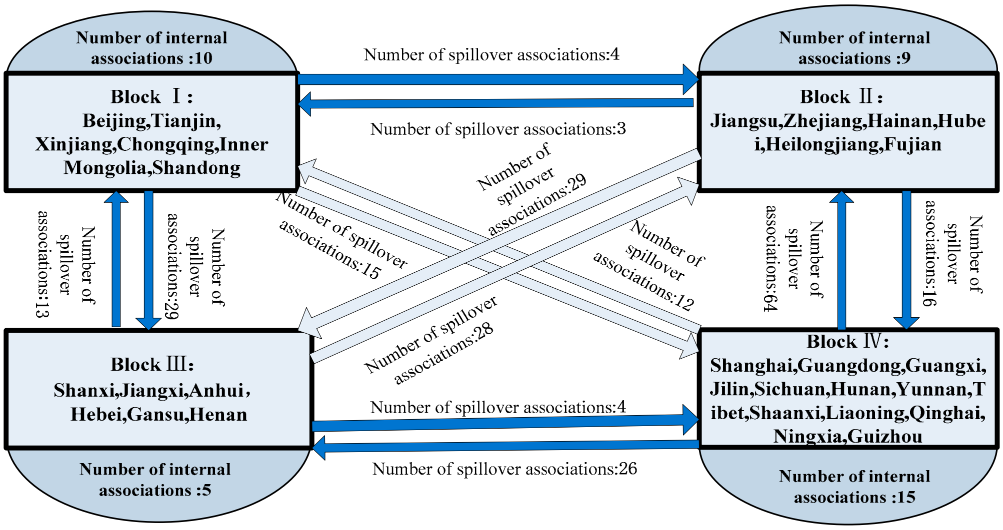

Figure 5. Interrelationships among the four major clusters in spatial association network.

Figure 5 demonstrated that China's agricultural green development exhibits pronounced spatial clustering, with the spatial association network being divided into four major blocks, totaling 282 relationships. Among these, internal relationships within blocks number 39, while inter-block relationships count for 243, indicating significant connections and spillover effects between blocks. The first block comprises six provinces and cities: Beijing, Tianjin, Xinjiang, Chongqing, Inner Mongolia, and Shandong, with an internal relationship count of 10, 45 outgoing relationships, and 31 incoming relationships. The gap between the incoming and outgoing relationships is relatively small, and the actual proportion of internal relationships exceeds the expected, categorizing it as a "Bidirectional spillover block". Within this block, Beijing and Tianjin, as significant economic and consumption centers in China, import agricultural products from other regions and export resources such as technology, capital, and information, displaying bidirectional resource flow characteristics. Provinces like Xinjiang, Chongqing, Inner Mongolia, and Shandong, endowed with rich natural resources and elements for agricultural green development, are key production bases for agricultural products in China and serve as important consumption and trading markets. The bidirectional flow of agricultural green resources with other regions is markedly evident.

The second block consists of six provinces and cities: Jiangsu, Zhejiang, Hainan, Hubei, Heilongjiang, and Fujian. This block has an incoming relationship count of 96, significantly exceeding its outgoing relationship count of 48, with the actual proportion of internal relationships being greater than the expected, categorizing it as a "Net beneficial block". Hainan Province, with its unique tropical climate, warm and moist conditions, and abundant sunshine, emerges as an important area for the cultivation and processing of tropical crops in China. The province's distinctive resource and environmental advantages in tropical agriculture attract substantial inflows of capital, talent, and technological resources, positioning Hainan within the "Net Gain block". Jiangsu, Zhejiang, Hubei, Heilongjiang, and Fujian provinces, with their natural advantages and market superiority in agricultural green development, have a solid foundation in agricultural development. These provinces have achieved high levels of agricultural production technology, management, and green agricultural standards, attracting and acquiring agricultural green development resources from other regions. The quantity of external resources these provinces attract and absorb significantly surpasses what they release, thus also categorizing them within the "Net beneficial block".

