Characteristics of the Spatial Association Network of Agricultural Resilience in China and Identification of Its Driving Factors

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Abstract

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Full Text

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Abstract: Based on panel data for 30 provinces (autonomous regions and municipalities directly under the Central Government) in China from 2014 to 2023, this study comprehensively applies the entropy weight method, social network analysis, and the Exponential Random Graph Model (ERGM) to systematically examine the structural characteristics of the spatial association network of agricultural resilience in China and its driving factors. The results show that: (1) China' s agricultural resilience has generally shown a steady upward trend, but development across dimensions is uneven; economic resilience and social resilience perform relatively well, whereas production resilience and ecological resilience lag behind. (2) The spatial association network of agricultural resilience shows a trend toward flattened development; the overall network remains highly accessible, but close associations have not yet formed, and most provinces (autonomous regions and municipalities) maintain one-way associations. (3) The spatial association of agricultural resilience presents a "west-central-east" radiation path; net spillover blocks are mostly concentrated in the central and western regions, while net beneficiary blocks are mainly distributed in the central and eastern regions, and broker blocks still have considerable room for improvement. (4) The formation of China's spatial association network of agricultural resilience is the result of the joint effects of endogenous structures, actor attributes, and the external environment. Endogenous structures such as reciprocity and cyclicity promote the formation of the agricultural resilience network; economic level, production conditions, industrial structure, and extreme heavy precipitation are the core driving forces behind the formation of the agricultural resilience network; and geographical proximity and trade exchanges are important external driving forces.

Key words: agricultural resilience; spatial association network; social network analysis; Exponential Random Graph Model

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Against the backdrop of multiple overlapping uncertain risks, including intensifying global climate change, frequent geopolitical conflicts, and the rise of trade protectionism, the pressure of risk transmission faced by agricultural systems continues to escalate, and improving agricultural resilience has become an important strategic goal for the sustainable development of global agriculture. With the continuous deepening of trade networks, research on agricultural resilience has gradually shifted from local regions to the national overall level, exhibiting significant characteristics of a spatial association network. Studying the overall characteristics of agricultural resilience and strengthening the overall resilience of industries have become new policy orientations. The 2025 Central No. 1 Document emphasized the concept of "strong industrial resilience" in the deployment for building China into an agricultural power, and proposed "focusing on improving the resilience and security level of industrial chains and supply chains." However, the strong regional dependence of agricultural production leads to natural barriers in factor flows and resource allocation, making it difficult to achieve efficient coordination across the entire territory. Under these constraints, accurately identifying the key characteristics and driving factors of the spatial association network of agricultural resilience is not only a way to solve the scientific problem of "vulnerability lock-in" in agricultural systems, but also an inevitable path for responding to the demand for regional collaborative governance in building China into an agricultural power.

Holling[1] first introduced the concept of "resilience" into ecology, defining it as the ability of a system to resist disturbances and maintain its core functions.

With the globalization of food security issues, this theory has been extended to agricultural systems. Research on agricultural resilience has mainly focused on three aspects. First is the measurement of agricultural resilience. At present, no unified standard has been formed for measuring agricultural resilience; existing approaches are mainly divided into three categories: the indicator synthesis method[2], the core variable method[3], and the counterfactual measurement method[4]. Second is the spatial disparity of agricultural resilience. Although China' s agricultural resilience has generally developed well[2], there are large interregional differences between major grain-producing areas and areas where grain production and sales are balanced, while major grain-consuming areas show large intraregional differences[5]. Third concerns the driving factors of agricultural resilience. Scholars have mainly focused on influencing factors such as government financial support[2], integration of rural industries[6], integration of digital technology and agriculture[7], and differences in the ecological environment[4]. Empirical studies show that the first three have significant positive effects on agricultural resilience, whereas differences in the ecological environment have no significant effect.

