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Analysis of Factors Affecting the Spatial Association Network of Food Security Level in China

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Abstract: Food security serves as the cornerstone of national security, intricately linked to social stability and economic progress. Currently, with the swift evolutions in social economy, logistics and transport, information dissemination, and technological advancements, there has been a marked increase in the cross-regional flow of food production, distribution, and consumption. Consequently, the spatial interdependence of food security across different regions has grown increasingly salient. This paper investigates the spatial interrelationship of food security levels in China through a network analysis framework, examining its determinants and network dynamics. The findings offer valuable insights for decision-makers aiming to optimize agricultural resource allocation and enhance national food security levels. This research establishes a comprehensive evaluation index system for assessing food security levels in China across four dimensions: production security, distribution security, supply security, and consumption security. Employing data from 30 provinces between 2008 and 2022, the entropy method quantifies food security levels, while a modified gravity model underpins the construction of a spatial association network. This framework subsequently examines the network's structural characteristics and the factors influencing its formation. The results reveal that: (1) China's food security levels demonstrate a consistent upward trajectory over the study period, though significant regional disparities persist. The central region surpasses the national average, while the eastern and western regions lag. Recently, the western region has shown accelerated improvements in food security, followed by the central area, with the eastern region maintaining steady growth. (2) A structurally robust spatial correlation network of food security has emerged, characterized by variations in the number of network relationships, fluctuations in network density, and a decline in network efficiency while still exhibiting pronounced small-world characteristics. (3) The network displays a clear core-periphery structure, with Shanghai, Beijing, and Jiangsu positioned centrally, playing pivotal intermediary roles, whereas remote provinces such as Gansu, Ningxia, and Liaoning occupy the periphery. (4) The four major regions demonstrate sparse internal connectivity yet robust inter-regional ties, resulting in pronounced spillover effects. (5) Various factors, including geographic distance, provincial proximity, disparities in economic development levels, variations in marketization, differences in agricultural human capital, and disparities in land productivity, significantly impact the establishment of spatial correlations in food security. The affirmative influences of geographic distance and neighboring relations, along with the beneficial shifts in economic development disparities, suggest that the flow of technology and resources plays a crucial role in reinforcing spatial connections.

Keywords: food security; spatial association networks; modified gravity model; social network analysis; QAP regression analysis

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1. Introduction

Food security, defined as the state where people have access to sufficient, safe, and nutritious food, has become a global concern [1]. It encompasses not only the dietary needs and food preferences of individuals but also forms the foundation of national security [2,3]. As the world's most populous developing country, China's food security significantly impacts domestic social stability and economic development. It also plays a crucial role in achieving global sustainable development goals [4]. Since the reform and opening-up policy, China's total grain production has increased from 304.8 million tons in 1978 to 686.5 million tons in 2022, indicating an overall improvement in food security [5]. However, rapid urbanization and industrialization have led to a substantial increase in food demand [6]. Concurrently, the reduction in arable land has further constrained the geographical space for food production [6]. The imbalance between food supply and demand has resulted in an expanding food gap, declining self-sufficiency rates, and increasingly prominent regional disparities [7–9]. In this context, spatial differences and distribution dynamics of food security have become research focal points, with scholars employing spatial econometric models to study the spatiotemporal evolution of food security [10,11]. As market-oriented reforms progress and rural-urban dual structure barriers gradually break down, the free flow and trade of production factors and agricultural products between provinces have led to increasing spatial correlations in food security [12–14]. Against this backdrop, analyzing the spatial correlation network characteristics of China's food security levels and identifying the driving factors influencing inter-provincial spatial correlations have significant theoretical and practical implications. These insights are crucial for comprehensively understanding the changing patterns of China's current food security network, grasping the spatial transmission mechanisms of regional food security, and formulating differentiated food policies for cross-regional collaborative development.

This study adopts a spatial correlation network analysis approach to investigate the following key questions: (1) What are the distinctive features of China's food security spatial correlation network? (2) How do different provinces function within the spatial correlation network of food security levels? (3) What are the interaction mechanisms among provinces within this spatial correlation network? (4) Which factors significantly influence the spatial correlation network of China's food security levels?

2. Literature Review

Current research on food security primarily focuses on three aspects: measuring food security levels while analyzing their spatial characteristics [15], examining factors influencing food security [16], and exploring food security assurance [17].

Measurement and Spatial Characteristics of Food Security: Scholars have employed comprehensive indicator systems, food self-sufficiency rates, and food supply-demand forecasts to measure food security levels and analyze their spatial characteristics. Yin et al. (2015) utilized a food security vulnerability index to assess county-level food security, identifying six types of food security regions to study regional disparities in China [10]. Lee et al. (2022) and Cheng et al. (2024) measured food security levels using multiple indicators related to food supply, access, and sustainability. They applied the Dagum Gini coefficient to analyze regional differences and distribution dynamics of food security levels [11,13], highlighting significant and widening disparities among Chinese provinces. Some researchers have combined food security measurements with exploratory spatial analysis methods. Qiao et al. (2022) used the Getis-Ord method to analyze spatial clustering and spatiotemporal changes in food-secure and food-insecure provinces [18]. Lee et al. (2024) employed Moran's I to study spatial correlations of food security between regions, revealing evident spatial agglomeration and correlation characteristics [13].

Factors Influencing Food Security: Scholars have primarily investigated factors affecting food security from supply and demand perspectives [19,20]. On the supply side, Ledda et al. (2021), Yang et al. (2023), and Lee et al. (2024) examined the impacts of natural conditions, climate change, and environmental pollution on food security [21–23]. Krishnamurthy et al. (2022) explored the relationship between food insecurity early warning diagnostics and food security through drought-related changes [24]. Gouvea et al. (2022) assessed the role of production technology advancements in improving food yields and mitigating food security risks, concluding that technological innovation positively impacts global food security [25]. On the demand side, Godfray et al. (2010) highlighted how continuous population growth increases food demand, threatening global food security [26]. However, food security also involves inter-provincial food circulation and cross-regional cooperation. Therefore, further research is needed to examine factors influencing spatial correlations between provinces.

Food Security Assurance: Different countries have varying objectives, leading scholars to propose diverse recommendations, primarily focusing on subsidy policies to promote food production. Vu et al. (2022) suggested prioritizing food relief policies for a few regions expected to be severely affected [27]. Adams et al. (2001) found that direct subsidy policies, such as market loss assistance, expanded crop cultivation areas, contributing to food security [28]. Tong et al. (2013) discovered that transportation infrastructure expenditure in U.S. states significantly positively impacted agricultural output [29]. Recently, some scholars have explored food security assurance from a regional cooperation perspective. Abdalla et al. (2022) called for a multi-sectoral, non-discriminatory European integration policy [30]. However, research on food security assurance from the perspective of inter-provincial, cross-regional cooperation and joint prevention and control remains limited.

Methodological Approaches: Existing methods for evaluating food security include gray relational analysis [31], data envelopment analysis [32,33], fuzzy comprehensive evaluation [34], and the entropy method [35]. The entropy method is widely used in comprehensive evaluations due to its objectivity and scientific nature [36,37]. Spatial characteristics of food security are often studied using exploratory spatial data analysis methods such as Moran's I and Getis-Ord [18]. However, these methods struggle to explain the interconnectedness of food security development among Chinese provinces and capture inter-provincial spatial correlations and interaction mechanisms. Social network analysis overcomes these limitations by analyzing network structure characteristics and associations of relational data. It has been widely applied in agricultural research. Chen et al. (2022) used social network analysis to explore spatial correlation network characteristics of agricultural green development [38]. Shang et al. (2022) analyzed the spatial correlation network of agricultural carbon emission efficiency using this method [39]. Given the complex spatial correlations between regions, conventional statistical methods such as multiple regression often fail to identify true relationships in relational data. Consequently, scholars frequently employ QAP regression to study factors influencing correlation networks [40,41].

While existing research has established a solid foundation for analyzing spatial correlation networks and influencing factors of food security levels, there are three areas that warrant further improvement. Firstly, although spatial disparities and agglomeration effects in regional food security have been confirmed, traditional spatial econometric techniques are limited to measuring geographical proximity or distance relationships. This makes it challenging to comprehensively grasp the structural characteristics of inter-provincial food security spatial correlations. Secondly, previous studies have primarily explored factors influencing food security levels from supply and demand perspectives without identifying the underlying mechanisms affecting spatial correlations of food security levels. Existing research has largely proposed food security assurance measures from the perspective of encouraging food production and supply. Further investigation is needed on enhancing food security through promoting local collaboration.