The third block is composed of six provinces: Shanxi, Jiangxi, Anhui, Hebei, Gansu, and Henan. This block has an incoming relationship count of 84 and an outgoing relationship count of 45, indicating a considerable volume of both incoming and outgoing relationships. However, the actual proportion of internal relationships is less than expected, categorizing it as the "Broker block". These provinces serve as geographical connectors facilitating the flow of agricultural resources between the eastern and western regions of China. Shanxi and Hebei provinces, located in North China, connect agricultural production areas and markets in the Northeast, East, and North China regions, playing a crucial "West-to-East" bridging role. Jiangxi and Anhui provinces, situated in the East China region, connect the flow of agricultural resources between South China and East China, acting as significant hubs. Gansu province, positioned in Northwest China, serves as an essential passage connecting the Northwest and Southwest regions, playing a vital role in the circulation and exchange of regional agricultural resources. These areas function as "bridges" and "intermediaries" in the circulation of agricultural products, resource allocation, and technology dissemination, making these provinces part of the "Broker block" within China's agricultural green development spatial association network.

The fourth block consists of 13 provinces and cities: Shanghai, Guangdong, Guangxi, Jilin, Sichuan, Hunan, Yunnan, Tibet, Shaanxi, Liaoning, Qinghai, Ningxia, and Guizhou. It has an outgoing relationship count of 105 and an incoming relationship count of 32, with the number of outgoing relationships far exceeding incoming ones. Additionally, the actual proportion of internal relationships is less than expected, categorizing it as a "Net spillover block". Shanghai and Guangdong, as economically developed areas of China, have industries dominated by manufacturing and services, with agriculture representing a very low proportion of the socioeconomic structure. The agricultural development potential in these regions is extremely limited, leading to an outflow of agricultural development funds, technology, and market resources.

The region of Heilongjiang, with its clear agricultural development advantages, exerts a strong attraction for agricultural resources in neighboring provinces such as Liaoning and Jilin, making these provinces part of the "Net spillover block". Provinces like Hunan, Sichuan, and Yunnan have advantages in agricultural technology, information, and talent within their regions, spilling over agricultural green development resources to surrounding provinces, thus also categorized as "Net spillover block". Western provinces such as Shaanxi, Guangxi, Sichuan, Yunnan, Tibet, Qinghai, Ningxia, and Guizhou, with their remote geographical locations and harsh ecological and climatic conditions, have weakened agricultural green development potential within their regions. This leads to an outflow of local agricultural resources, displaying a clear characteristic of resource outflow and categorizing them as "Net spillover block".

4.4. Analysis of Driving Factors in China's Spatially Correlated Network

To identify the driving factors for the development of the spatial network in China's agricultural green development, this study selects variable data from the years 2003, 2006, 2011, 2014, 2017, and 2020, based on the criteria established earlier. The number of random permutations was set at 5000 (Table 6). The adjusted goodness of fit, R^2, ranged between 0.368 and 0.522, indicating an overall satisfactory fit.