Previous studies in the field of agricultural resilience have achieved abundant results, but there is still room for further expansion in the following respects: first, agricultural resilience indicators

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The systematicity and practicality of the system still need to be further deepened. Existing agricultural-resilience indicator systems mostly emphasize the economic, ecological, and production dimensions, and seldom examine, from the social dimension, the role of grassroots governance in enhancing agricultural resilience. In particular, since the implementation of the rural revitalization strategy, grassroots governance has achieved notable results in improving agricultural resilience. Second, existing studies have focused more on the spatial pattern of agricultural resilience, but have discussed spatial association networks less often; social network analysis can use the gravity model to quantify intangible relational networks into tangible matrices, thereby revealing the internal associations of the network. Third, research on the driving factors of agricultural resilience is relatively abundant, but most studies are limited to the driving effects on agricultural resilience itself, with little attention to the driving effects of the spatial association network of agricultural resilience. The exponential random graph model (ERGM), by contrast, can use hypothesized network forms and structural configurations to capture network regionalization and interaction. Therefore, this paper constructs a four-dimensional agricultural-resilience indicator system covering the economy, production, ecology, and society, and uses social network analysis and the ERGM model to explore the characteristics and driving factors of China' s agricultural-resilience spatial association network. The aim is to provide theoretical support and decision-making references for agricultural-resilience evaluation and collaborative governance.

1 Data and Methods

1.1 Data Sources

The study period of this paper is 2014–2023, and the research units are 30 provinces in China (including autonomous regions and municipalities directly under the central government). Due to limitations in data availability, the data used in this study do not include those for the Tibet Autonomous Region, Hong Kong, Macao, or Taiwan. The main data sources are the successive editions of the *China Statistical Yearbook*, *China Agriculture Yearbook*, *China Rural Statistical Yearbook*, *China Population and Employment Statistical Yearbook*, *China Statistical Yearbook on Environment*, *China Civil Affairs Statistical Yearbook*, and *China Insurance Statistical Yearbook*, the statistical yearbooks of the provinces (autonomous regions and municipalities directly under the central government), and Global Surface Summary of the Day (GSOD) data. Among them, the determination of the number of days with extreme temperature and the number of extreme heavy-precipitation events refers to relevant literature[^8]. A small amount of missing data was supplemented using linear interpolation, median imputation, and other methods.

1.2 Construction of the Indicator System

Agricultural resilience refers to the comprehensive capacity of an agricultural system, when coping with internal and external disturbances such as natural disasters, climate change, market fluctuations, and policy changes, to maintain the stability of its core functions, effectively resist shocks, and achieve adaptive adjustment or transformational development. Its theoretical connotation is manifested as multidimensional coordination. Economic resilience is the core hub through which the agricultural system responds to external shocks; by optimizing the industrial structure and strengthening financial support, it provides key support for agricultural risk resistance and sustainable development. Production resilience is the key support for ensuring the continuous supply of agricultural products; relying on the upgrading of technical equipment and the efficient use of resources, it consolidates the foundation for disaster resistance and recovery in the agricultural production system. Ecological resilience is the basic barrier that sustains sustainable agricultural development; through the coordination of resources and ecological governance, it realizes environmental stability and green transformation of the system. Social resilience is the fundamental guarantee for the long-term stability of the agricultural system; with the improvement of human resources and the optimization of organizational effectiveness as its core, it enhances the system' s adaptability and capacity for innovation. These four dimensions are intertwined and mutually supportive, together constituting the core capability system through which the agricultural system resists uncertainty and achieves sustainable development.

Drawing on previous studies[^2,^6,^9], and based on the connotation of agricultural resilience, this paper follows the principles of policy anchoring, systemic completeness, and data availability, and selects 20 indicators from the four dimensions of economic resilience, production resilience, ecological resilience, and social resilience to construct an agricultural-resilience evaluation indicator system (Table 1).

1.3 Research Methods

1.3.1 Entropy Weight Method

Most measurement methods in the existing literature use quantitative methods or a combination of quantitative and qualitative methods. Compared with qualitative weighting, quantitative weighting can better eliminate interference arising from differences in the attributes of the data[^9]. Therefore, this paper uses the entropy weight method to measure indicator weights and agricultural resilience.