This study makes three main contributions: (1) Building upon existing research on spatial disparities and spatiotemporal distribution of food security, this paper constructs a spatial correlation network of China's food security levels. It analyzes the network's overall and individual structural characteristics, as well as inter-regional interaction mechanisms. The findings reveal that Chinese provinces have established interactive relationships with both neighboring and non-neighboring provinces, forming a relatively stable spatial correlation network with distinct core-periphery structures and close inter-regional interactions. (2) Based on the analysis of network structural characteristics, this study employs QAP regression to investigate factors influencing the spatial correlation network. Results indicate that geographical distance increasingly affects correlations, while differences in economic development and marketization levels, as well as similarities in agricultural human capital and land productivity, influence inter-provincial food security collaboration. (3) Drawing on the analysis of network characteristics and influencing factors, this paper proposes enhancing the radiating effects of central network provinces such as Beijing, Shanghai, and Jiangsu while strengthening their cooperation with peripheral provinces such as Gansu, Liaoning, and Ningxia. Based on the impact analysis of various factors, the study suggests improving transportation infrastructure in remote areas and enhancing educational support for rural residents to ensure food security.

The paper is structured as follows: Section 2 describes the research methodology and data sources. Section 3 presents and analyzes the research results. Section 4 concludes the study and proposes policy recommendations for food security assurance based on the spatial correlation network perspective.

3. The Data and Methodology

3.1. Construction of China's Food Security Level Indicator System

This study establishes a comprehensive evaluation framework for China's food security level (Table 1). Drawing on relevant scholars' experiences in constructing food security indicator systems [42,43], we adhere to principles of completeness, scientific validity, and accessibility. The framework encompasses fourteen indicators across three dimensions: supply security, consumption security, and production security. These indicators are designed to measure various aspects of food security.

Table 1. The indicator system for China's food security level.

	Normative Level	Indicator Level	Causality
Food Security	supply security	Food production per capita	+
		Yield per unit area	+
		Gross power of agricultural machinery	+
		Proportion of arable land area	+
	consumer safety	Consumer price index for food for the population	−
		Proportion of children under 5 years of age with moderate to severe malnutrition	−
		Rural Engel coefficient	−
		Rural disposable income per capita	+
	production security	Pesticide application rate	−
		Fertilizer application rate	−
		Plastic film application rate	−
		Area affected	−
	Circulation security	Urban road space per capita	+
		Railway freight	+

Supply security focuses on food production volume and yield per unit area. It includes four indicators: per capita grain production, yield per unit area, total agricultural machinery power, and arable land ratio. These metrics assess production adequacy and efficiency.

Consumption security examines residents' food demand satisfaction and price factors. Its four indicators are: grain consumption price index, severe malnutrition rate in children under five, rural Engel coefficient, and rural per capita disposable income. These reflect price trends, nutritional status of vulnerable groups, and rural economic conditions.

Production security addresses environmental and resource efficiency issues in agricultural processes. Its four indicators include pesticide application, fertilizer application, plastic film application, and disaster-affected area. These measure environmental impacts and natural disaster losses in food production.

Distribution security considers food transportation and storage conditions. It utilizes two indicators: urban per capita road area and railway freight volume. These reflect the development of transportation infrastructure, crucial for food distribution.

3.2. Data Sources

This study focuses on 30 provinces in China, excluding Tibet Autonomous Region, Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province due to data availability constraints. Key data points, including per capita grain production, grain yield per unit area, pesticide usage, total agricultural machinery power, and grain consumer price index, were obtained from the official website of China's National Bureau of Statistics (https://www.stats.gov.cn/, accessed on 2 July 2022). Cultivated land area data were sourced from the China Statistical Yearbook and provincial statistical yearbooks. Information on the prevalence of moderate to severe malnutrition among children under five and disaster-affected areas was retrieved from the Zhejiang Statistical Yearbook and the EPS data platform (https://www.epsnet.com.cn/index.html#/Home, accessed on 18 July 2022). Missing data for certain years were supplemented using linear interpolation methods. In the QAP regression analysis, all variables are represented by 30×30 matrices. The diagonal elements of these matrices are set to zero. Consequently, the number of observations is calculated as $30 \times (30 - 1) = 870$.

3.3. Research Methodology

Based on the constructed indicator system, this study employs the entropy weight method to determine indicator weights and calculate the food security level index. Subsequently, a modified gravity model is utilized to construct the spatial correlation network of food security among provinces, revealing the evolutionary characteristics of spatial correlations. To thoroughly investigate the structure of the food security level spatial correlation network, this research applies social network analysis from three dimensions: overall network characteristics, individual network characteristics, and block model analysis. Finally, this study employs the Quadratic Assignment Procedure (QAP), a non-parametric testing method, to identify key factors influencing the spatial correlation patterns of food security levels. This comprehensive approach allows for a nuanced understanding of the spatial dynamics and underlying factors shaping food security relationships across Chinese provinces.

3.3.1. Entropy Method

In the process of comprehensive indicator evaluation, various methods are available, including the Analytic Hierarchy Process [44], the Delphi Method [45], Goal Linear Programming [46], and the Entropy Weight Method [47]. The Entropy Weight Method has emerged as a mainstream approach due to its scientific nature and objectivity [48]. This method determines weights by calculating the entropy value of each indicator, effectively avoiding subjective interference and ensuring the objectivity of evaluation results [49]. Furthermore, it reflects the differences between indicators, enhancing the accuracy and reliability of the assessment [50]. Consequently, this study adopts the Entropy Weight Method to evaluate food security indicators [51]. The approach treats all sample observations for each indicator as a system, utilizing information entropy formulas to measure the relative information entropy of each indicator subsystem. This measurement gauges the degree of variation in the indicator subsystem and facilitates objective weighting among indicators. This method has been widely applied in economic research due to its ability to accurately reflect the importance of various indicators, thereby avoiding potential biases associated with subjective weighting [52]. The specific calculation steps are as follows [53]:

First, the indicator data undergo standardization:

Positive indicators:

$$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

Negative indicators:

$$x'_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \tag{2}$$

Calculate the information entropy (e_j) for indicator j

$$e_j = -\frac{\sum_{i=1}^{m} w_{ij} \times \ln w_{ij}}{\ln m} \tag{3}$$

Calculate the information entropy redundancy of the jth indicator p_j

$$p_j = 1 - e_j \tag{4}$$

Calculate the weights of the indicators W_j

$$W_j = \frac{p_j}{\sum_{i=1}^{m} p_j} \tag{5}$$

The weights of the indicators and the standardized values of the indicators were multiplied and summed to derive a composite index of China's food security level:

$$I = \sum_{i=1}^{m} W_j x'_{ij} \tag{6}$$

3.3.2. Modified Gravitational Modeling

The key to constructing China's food security spatial correlation network lies in establishing the relational connections. Existing research primarily employs modified gravity models and Granger causality analysis to determine spatial relationships. However, Granger causality analysis is overly sensitive to lag order selection and unsuitable for data with short time spans [54]. In contrast, the gravity model offers greater applicability. It can account for both scale and regional distance while revealing the evolutionary characteristics of spatial correlations [55]. Consequently, this study adopts a modified gravity model to measure the spatial correlations between provinces. The specific model is as follows:

$$F_{ij} = K_{ij} \frac{M_i \cdot M_j}{\left[D_{ij}/(G_i - G_j)\right]^b} \tag{7}$$

$$K_{ij} = M_i / M_i + M_j \tag{8}$$

In this model: F_{ij} represents the degree of connection between provinces i and j. M_i and M_j denote the food security indices of provinces i and j, respectively. K_{ij} is the contribution of province i to F_{ij}. D_{ij} represents the geographical distance between provinces i and j. G_i and G_j indicate the economic development levels of provinces i and j, measured by GDP per capita. b is the distance decay coefficient, typically set to 2 for provincial-level studies.