From Table 6, it is discernible that: (1) The coefficient of geographical spatial proximity is significantly positive, indicating that neighboring regions are more likely to facilitate the exchange of elements, thereby forming spatial associations. Observing the changes in coefficients, the coefficient of geographical spatial proximity grew from 0.160 to 0.277, suggesting that as time progresses, the role of geographical spatial proximity in enhancing the spatial associations of agricultural green development becomes increasingly significant. (2) The coefficients for the difference in economic development levels across regions are significantly negative, indicating that the closer the economic development levels between regions, the stronger the spatial association in agricultural green development. This is because when economic development levels are similar, land use patterns and demands for technology and labor in the two regions are alike. Additionally, under the influence of market mechanisms, agricultural resource elements are more easily transferred between regions with similar levels of economic development. (3) The coefficients for the difference in informatization levels between regions were not significant initially, but became significantly negative later on, indicating an increasing significance of informatization levels on the spatial associations of agricultural green development. This is primarily due to the advancement of the digital economy, where similar levels of informatization between regions facilitate the easier spread and sharing of technology, knowledge, and information. (4) The coefficients indicating the difference in openness levels between regions are significantly negative, showing that the closer the openness levels between regions, the stronger the spatial association in agricultural green development. The reason is that similar levels of openness allow agricultural producers and related industries to introduce and share resources, information, and market opportunities, fostering a synergistic effect on agricultural green development and reflecting tighter economic ties and market integration between regions more easily. (5) The coefficient for the difference in agricultural science and technology investment levels between regions is significantly negative, suggesting that the closer the agricultural science and technology investment levels between regions, the easier it is for technology and knowledge to spread and be shared, strengthening the spatial association in agricultural green development. (6) The coefficient for the difference in fiscal support for agriculture between regions is significantly positive, indicating that the greater the gap in fiscal support for agriculture between regions, the stronger the spatial association in agricultural green development. This may be because regions with greater fiscal support for agriculture can effectively attract resources such as technology, talent, and research and development funds, enhancing the spatial association in agricultural green development. (7) The coefficients for the difference in levels of environmental regulation, human capital, industrial structure, and urbanization between regions are not significant and all negative, indicating that the closer the levels of human capital, industrial structure, and urbanization between regions, the stronger the spatial association in agricultural green development. However, their current role and impact are very limited.

Table 6. QAP regression results for driving factors.

	2003	**2006**	**2009**	**2011**	**2014**	**2017**	**2020**
Distance	0.160 *** (0.000)	0.170 *** (0.000)	0.200 *** (0.000)	0.190 *** (0.000)	0.207 *** (0.000)	0.268 *** (0.000)	0.277 *** (0.000)
Pgdp	−0.020 ** (0.036)	−0.070 *** (0.010)	−0.096 ** (0.028)	−0.088 ** (0.047)	−0.054 * (0.088)	−0.011 ** (0.043)	−0.036 ** (0.026)
Infor	−0.006 (0.452)	−0.006 (0.461)	−0.018 (0.361)	−0.024 ** (0.029)	−0.057 ** (0.036)	−0.009 ** (0.043)	−0.105 ** (0.039)
Open	−0.106 ** (0.016)	−0.003 ** (0.047)	−0.081 ** (0.032)	−0.070 ** (0.048)	−0.132 *** (0.001)	−0.100 ** (0.015)	−0.007 ** (0.043)
AgriS	−0.050 (0.184)	−0.124 *** (0.003)	−0.060 ** (0.089)	−0.049 ** (0.012)	−0.031 ** (0.021)	−0.164 *** (0.000)	−0.126 *** (0.005)
Envi	−0.001 (0.482)	−0.052 (0.128)	−0.055 (0.108)	−0.032 (0.248)	−0.027 (0.244)	−0.089 ** (0.034)	−0.050 (0.156)
Fin	0.078 ** (0.035)	0.061 * (0.082)	0.109 ** (0.013)	0.118 *** (0.006)	0.063 * (0.072)	0.009 ** (0.042)	0.035 ** (0.028)
Human	−0.081 ** (0.045)	−0.071 * (0.075)	−0.059 (0.109)	−0.009 (0.451)	−0.019 (0.324)	−0.019 (0.354)	−0.013 (0.385)
Indus	−0.009 (0.423)	−0.037 (0.216)	−0.088 ** (0.028)	−0.082 ** (0.034)	−0.035 (0.171)	−0.036 (0.240)	−0.054 (0.159)
Urban	−0.111 ** (0.022)	−0.011 (0.121)	−0.086 * (0.053)	−0.050 (0.176)	−0.074 * (0.058)	−0.061 (0.115)	−0.044 (0.211)
Adj-R^2	0.522	0.498	0.401	0.368	0.506	0.454	0.374
Number	5000	5000	5000	5000	5000	5000	5000

Note: ***, ** and * indicate that coefficients are statistically significant at 1%, 5% and 10%, respectively.