1.3.2 Modified Gravity Model

Attribute indicators can only reflect the characteristics of a province (autonomous region or municipality directly under the central government) itself, and cannot establish links with the characteristic data of other provinces (autonomous regions or municipalities directly under the central government). Therefore, establishing a modified gravity model can transform the attribute data of each province (autonomous region or municipality directly under the central government) into relational data, and then construct a spatial association matrix, laying the foundation for subsequent social network analysis. The calculation formula is as follows:

$$Y_{ij} = k_{ij} \frac{\sqrt[3]{P_i \mathrm{Agr}_i G_i}\,\sqrt[3]{P_j \mathrm{Agr}_j G_j}}{D_{ij}^2}, \qquad k_{ij} = \frac{\mathrm{Agr}_i}{\mathrm{Agr}_i + \mathrm{Agr}_j}, \qquad D_{ij} = \frac{d_{ij}}{g_i - g_j} \tag{1}$$

where: Y_{ij} is the connection strength between provinces (autonomous regions or municipalities directly under the central government) i and j; k_{ij} is the correction factor; Agr_i and Agr_j are the agricultural resilience of provinces (autonomous regions or municipalities directly under the central government) i and j, respectively; P_i and P_j are the year-end rural population of provinces (autonomous regions or municipalities directly under the central government) i and j, respectively (10^4 persons); G_i and G_j are the real GDP of provinces (autonomous regions or municipalities directly under the central government) i and j, respectively (10^8 yuan); D_{ij} is the economic-geographic distance between provinces (autonomous regions or municipalities directly under the central government) i and j ($\mathrm{km} \cdot \mathrm{yuan}^{-1}$); d_{ij} is the geographic distance between the geometric centers of provinces (autonomous regions or municipalities directly under the central government) i and j (km); and g_i and g_j are the per capita regional agricultural gross output value of provinces (autonomous regions or municipalities directly under the central government) i and j, respectively ($\mathrm{yuan} \cdot \mathrm{person}^{-1}$). According to formula (1), the agricultural-resilience gravity matrix is calculated, and this spatial association gravity matrix is then transformed into an asymmetric binary adjacency matrix[^10].

1.3.3 Social Network Analysis

Social network analysis originates from sociology. It quantifies "relationships" through mathematical methods and presents them in tangible form through topological graphs and other means, giving it significant advantages in depicting various relationships in social association networks. Starting from the three perspectives of the overall network, individual networks, and block models[^11-^12], this paper explores the provinces of China.

Table 1. Indicator system for assessing agricultural resilience

First-level indicator	Second-level indicator	Third-level indicator	Attribute	Weight
Economic resilience	Agricultural structure	Share of livestock and aquaculture output value in the total output value of agriculture, forestry, animal husbandry, and fisheries	+	0.0193
Economic resilience	Agricultural structure	Share of added value of agriculture, forestry, animal husbandry, and fishery services in the added value of agriculture, forestry, animal husbandry, and fisheries	+	0.0297

First-level indicator	Second-level indicator	Third-level indicator	Attribute	Weight
Economic resilience	Agricultural structure	Operating revenue of the agricultural product processing industry / main business revenue of agriculture, forestry, animal husbandry, and fisheries	+	0.1006
Economic resilience	Financial and fiscal support	Depth of agricultural insurance	+	0.1172
Economic resilience	Financial and fiscal support	Share of expenditure on agriculture, forestry, and water affairs in the added value of agriculture, forestry, animal husbandry, and fisheries	+	0.1743
Economic resilience	Financial and fiscal support	Expenditure on agricultural innovation inputs (enterprise investment)	+	0.0845