After calculating the connection strength between provinces using the modified gravity model, a connection strength matrix is constructed. The average value of each row in this matrix is then used as a threshold. If the connection strength between two provinces exceeds this threshold, it is marked as 1, indicating a spatial correlation in food security between these provinces. Conversely, if the connection strength falls below the threshold, it is marked as 0, signifying no spatial correlation. This process results in a 30 × 30 directed binary spatial correlation matrix.

3.3.3. Analysis of the Structure of the Spatial Association Network

Network space, as a dynamic spatial structure, comprises nodes of various economic units, facilitating the flow of both tangible and intangible elements. Essentially, this falls within the realm of technological spillovers, emphasizing functional connections between different nodes and their resulting external effects. Social Network Analysis (SNA) enables a detailed examination of the connectivity and structural characteristics of this network space based on constructed social relationship matrices. This study analyzes China's food security level spatial correlation network from three aspects: overall network characteristics, individual network characteristics, and block model analysis.

Overall network structure characteristics are depicted through overall structural features and small-world network properties. The analysis focuses on network density, network relationships, network efficiency, and network hierarchy [56]. Network density reflects the network's cohesiveness, with higher values indicating stronger inter-city connections and greater impact on food security. Network connectivity demonstrates the network's robustness and vulnerability. Lower connectivity suggests less stability when multiple routes pass through a city, while higher connectivity indicates a more robust network. Network hierarchy reveals the accessibility and hierarchical structure of cities within the network. Higher values suggest a more rigid hierarchy, potentially placing more cities in subordinate or peripheral positions. Network efficiency reflects the connection efficiency between cities, with lower values indicating more inter-city connections and a more stable network, facilitating food security flows.

Individual network structure characteristics are analyzed through degree centrality, closeness centrality, and betweenness centrality [57]. Degree centrality reflects a province's connectivity with others, with higher values indicating a central network position and stronger influence. Closeness centrality shows a province's independence within the network, with higher values suggesting more direct connections and a "central actor" role. Betweenness centrality indicates a province's control over other provinces' interactions, with higher values suggesting a core network position that may limit other provinces' development.

Block model analysis, using the Convergence of Iterated Correlations (CONCOR) method, clusters and segments the spatial correlation network. It reveals the network's internal structure and spillover pathways, analyzing intra-block and inter-block correlation characteristics. This analysis provides a clearer understanding of each block's role and position within the spatial correlation network [55].

3.3.4. QAP Regression Analysis

In the study of China's food security spatial correlation network, all variables are relational data. Traditional statistical methods are inadequate for verifying relationships between these variables due to potential high correlations among relational data. Therefore, this study employs the Quadratic Assignment Procedure (QAP), a non-parametric method that does not assume independence among independent variables, offering greater robustness compared to parametric methods [58]. QAP enables hypothesis testing at the relationship-relationship level, exploring the mechanisms of food security level differences among provinces and cities. It is based on matrix permutation, comparing the similarity of elements between two matrices to derive correlation coefficients and conduct non-parametric tests [59–61].

In selecting influencing factors across four dimensions—spatial, economic, infrastructure, and resources—we considered the following: (1) Spatial Factors: According to the First Law of Geography, geographical proximity enhances spatial associations [62]. This implies that provinces in close proximity may exhibit stronger relationships and spillover effects in food security levels. Hence, we included geographic distance between provincial capitals and adjacency between provinces as key spatial influencing factors. (2) Economic Factors: The spatial correlation of food security levels among provinces is closely linked to local economic development. Variations in economic development levels can lead to differences in local food supply and demand [63]. Additionally, rural human capital and the degree of marketization can affect the spatial association network. (3) Infrastructure Factors: Transportation facilities are crucial for food distribution. Therefore, we considered transportation infrastructure as one of the influencing factors. (4) Resource Factors: Based on previous studies [64,65], land productivity influences the network structure. Consequently, we incorporated this indicator as a resource-related influencing factor. We constructed the following model to analyze these factors.

$$N_i = f(D, W, R, M, N, P, E) \tag{9}$$

In this context, N_i signifies the spatial correlation network for year i; D denotes the matrix that calculates geographic distances among provincial capital cities; W is the matrix representing inter-provincial proximity, where proximity is denoted as 1 and non-proximity as 0; R illustrates the variations in rural human capital, quantified by the average years of schooling within the rural populace; M reflects the disparities in marketization levels, assessed using the marketization index; N indicates the differences in transport infrastructure, specifically measured by railway mileage; P pertains to the land production capacity, calculated as the ratio of total agricultural output value to the sown area for crops; and E denotes the variations in economic development levels, measured by the per capita GDP of each province.

To clearly reflect the evolutionary characteristics of factors influencing China's food security level spatial correlations, this study conducts analyses at three time points: 2008, 2015, and 2022.

These research methods provide a comprehensive perspective for understanding the spatial correlation network characteristics of food security levels across Chinese provinces and their underlying driving mechanisms. Based on the determined research methods and relevant variables, a conceptual framework for this study is constructed, as illustrated in Figure 1:

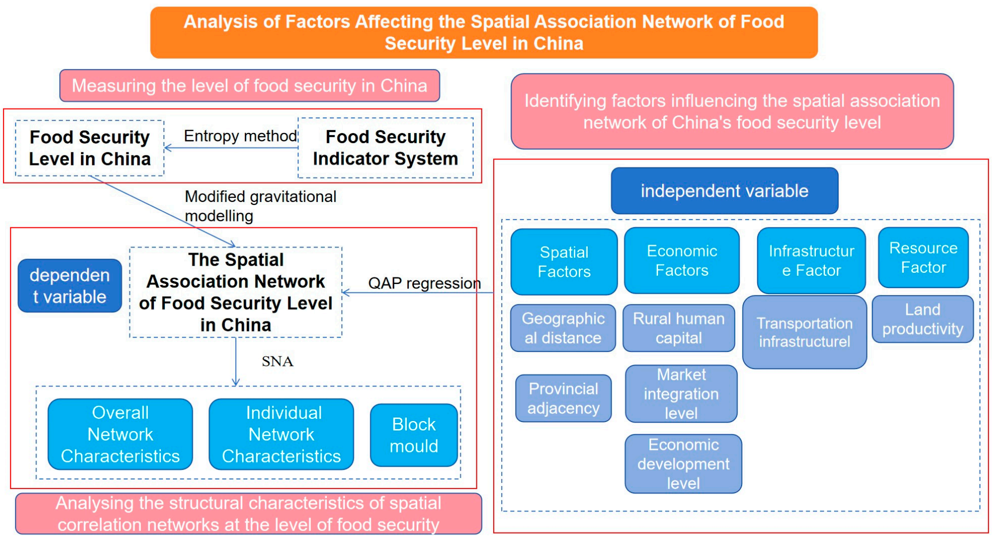


Figure 1. Conceptual Framework.

As illustrated in the figure, this study focuses on the factors influencing the spatial correlation network of China's food security levels. Initially, an indicator system for measuring food security levels is developed, applying the entropy method to assess these levels across China. Building on this, a modified gravity model is used to depict the spatial correlation network of China's food security. Subsequently, the structural characteristics of this network are analyzed using social network analysis. Finally, we employed QAP regression analysis to explore the impact of seven indicators across four dimensions—spatial, economic, infrastructure, and resources—on the spatial association network of food security levels in China.

4. Results and Analysis

4.1. Analysis of the Level of Food Security in China

Figure 2 illustrates the trends in China's food security levels from 2008 to 2022. The overall national average increased from 0.230 to 0.348, with an annual growth rate of 3.02%. This improvement reflects the combined effects of government policy support, agricultural technological advancements, and infrastructure development over the past 15 years. However, with an overall average of 0.291, there remains significant room for enhancement in food security levels. At the regional level, all three major areas experienced consistent growth in food security levels. Notably, the spatial pattern evolved from Central > Eastern > Western in 2008 to Central > Western > Eastern in 2022 (Figure 2a). The Western region demonstrated the fastest annual growth rate, followed by the Central region, with the Eastern region showing the slowest progress. This shift can be attributed to increased national support for central and western regions through fiscal transfers and poverty alleviation projects, which stimulated local economic development and subsequently improved agricultural production and food security. At the provincial level, all provinces showed varying degrees of improvement in food security from 2008 to 2022 (Figure 2b–d). However, significant inter-provincial disparities persist. Inner Mongolia (0.506), Heilongjiang (0.452), and Shandong (0.431) ranked as the top three in average food security levels nationwide. In contrast, Qinghai (0.178) and Hainan (0.172) ranked the lowest, with the highest-ranking province's average being approximately three times that of the lowest.