5. Discussion

This paper analyzed the interprovincial panel data on agricultural green development of 31 provinces in China from 2003 to 2020, employing social network analysis and QAP regression methods to deeply explore the structure and evolution of the spatial association network in agricultural green development, as well as its driving factors. The findings not only reveal the spatial associations and network characteristics of China's agricultural green development, but also identify the key factors influencing the formation and evolution of these spatial relationships.

Initially, unlike current academic achievements regarding the spillover effects of agricultural green development [18–22,39–41], this paper is the first to apply social network analysis to this field. It meticulously examines the structure and evolution of the interprovincial agricultural green development network in China. By constructing a spatial association network, it reveals dynamic changes in the network structure, offering a fresh perspective for understanding the spatial patterns of agricultural green development. It also highlights the changing roles of regions within the network, particularly noting the long-standing central positions of Jiangsu, Zhejiang, and Fujian, due to their natural conditions and market advantages. Thus, it underscores the importance of considering regional characteristics and the necessity of optimizing agricultural resource allocation when formulating related policies.

Furthermore, the study finds that the overall connectivity of China's agricultural green development spatial association network is robust, with no isolated entities. This indicates that agricultural green development relationships are tightly interwoven and mutually dependent across the country, exhibiting a clear spatial spillover effect, consistent with findings from other researchers [11,14,60,61]. However, there is significant room to enhance the connectivity and stability of China's agricultural green development network, suggesting a future need to further strengthen regional cooperation and resource sharing.

Additionally, this paper analyzes the internal structure of China's agricultural green development network, classifying it into four distinct functional blocks, thereby deepening understanding of interactive patterns between regions in the process of agricultural green development. The identification of the Broker block, in particular, provides evidence of the key role in regional information flow and resource sharing, a topic seldom discussed in previous studies. Finally, the research on the drivers of the agricultural green development spatial association network reveals that geographic proximity and economic development levels significantly influence the formation of this network, aligning with conclusions from other scholars. These insights offer a foundation for devising targeted policies aimed at reinforcing regional cooperation and promoting coordinated development.

Although this study provides a deep understanding of the structure and evolution of China's agricultural green development spatial association network, it has its limitations. Firstly, due to data availability constraints, this study could not incorporate data at the prefectural city level, which could enhance the precision of future analyses if included. Additionally, agricultural green development is influenced by a myriad of complex factors, and while this study focused on specific ones, future research should consider a broader array of potential influencing factors to gain a more comprehensive understanding. In summary, by systematically analyzing and discussing the spatial association network and its drivers in China's agricultural green development, this study not only enriches existing research, but also offers valuable insights for formulating policies that promote agricultural green development. Future studies could delve deeper into the characteristics and changes in the spatial association network under different geographical and socioeconomic backgrounds, providing more detailed strategies and recommendations for achieving sustainable development goals in Chinese agriculture.

6. Conclusions and Policy Implications

This study utilized provincial panel data from China spanning 2003–2020, employing social network analysis and QAP regression methods to systematically explore the spatial association network structure of China's agricultural green development and its evolutionary process, as well as to analyze the factors driving these network changes. The main findings are as follows:

(1) From an overall network perspective, there is a significant spatial association effect in the interprovincial agricultural green development of China. No province is isolated within the network; each is connected directly or indirectly with others, showing good connectivity and accessibility. The network has a hierarchical nature, although this hierarchy is on a declining trend. The agricultural green development network in China experiences considerable overlapping, indicating that network stability needs further enhancement.

(2) From the perspective of individual network characteristics, as urbanization and industrialization progress in China, regions such as Beijing, Shanghai, and Tianjin have seen a declining trend in their status within the agricultural green development spatial association network. Provinces like Jiangsu, Zhejiang, and Fujian, with superior agricultural development conditions, advanced agricultural technologies, and large consumer markets, have a significant impact on the agricultural green development of other regions and maintain a core position in the network over the long term. Heilongjiang Province, leveraging its abundant arable land, water resources, and favorable climatic conditions, has rapidly developed its green agriculture, increasingly influencing other regions and rapidly rising in role and influence within the network. Some central and western provinces, such as Gansu, Shanxi, and Guizhou, also play vital roles in regional agricultural cooperation and resource flow.