First-level indicator	Second-level indicator	Third-level indicator	Attribute	Weight
Production resilience	Agricultural production conditions	Comprehensive mechanization rate of crop plowing, sowing, and harvesting	+	0.0176
Production resilience	Agricultural production conditions	Effective utilization coefficient of irrigation water in farmland	+	0.0319
Production resilience	Agricultural output efficiency	Agricultural land output rate	+	0.0549
Production resilience	Agricultural output efficiency	Agricultural labor productivity	+	0.0461
Ecological resilience	Environmental pressure	Intensity of fertilizer input	−	0.0110
Ecological resilience	Environmental pressure	Intensity of pesticide input	−	0.0083
Ecological resilience	Ecological governance	Forest coverage rate	+	0.0389
Ecological resilience	Ecological governance	Soil-erosion control index	+	0.0627
Ecological resilience	Ecological governance	Crop disaster rate	−	0.0028
Social resilience	Human capital	Share of the rural population aged 15–64	+	0.0239

First-level indicator	Second-level indicator	Third-level indicator	Attribute	Weight
Social resilience	Human capital	Number of rural doctors and health workers	+	0.0639
Social resilience	Human capital	Per capita years of education in rural areas	+	0.0093
Social resilience	Organizational development	Share of village committee members with a college diploma or above	+	0.0572
Social resilience	Organizational development	Share of cases in which the director and Party secretary are held by the same person ("one-shoulder carrying")	+	0.0460

Note: "+" and "−" indicate positive and negative indicators, respectively.

the functions of agricultural resilience in provinces (autonomous regions and municipalities directly under the Central Government) within the spatial association network and their network characteristics.

1.3.4 ERGM model

Previous studies on the driving factors of agricultural resilience have mostly used the geographical detector[13] and the spatial Durbin model[2,4]. However, the former cannot explain the generation of the network topology of regional associations, while the latter, because it presupposes variable independence, neglects nonlinear interaction effects among factors. This paper selects the ERGM model as the analytical tool for driving factors. By quantitatively testing the dependence among endogenous network structural variables, actor-attribute variables, and external environmental variables, the ERGM model analyzes configurations of local network structures in the form of an exponential function and ultimately determines the overall network structure[14]. The specific model is as follows:

$$\Pr(Y = y \mid \theta) = \frac{\exp\left[\theta_\alpha^T g_\alpha(y) + \theta_\beta^T g_\beta(y,x) + \theta_\gamma^T g_\gamma(y,\bar{g})\right]}{K(\theta)} \tag{2}$$

where: $\Pr(Y = y \mid \theta)$ is the probability that, under condition θ, the explained variable y is realized in the feasible set Y; $K(\theta)$ is the normalizing term; $g_\alpha(y)$ is the "endogenous structural network statistic" that may affect the formation of the agricultural-resilience network itself; $g_\beta(y,x)$ is the network statistic reflecting the attributes of nodes (x) in the agricultural-resilience network, also called the "actor-attribute variable"; $g_\gamma(y,\bar{g})$ is the network statistic of external environmental factors $(\bar{g})$; and θ_α^T, θ_β^T, and θ_γ^T are the model coefficient vectors to be estimated.

2 Results and Analysis

2.1 Analysis of agricultural-resilience evaluation results

Using the entropy-weight method, the results for each dimension of China' s agricultural resilience from 2014 to 2023 were obtained (Fig. 1). Overall, China' s agricultural resilience rose from 0.2064 in 2014 to 0.2760 in 2023, indicating a significant improvement in agricultural resilience. In particular, in 2021, the increase in agricultural resilience

Fig. 1. Dynamic evaluation results for various dimensions of agricultural resilience in China from 2014 to 2023

the increase was marked, rising from 0.2200 in 2020 to 0.2626, with a growth rate of 19.36%. This indicates that, after China achieved a moderately prosperous society in all respects, the agricultural system improved significantly in terms of economic, production, and social resilience. By dimension, economic resilience developed the best and constitutes the core driving force supporting agricultural resilience; next is social resilience, which provides human-resource and organizational support for agricultural resilience; third is production resilience, which developed relatively slowly during 2014–2020 but improved more markedly after 2020, a change related to China's comprehensive implementation of the rural revitalization strategy; last is ecological resilience, indicating that China' s agricultural ecosystem faces considerable environmental pressures, such as severe agricultural pollution and ecological imbalance. In summary, China' s agricultural resilience generally shows an upward trend, but it also faces deep-seated structural contradictions arising from imbalanced development among dimensions. Behind this phenomenon are both objective constraints imposed by natural conditions and the pains of transforming the development model. It is therefore necessary to deepen the new development concept of shifting from "passive construction" to "active construction."