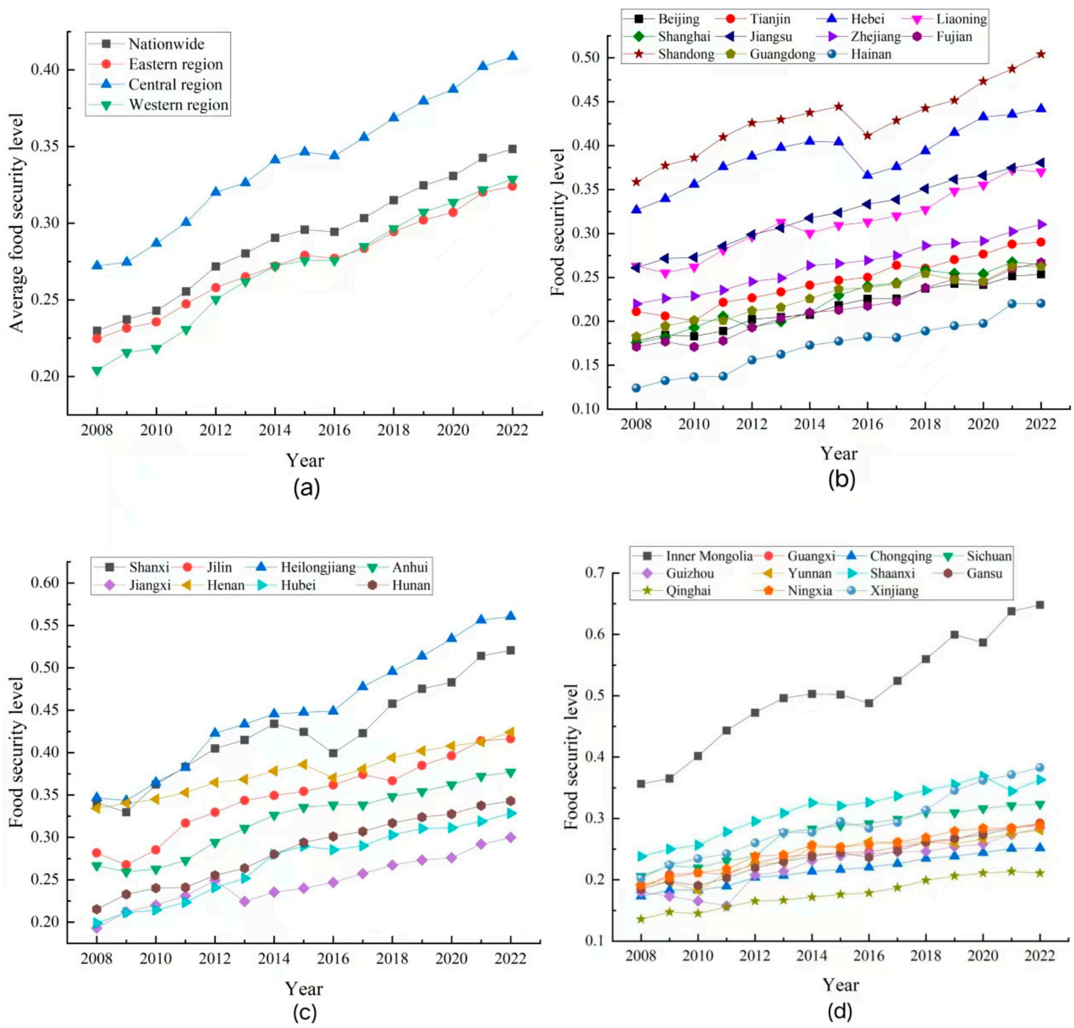
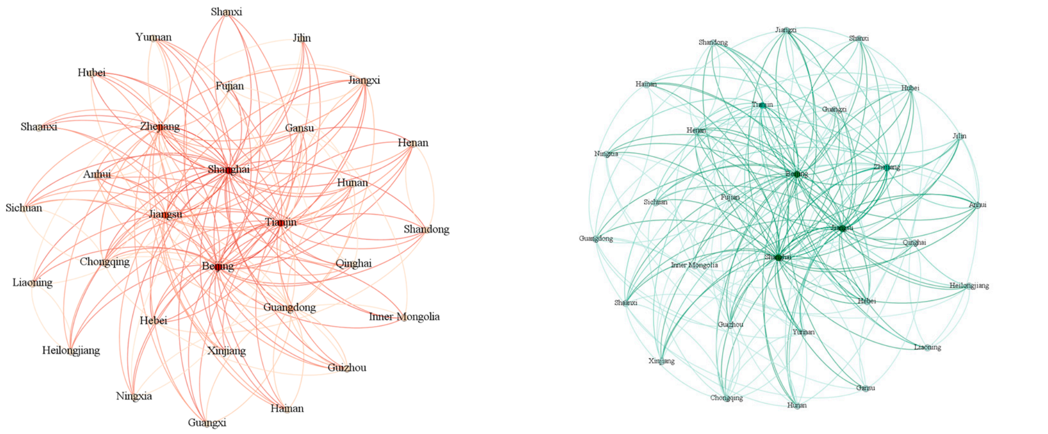


Figure 2. The changing trend of China's food security level from 2008 to 2022. (**a**) Nationwide and Three Regions; (**b**) Eastern region; (**c**) Central Region; (**d**) Western Region;.

4.2. Analysis of the Overall Network Characteristics

Based on the spatial association matrices of China's food security levels from 2008 to 2022, spatial association networks were constructed. Due to space limitations, this study focuses on two cross-sections: 2008 and 2022. Figure 3 presents visualizations of these networks using Gephi software 0.9.2.



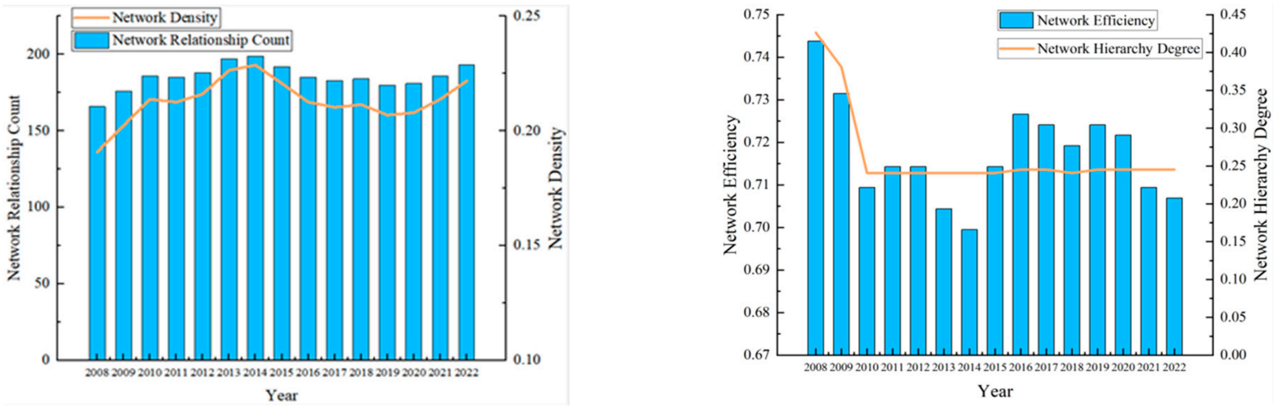
(**a**) (**b**)

Figure 3. China's food security spatial association network. (**a**) Spatial association network 2008; (**b**) Spatial association network 2022.

Figure 3 demonstrates that each province's food security level influences both neighboring and non-neighboring provinces. This indicates the establishment of associative relationships between provinces, regardless of proximity, forming an indivisible spatial association network. Visual inspection of the figures reveals a denser association network in 2022, suggesting a year-on-year increase in the spatial association of China's food security levels. This trend poses significant challenges for food security policy formulation. Consequently, food security planning and management require a holistic, comprehensive perspective. This approach is essential to address the complex interrelationships within the evolving spatial network of food security across China's provinces.