(3) From the perspective of spatial clustering features, the network of China's agricultural green development can be divided into four blocks. The first block, the "Bilateral spillover block", consists of Beijing, Tianjin, Xinjiang, Chongqing, Inner Mongolia, and Shandong. These regions are characterized by a bidirectional flow of agricultural green resources. The second block, the "Net beneficiary block", includes Jiangsu, Zhejiang, Heilongjiang, Fujian, Hainan, and Hubei, where there is a predominant inflow of agricultural green development resources. The third block, the "Broker block", is made up of Shanxi, Jiangxi, Anhui, Hebei, Gansu, and Henan. Due to socio-economic development and geographical factors, these provinces play a pivotal "East-to-West gateway" role in China's agricultural green development spatial association network. The fourth block, the "Net spillover block", comprises Shanghai, Guangdong, Guangxi, Jilin, Sichuan, Hunan, Yunnan, Tibet, Shaanxi, Liaoning, Qinghai, Ningxia, and Guizhou. Influenced by socio-economic development and agricultural resource endowments, these regions function as a "Net spillover block" within the network.

(4) As for driving and influencing factors, geographical proximity, economic development level, level of informatization, openness, and agricultural technology investment significantly impact the formation of China's agricultural green development spatial association network. This indicates that the closer these factors align, the stronger the spatial network association between regions.

Based on the conclusion of this study, the following policy recommendations can be extended:

(1) To optimize the top-level design of agricultural green development, it is imperative that the nation strengthen the regulation and formulation of macro policies to ensure that the overarching plans for agricultural green development align with their execution. This includes establishing and enhancing laws and regulations related to agricultural green development, providing policy guidance, and fiscal support to ensure the coherence and effectiveness of agricultural green development policies. Additionally, it is crucial to bolster interprovincial agricultural cooperation mechanisms to facilitate the cross-regional flow and sharing of technology, capital, and information. Finally, the government should promote dialogues and cooperation on agricultural green development between regions, establish win–win mechanisms, and address potential conflicts and barriers in cross-regional cooperation, thereby optimizing the allocation and flow of agricultural resources.

(2) To implement targeted agricultural green development policies, it is crucial to develop differentiated strategies based on the status and role of each province within the agricultural green development network. For instance, core provinces such as Jiangsu and Zhejiang could be governed by policies that encourage them to continue leading in technological innovation and resource allocation. For provinces serving as "brokers" like Gansu and Henan, their functions in regional coordination and resource distribution should be strengthened by providing specific incentives and resource support to enhance their intermediary roles. Furthermore, establishing support mechanisms that enable resource-rich provinces to assist less developed ones should be explored. This could include sharing and promoting funds, technology, and management expertise, thus fostering balanced green development across regional agriculture.

(3) To deeply implement a strategy of coordinated regional development, firstly, explore reforms in market systems and the market-oriented allocation of production factors to enhance the efficiency and effectiveness of agricultural resource allocation. This includes simplifying administrative procedures, reducing barriers to agricultural mobility across provinces and cities, enhancing market transparency and fairness, and facilitating the free flow of capital, technology, and labor nationwide. Secondly, strengthen inter-regional cooperation in agricultural science and technology, particularly in the fields of digital and smart agriculture. Utilize modern information technologies such as big data, cloud computing, and the Internet of Things to increase the precision and sustainability of agricultural production. Lastly, further enhance the openness of central and western regions by introducing advanced agricultural technology and production experience from developed countries and regions to promote green agricultural development in these areas. Simultaneously, increase fiscal support for agriculture in the central and western regions, optimize the agricultural investment environment, and strengthen agricultural production technology education and training. These measures aim to enhance the attractiveness of these regions for green agricultural development, promoting the inflow of capital, talent, and technology, and thus supporting the transformational goals of green agricultural development in the central and western regions.

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