4.2.1. Characteristics of the Overall Structure of the Network

To further characterize the overall structural features of spatial association networks across years, this study utilized Ucinet software 6 to calculate various network metrics, including the number of relationships, network density, network connectivity, network efficiency, and network hierarchy. These results are illustrated in Figure 4. Figure 4a reveals that network density remains relatively low, with a maximum value of 0.2287. The maximum number of network relationships is 199, significantly lower than the theoretical maximum of 870, calculated using the formula $n(n-1)$. This indicates that the spatial association network of food security levels remains relatively sparse in reality. This sparsity can be attributed to the regional nature of food production, where different areas focus on specific types of agricultural products based on their natural conditions and resource endowments rather than maintaining direct food trade or cooperation with all regions. However, both the number of network relationships and network density show an overall upward trend with fluctuations. This change can be primarily attributed to national policies promoting market-oriented grain purchase and sales, grain subsidy policies, and regulations supporting agricultural technological innovation. Additionally, the application of efficient logistics systems has further enhanced inter-regional connections in terms of food security. The network connectivity for each year remains constant at 1, reflecting a stable network structure despite fluctuations in the number of relationships. This indicates the formation of a stable spatial association network for food security at the provincial level. Figure 4b demonstrates a notable decline in network efficiency. This suggests that as associative relationships increase, there is a growing phenomenon of multiple overlapping channels between provinces, leading to redundancy and decreased efficiency. This situation reflects some regions' tendency towards redundant construction or overinvestment in strengthening food security without fully considering the cost-effectiveness at the system level. The network hierarchy decreased from 0.426 in 2008 to 0.2454 in 2022. Some provinces that once held central positions in the network are experiencing a gradual decline in their importance. This transformation aligns closely with China's implementation of the Rural Revitalization Strategy. As this strategy progresses, provinces previously on the network's periphery are steadily enhancing their influence. This shift is characterized by increased agricultural technology and resource sharing among provinces. The evolving network structure reflects a more balanced distribution of influence in China's food security landscape.



(**a**) (**b**)

Figure 4. Characteristics of the overall structure of the network. (**a**) Spatial association network density and network; (**b**) Spatial association network efficiency and network relationship hierarchy.

4.2.2. Characteristics of the Networked Small World

In social network theory, the small-world characteristic is primarily used to measure network accessibility. Figure 5 illustrates the trends in clustering coefficient and average path length of China's spatial association network for food security levels. As shown in Figure 5, the network clustering coefficient exhibits a fluctuating downward trend with a relatively small overall decrease. This indicates that China's spatial association network for food security levels has gradually dispersed from initial small-scale clusters, moving towards a more balanced network connectivity. Additionally, the average path length displays an "M-shaped" trend with the 2022 level essentially returning to that of 2008. This suggests that provinces can leverage the network structure to achieve effective coordination in food security management, enhancing efficiency and reducing network redundancy. Overall, China's spatial association network for food security levels demonstrates certain small-world characteristics. This network structure facilitates efficient information flow and resource allocation among provinces, potentially leading to more coordinated and effective food security policies at the national level.

4.3. Analysis of the Individual Characterization

The degree centrality, intermediate centrality, and near centrality of the spatial correlation network in 2022 were measured by Ucinet software, and the results are shown in Table 2.

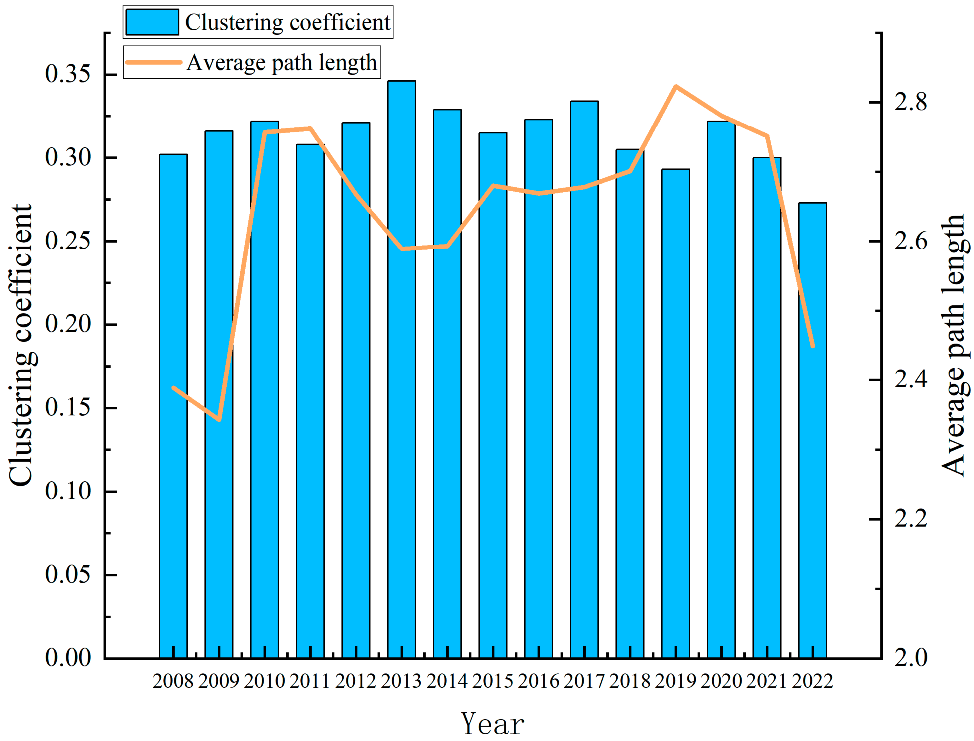


Figure 5. Evolution of small world characteristics of spatial association network.

Table 2. Individual characteristics of spatial association network of food security level in China in 2022.

Province	Degree Centrality			Middle Centrality	Close to Centrality	
	Point-Out	Point-In	Centrality		Inside Proximity Centricity	Outer Proximity Centricity
Beijing	25	6	86.207	11.543	87.879	14.796
Tianjin	13	2	44.828	0.287	63.043	13.679
Hebei	7	5	27.586	2.928	55.769	15.104
Shanxi	2	6	20.690	0.208	48.333	15.183
Inner Mongolia	10	6	37.931	9.852	59.184	15.676
Liaoning	2	5	20.690	0.123	3.571	20.714
Jilin	1	7	24.138	0.369	3.567	21.642
Heilongjiang	0	7	24.138	0	3.333	27.358
Shanghai	26	8	93.103	15.381	90.625	15.676
Jiangsu	23	3	79.310	5.796	82.857	15.026
Zhejiang	14	4	51.724	1.706	64.444	14.872
Anhui	5	4	20.690	0.521	52.727	14.721
Fujian	8	8	41.379	14.418	43.284	17.059
Jiangxi	6	6	24.138	12.794	53.704	16.292
Shandong	3	6	20.690	0.293	52.727	14.872
Henan	7	8	31.034	4.370	56.863	15.591
Hubei	7	7	34.483	5.959	55.769	15.847
Hunan	3	7	24.138	4.230	40.278	16.571
Guangdong	5	7	27.586	2.673	32.222	17.059
Guangxi	4	9	31.034	7.471	33.333	17.791
Hainan	2	7	24.138	0.066	26.852	17.059
Chongqing	5	9	31.034	12.245	29.293	17.791
Sichuan	1	7	24.138	0.107	22.835	17.365
Guizhou	3	8	27.586	4.669	32.955	17.683
Yunnan	1	8	27.586	0.235	22.835	17.683

Table 2. *Cont.*

Province	Degree Centrality			Middle Centrality	Close to Centrality	
	Point-Out	Point-In	Centrality		Inside Proximity Centricity	Outer Proximity Centricity
Shaanxi	2	9	31.034	3.856	28.713	17.683
Gansu	3	5	17.241	5.811	31.522	16.571
Qinghai	3	5	24.138	0.837	29.293	16.022
Ningxia	2	6	20.690	6.472	38.667	16.111
Xinjiang	0	8	27.586	0	3.333	20.423

Degree centrality can be used to measure the status of each province within the network. Shanghai, Beijing, and Jiangsu rank in the top three, indicating that these regions have the most connections with other provinces and exert the greatest influence on their food security levels, occupying central positions in the network. Conversely, provinces such as Gansu, Ningxia, and Liaoning rely more on internal consumption and a few major grain consumption markets, resulting in fewer spatial associations with other provinces and less influence, placing them at the network's periphery. This distribution of degree centrality is closely related to market radiation capacity, infrastructure, and geographical location. Shanghai and Beijing, with their large and stable food demand, exert strong market attraction on surrounding provinces and even nationwide, establishing stable food supply chain relationships with numerous provinces. Jiangsu Province, located in China's eastern coastal region, benefits from a developed transportation network facilitating rapid grain transport and logistics. Its proximity to the Yangtze River Delta economic zone enhances connections with neighboring provinces and major consumer markets. Provinces such as Gansu, Ningxia, and Liaoning, with substantial grain production capacity, may rely more on internal consumption and a few major grain markets. Their remote locations increase logistics costs, reducing direct connections with other provinces. In-degree centrality reflects the extent to which a node is influenced by others, indicating beneficiary effects, while out-degree centrality shows a node's influence on others, representing spillover effects. Shanghai, Beijing, Zhejiang, Jiangsu, and Tianjin have high in-degree centrality, significantly exceeding their out-degree centrality, indicating a strong "siphon effect" and substantial beneficiary effects. Regions such as Guizhou, Sichuan, and Yunnan have higher out-degree than in-degree centrality. Notably, Xinjiang and Heilongjiang have zero in-degree centrality, demonstrating significant net spillover effects. The grain resources from these regions flow largely into central and eastern areas under the influence of the "siphon effect," resulting in pronounced spillover effects.

Betweenness centrality measures the intermediary role of provinces within the network, reflecting their ability to control resources. There are significant differences in betweenness centrality, with a range of 15.381. Shanghai, Fujian, Jiangxi, and Beijing exhibit high betweenness centrality, indicating their crucial "bridge" roles in inter-nodal communication and strong resource control capabilities. Notably, remote regions such as Xinjiang and Heilongjiang have zero betweenness centrality, suggesting they have yet to play intermediary roles in the network.

In-closeness centrality reflects a node's influence on others. Shanghai, Beijing, and Jiangsu rank highest, exerting the greatest influence on other provinces' food security levels, primarily due to their market radiation effects. Conversely, out-closeness centrality indicates a node's susceptibility to influence from others. Heilongjiang, Jilin, Liaoning, and Xinjiang rank highly in this metric, suggesting their food security levels are more vulnerable to influences from other provinces. This reflects that these provinces, with fewer associative relationships, are more easily affected by their connected provinces.

Overall, while provinces' roles and positions in the network exhibit complex characteristics, the results from degree centrality, betweenness centrality, and closeness centrality analyses are largely consistent, revealing a significant core-periphery structure. Provinces and municipalities such as Shanghai, Beijing, and Jiangsu, with developed economies, high food consumption levels, and strong transportation infrastructure, have more connections with other provinces. They occupy central network positions, playing important intermediary roles with significant beneficiary effects. In contrast, provinces such as Xinjiang and Heilongjiang, with high grain production and self-sufficiency but remote locations, have fewer connections with other provinces. They occupy peripheral network positions, and their food security levels are more susceptible to influences from other provinces.

4.4. Block Mold Analysis

The preceding analysis reveals heterogeneity in the status and roles of provinces within the network, with significant regional differences. To further elucidate the roles of individual provinces and characterize inter-provincial interactions, this study employed the CONCOR algorithm in Ucinet software. Based on the spatial association network of food security levels in 2022, China was partitioned into four distinct blocks, as shown in Table 3. This block partitioning approach provides a more nuanced understanding of the network structure, allowing for the identification of subgroups with similar patterns of relationships. Such an analysis can offer valuable insights into the complex dynamics of food security interactions across China's diverse provinces.

Table 3. Division of spatial association network of China's food security.

Plate	**Relationship Matrix**				**Number of Board Members**	**Desired Internal Relationship Ratio (%)**	**Proportion of Actual Internal Relationships (%)**	**Number of Intraplate Relationships**	**Number of Relationships Issued**	**Number of Relationships Received**	**Plate Characteristics**
	1	**2**	**3**	**4**							
1	2	1	9	0	2	3.450	16.67	2	10	33	Main Beneficiary Sectors
2	2	9	7	19	6	17.240	24.32	9	28	66	Main Beneficiary Sectors
3	23	33	28	4	14	44.830	31.82	28	60	22	Main overflow boards
4	8	32	6	2	8	24.140	4.17	2	46	23	Main overflow boards

Table 3 reveals that in 2022, China's food security level exhibited 169 spatial associative relationships. Of these, 41 were intra-block relationships, while 144 were inter-block relationships. This indicates that spatial associations in China's food security levels predominantly occur between blocks, with relatively weak associations within blocks. Block 1 has 2 internal relationships, 33 receiving relationships from other blocks, and 10 spillover relationships. The expected and actual internal relationship proportions are 3.45% and 16.67%, respectively. This block, characterized by numerous receiving relationships and relatively few internal relationships, can be classified as a primary beneficiary block. Block 2 has 9 internal relationships, 66 receiving relationships from other blocks, and 28 spillover relationships. The expected and actual internal relationship proportions are 17.24% and 24.32%, respectively. This block, also characterized by numerous receiving relationships, can be classified as another primary beneficiary block. Inner Mongolia's climate is characterized by distinct seasons, with warm summers and abundant sunlight conducive to crop growth. The cold winters help reduce pest and disease incidence, contributing to its status as a crucial region for China's grain production. The region's unique agricultural resources and environmental advantages have attracted significant inflows of capital, talent, and technological resources. Consequently, Inner Mongolia is classified as a primary beneficiary in the network. Provinces such as Beijing, Jiangsu, Zhejiang, Shanghai, and Fujian exhibit high grain demand. These regions attract and absorb external resources in quantities that substantially exceed their outflows. As a result, they are also categorized as primary beneficiaries within the network structure. Block 3 has 28 internal relationships, 22 receiving relationships from other blocks, and 60 spillover relationships. The expected and actual internal relationship proportions are 44.83% and 31.82%, respectively. Due to its numerous spillover relationships, this block can be classified as a primary spillover block. Block 4 has 2 internal relationships, 23 receiving relationships from other blocks, and 46 spillover relationships. The expected and actual internal relationship proportions are 24.14% and 4.17%, respectively. This block, also characterized by numerous spillover relationships, can be classified as another primary spillover block. Most provinces in Blocks 3 and 4 are located in the Northeast and North China Plain. These regions benefit from fertile soil, favorable climate, and abundant water resources, leading to high grain yields. Their agricultural output often surpasses local demand, allowing them to supply food resources to other areas. Due to their numerous external spillover connections, these regions are classified as primary spillover producers in the network. This classification highlights their vital role in supplying surplus agricultural products to meet wider regional needs.

To illustrate the spillover relationships between blocks, this study calculated the density matrix for intra-block and inter-block relationships in 2022. Using the overall network density of 0.2218 as a benchmark, an image matrix for intra-block and inter-block relationships was derived (Table 4). Additionally, to provide a clearer visualization of the spillover relationships between blocks, an interaction diagram of the four major blocks was constructed (Figure 6).

Table 4. Density matrix and image matrix of China's food security.

	Density Matrix				Image Matrix			
Plate	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	1	0.083	0.321	0	1	0	1	0
2	0.167	0.300	0.083	0.396	0	1	0	1
3	0.821	0.393	0.154	0.036	1	1	0	0
4	0.500	0.833	0.054	0.036	1	1	0	0

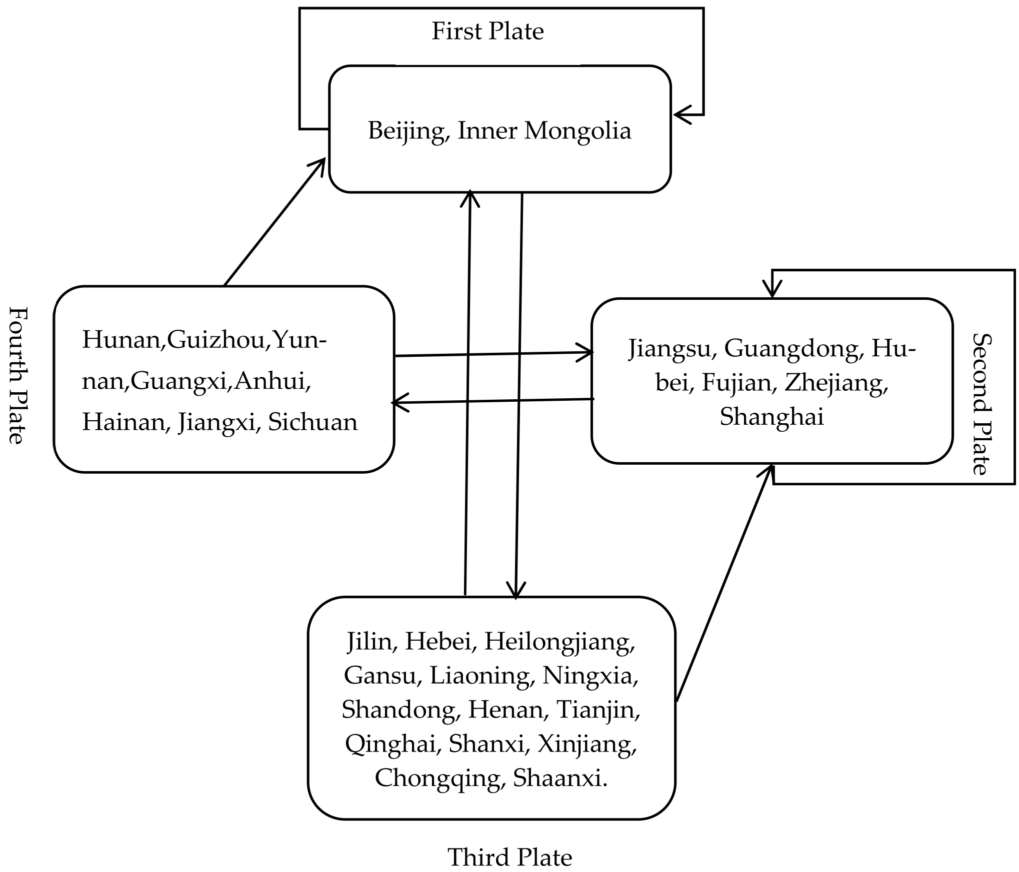


Figure 6. Interaction of the four segments.

The results indicate that the first and second blocks exhibit relatively strong internal associations, while the remaining two blocks demonstrate looser internal connections. Inter-block spillover effects are pronounced, with Blocks 3 and 4 primarily generating spillover effects towards Blocks 1 and 2. This pattern reveals significant spillover effects from Blocks 3 and 4, and notable beneficiary effects in Blocks 1 and 2. Blocks 1 and 2, leveraging their locational advantages, absorb substantial growth momentum in food security levels from Blocks 3 and 4. This absorption continuously drives improvements in food security levels within these blocks. However, this dynamic may impede the coordinated and balanced development of national food security levels.

In summary, spatial associations in China's food security levels occur both between and within blocks. The roles of each block within the network exhibit heterogeneity. Blocks 1 and 2 function as primary beneficiary blocks, receiving numerous external relationships. Conversely, Blocks 3 and 4 serve as primary spillover blocks, generating multiple external spillover relationships. This block-level analysis provides valuable insights into the complex dynamics of China's food security network, highlighting the need for policies that promote more balanced development and equitable distribution of resources across all regions.

4.5. Analysis of Factors Affecting the Spatial Association Network of China's Food Security Level

4.5.1. Correlation Analysis

This study employed UCINET software to conduct 5000 random permutations. The analysis yielded correlation coefficients between the spatial association matrices of China's food security levels and various influencing factors for the years 2008, 2015, and 2022 (Table 5). The coefficients for the geographic distance matrix are consistently negative, while those for the provincial adjacency matrix are positive. This preliminarily indicates that closer geographical proximity between provinces correlates with stronger spatial associations in food security levels. In 2008, the economic development disparity matrix showed a negative correlation with the spatial association matrix, suggesting that smaller economic disparities between provinces facilitated the establishment of spatial associations during this period. However, in 2015 and 2022, this correlation became significantly positive, indicating that larger economic disparities between provinces promoted spatial associations in these later years. Differences in marketization levels and agricultural human capital both show positive correlations, preliminarily suggesting a positive influence on the establishment of China's food security spatial association network. The transportation infrastructure disparity matrix exhibits a negative correlation with the spatial association matrix. In 2008 and 2015, the land productivity disparity matrix shows positive correlation coefficients, preliminarily reflecting that greater differences in land productivity facilitated the establishment of spatial associations. However, in 2022, the correlation coefficient for the land productivity disparity matrix did not pass the significance test, suggesting that land productivity differences may not have significantly influenced inter-provincial associations in that year. These findings provide valuable insights into the evolving dynamics of China's food security network and the changing influence of various factors over time. Further investigation into these relationships could inform targeted policy interventions to enhance food security across the country.

Table 5. Correlation analysis.

Variant	2008	Significance Level	2015	Significance Level	2022	Significance Level
D	−0.240 ***	0	−0.314 ***	0	−0.300 ***	0
W	0.146 ***	0	0.205 ***	0	0.257 ***	0
E	−0.442 ***	0	0.397 ***	0	0.383 ***	0
M	0.339 ***	0	0.285 ***	0	0.252 ***	0.001
R	0.210 **	0.020	0.195 **	0.019	0.180 **	0.023
N	−0.189 ***	0.010	−0.154 **	0.019	−0.144 **	0.029
P	0.257 ***	0.004	0.224 ***	0.008	0.047	0.256

Note: **, and *** indicate statistical significance at the 5%, and 1% levels, respectively.

4.5.2. Regression Analysis

Prior to conducting the Quadratic Assignment Procedure (QAP) regression analysis, a multicollinearity test was performed on five explanatory variables. This test excluded the geographical distance and provincial adjacency variables. The results of multicollinearity analysis are presented in Table 6. The results indicate that all VIF values are below 10. This finding suggests that there is no significant multicollinearity among the explanatory variables.

Table 6. Multicollinearity test.

Explanatory Variable	VIF	Tolerance
R	1.961	0.510
M	2.665	0.375
N	1.054	0.949
P	1.873	0.534
E	2.838	0.352

A QAP regression analysis was conducted using Ucinet software to examine the relationship between China's food security spatial association matrices and various influencing factors for the years 2008, 2015, and 2022. The study conducted 2000 random permutations, with results presented in Table 7. The adjusted R^2 values for the three years are 0.270, 0.264, and 0.256, respectively, all significant at the 1% level. These results indicate that the selected factors effectively explain variations in spatial associations of food security levels across China. The regression results reveal significant differences in both the magnitude and direction of influence among the various indicators on China's food security spatial association network. This suggests a complex interplay of factors shaping the spatial relationships of food security across the country. Specific analyses are as follows:

Table 7. QAP regression analysis.

Variant	2008			2015			2022		
	Ratio	Probability 1	Probability 2	Ratio	Probability 1	Probability 2	Ratio	Probability 1	Probability 2
D	−0.221 ***	1.000	0.000	−0.280 ***	1.000	0.000	−0.229 ***	1.000	0.000
W	0.040	0.211	0.789	0.070 *	0.062	0.939	0.147 ***	0.003	0.998
E	−0.499 ***	1.000	0.000	0.468 ***	0.000	1.000	0.401 ***	0.000	1.000
M	0.180 ***	0.008	0.993	0.072 *	0.099	0.901	0.042	0.251	0.749
R	−0.140 ***	0.994	0.007	−0.089 **	0.953	0.047	−0.055	0.832	0.168
N	−0.189 ***	1.000	0.000	−0.018	0.672	0.329	−0.029	0.742	0.259
P	−0.062 *	0.926	0.074	−0.113 **	0.979	0.021	−0.089 **	0.978	0.022
R^2	0.275 ***			0.269 ***			0.261 ***		
Adj R^2	0.270 ***			0.264 ***			0.256 ***		
Number of Observations		870			870			870	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The regression coefficients for geographic distance matrices in 2008, 2015, and 2022 are −0.221, −0.280, and −0.229, respectively, all significant at the 1% level. This indicates that smaller inter-provincial distances facilitate stronger spatial associations. The increasing absolute values of these coefficients suggest a growing impact of geographic proximity over time.

Adjacency matrix coefficients (0.040, 0.070, 0.147) are consistently positive, with significance in 2015 (10% level) and 2022 (1% level), further emphasizing the increasing importance of proximity in establishing spatial relationships.

Economic development disparity coefficients (−0.499, 0.468, 0.401) are significant at 1% across all years. This shift from negative to positive values indicates that while smaller economic gaps initially fostered spatial associations, larger disparities now promote such relationships. This change may be attributed to enhanced technology and resource flow between regions with different economic levels.

Market development disparity coefficients (0.180, 0.072, 0.042) are positive and significant in 2008 (1% level) and 2015 (10% level), but not in 2022. This suggests a diminishing influence of market disparities, possibly due to increased regional cooperation mechanisms.

Agricultural human capital disparity coefficients (−0.140, −0.089, −0.055) are negative and significant in 2008 (1% level) and 2015 (5% level), but not in 2022. This trend may reflect the decreasing impact of human capital differences on spatial associations.

Transportation infrastructure disparity coefficients (−0.189, −0.018, −0.029) are significant only in 2008 (1% level), indicating a diminishing influence. This may result from significant improvements in national transportation networks.

Land productivity disparity coefficients (−0.062, −0.113, −0.089) are significant at varying levels across all years. The negative values suggest that smaller disparities in land productivity promote spatial associations, possibly due to enhanced cooperation potential in agricultural value chains.

5. Discussion

This study advances the understanding of China's food security by employing social network analysis and QAP regression to examine the spatial association network of food security levels across provinces. Our research reveals both the spatial correlations and network characteristics of food security levels in China, while identifying key factors influencing the network structure.

In contrast to existing studies on spatial characteristics of food security [10,11,13,15,18], we innovatively apply social network analysis to this field. By constructing and analyzing the dynamic changes in the spatial association network of food security levels, we provide a novel perspective on China's food security landscape. Our findings indicate that provincial food security levels influence both neighboring and non-neighboring provinces, forming an interconnected spatial network. This aligns with previous research highlighting strong spatial correlations in China's food security [13,14]. We further categorize Chinese provinces into four major blocks, enhancing our understanding of regional interactions in food security development. This categorization, rarely discussed in existing literature, provides evidence for recognizing the status and role of each province within the spatial association network. Additionally, our analysis of factors influencing this network reveals significant impacts of geographical distance, economic development, market integration, agricultural human capital, and land productivity on establishing spatial associations in food security. These insights, consistent with other scholars' conclusions [62,63,65], provide a foundation for targeted food security policies and coordinated development strategies.

While this study offers profound insights into the structure and evolution of China's food security spatial association network, it has limitations. Data availability constraints prevented the inclusion of city-level data, which could enhance the precision of future analyses. Moreover, food security is influenced by numerous complex factors. Although our study focused on specific elements, future research should consider a broader range of potential influencing factors for a more comprehensive understanding.

6. Conclusions and Policy Recommendations

6.1. Conclusions

This study employed the entropy method to measure food security in 30 Chinese provinces from 2008 to 2022. Based on these measurements, a spatial association network of China's food security levels was constructed using a modified gravity model. Network structure analysis was conducted, followed by QAP regression analysis to investigate influencing factors. The key findings are as follows:

(1) China's food security level exhibits an overall upward trend with fluctuations. The central region consistently outperforms the national average and both eastern and western regions. In recent years, the western region has shown the fastest growth in food security levels, followed by the central region, while the eastern region has maintained relatively stable growth.

(2) Overall network analysis reveals that provinces have established interactions with both neighboring and non-neighboring provinces, forming a relatively stable spatial association network of food security levels. The number of network relationships and network density show an increasing trend with fluctuations. Network hierarchy and efficiency demonstrate a declining trend, indicating an increase in redundant channels between nodes. However, the network still exhibits strong small-world characteristics. Provinces should enhance their identification of redundant channels to further improve network efficiency.
(3) Individual characteristic analysis reveals a distinct core-periphery structure within the network. Provinces and municipalities such as Shanghai, Beijing, and Jiangsu occupy central network positions due to their significant locational advantages, playing crucial intermediary roles. In contrast, provinces such as Gansu, Ningxia, and Liaoning, due to their remote locations, have fewer connections and occupy peripheral positions in the network, making their food security more susceptible to influences from other provinces.
(4) Block model analysis reveals that China's food security spatial association network comprises four major blocks. The first and second blocks exhibit relatively strong internal associations, while the remaining two blocks demonstrate looser internal connections. Inter-block relationships are close, with evident spillover effects. The roles of each block within the network exhibit heterogeneity. Eastern coastal regions, including Beijing, Inner Mongolia, Shanghai, Jiangsu, and Zhejiang, demonstrate a significant "siphon effect" and act as primary beneficiary blocks. Most provinces in central and western regions serve different roles in the network.
(5) QAP regression analysis indicates that geographic distance, adjacency, economic development disparity, market development disparity, agricultural human capital disparity, and land productivity disparity matrices significantly influence the establishment of food security spatial associations. Specifically, geographic distance, agricultural human capital disparity, and land productivity disparity matrices show negative regression coefficients. Adjacency, economic development disparity, and market development disparity matrices exhibit positive regression coefficients. The impact of geographic distance on associations shows an increasing trend over time. Larger disparities in economic development and market development levels facilitate inter-provincial food security cooperation. Closer similarities in agricultural human capital and land productivity promote cooperation between provinces.

6.2. Policy Recommendations

The findings of this study partially support the view that China's food security levels exhibit significant spatial heterogeneity and spillover characteristics. They also expand the exploration of inter-provincial food security associations, providing essential guidance for enhancing food security and fostering spatial interactions with other regions. Based on these conclusions, the following policy recommendations are proposed:

(1) Implement a regional collaborative development strategy for food security. Conduct comprehensive assessments of each region's natural resources, agricultural production conditions, economic bases, and market demands. Clearly define each region's role within the national food security strategy. For instance, eastern coastal areas can focus on developing high-value-added grain industries, while central and western regions should work to increase overall grain production. The government should optimize agricultural subsidy policies, enhance support for major grain-producing areas, and use tax incentives to attract investment. This would encourage the flow of capital, technology, and talent to regions with high grain production potential, while ensuring food security in ecologically vulnerable areas. Strengthening cooperation between central/western regions and the eastern coast through regional cooperation platforms can facilitate information sharing, technical exchanges, and market integration, creating a development model of complementary advantages. Eastern regions

can support central and western regions in terms of capital, technology, and market access, while central and western regions can provide consistent grain supplies to the east.

(2) The spatial association pattern of China's food security levels has undergone significant changes. The strengthening of inter-provincial spatial associations suggests that a province's food security is influenced not only by internal factors but also by the food security status of other provinces. Therefore, food security policies must adequately consider these inter-regional spatial associations and work to enhance their strength and broaden spillover channels. Strengthening cooperation both within and between regions will boost network density. The state should accurately assess each province's role and position in the network, refine mechanisms for collaborative innovation, and leverage the central roles of key provinces such as Beijing, Shanghai, and Jiangsu. This can enhance their interaction with peripheral provinces such as Gansu, Liaoning, and Ningxia, promoting coordinated development in regional food production, consumption, supply, and distribution.

(3) Continuously optimize transportation infrastructure in remote and major grain-producing areas, especially logistics networks. Leverage modern information technology to improve logistics management efficiency. Encourage technology transfer and resource sharing from developed to less developed regions to promote balanced development and grain complementarity. Support cross-regional cooperation through fiscal subsidies and other policies. Deepen agricultural market reforms and refine pricing mechanisms, reducing administrative interventions and enhancing cooperation between local governments. Strengthen rural human resource development, enhance farmers' vocational skills, and facilitate rational labor mobility. Optimize the logistics system, especially cold chain logistics facilities, to ensure grain quality and safety. Implement precision agriculture policies and develop differentiated strategies based on regional land resources to improve land use and productivity. These measures will contribute to promoting national food security and sustainable development.

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