2.2 Analysis of the Characteristics of the Spatial Correlation Network of Agricultural Resilience

2.2.1 Overall network characteristics

Using the 2014-2023 relational matrix of average agricultural resilience in China, this study calculated the composite values of overall network characteristics. Combined with the overall characteristics of the spatial correlation network of agricultural resilience in each year (Fig. 2), the following findings were obtained: (1) the comprehensive network density is 0.2816, and the network density from 2014 to 2023 ranges from 0.2483 to 0.2724, indicating that the spatial correlation network of agricultural resilience as a whole has not yet formed close connections and still has considerable room for improvement; (2) the network connectedness is consistently 1, indicating that the overall network has a high degree of accessibility, and that provinces (autonomous regions and municipalities) maintain either direct or indirect connections with one another; (3) the comprehensive network hierarchy is 0.0667 and fluctuates during the observation period. The interaction among provinces (autonomous regions and municipalities) is strong, and most of them can send one-way external connections; (4) the comprehensive number of relations is 245, while the number of relations from 2014 to 2023 ranges from 216 to 238, which is still far below the maximum possible number of relations among provinces (autonomous regions and municipalities) (870), indicating that there remains considerable room for improvement in promoting linkages among provinces (autonomous regions and municipalities); (5) the comprehensive network efficiency is 0.6330. Network efficiency fluctuated between 0.5788 and 0.6650 during 2014-2019, and remained stable within the range of 0.6232-0.6379 during 2020-2023. This indicates that the efficiency of information and resource transmission in the spatial correlation network of agricultural resilience has improved, the trend toward flattening has intensified, and stability has gradually strengthened.

Fig. 2 Overall characteristics of the agricultural resilience spatial correlation network in China from 2014 to 2023

2.2.2 Individual network characteristics

Based on the 2014-2023 relational matrix of average agricultural resilience in China, centrality analysis (Table 2) was used to reveal

Tab. 2 Centrality characteristics of the spatial correlation network of average agricultural resilience across all provinces (autonomous regions, municipalities) in China from 2014 to 2023

Province (autonomous region, municipality)	Degree centrality: spillover	Degree centrality: reception	Closeness centrality: spillover	Closeness centrality: reception	Betweenness centrality
Beijing	24.14	58.62	24.79	65.91	3.97
Tianjin	17.24	13.79	24.37	46.03	0.12
Hebei	20.69	31.03	27.88	54.72	0.55
Shanxi	27.59	44.83	32.22	59.18	7.22
Inner Mongolia	24.14	37.93	27.88	52.73	2.41
Liaoning	31.03	10.34	29.00	49.15	1.93
Jilin	10.34	6.90	23.97	45.31	0.00
Heilongjiang	31.03	75.86	29.00	78.38	12.47
Shanghai	3.45	55.17	20.71	69.05	0.11
Jiangsu	10.34	55.17	25.66	69.05	4.67
Zhejiang	20.69	48.28	29.00	65.91	6.65
Anhui	24.14	51.72	31.87	67.44	10.12
Fujian	24.14	10.34	31.87	43.28	1.60
Jiangxi	27.59	31.03	34.12	46.03	3.66
Shandong	34.48	31.03	29.29	58.00	3.72
Henan	34.48	27.59	33.33	56.86	3.14
Hubei	31.03	34.48	32.95	55.77	8.97
Hunan	31.03	27.59	34.52	45.31	4.24
Guangdong	31.03	27.59	34.52	45.31	8.41
Guangxi	27.59	6.90	33.72	33.33	0.17
Hainan	24.14	24.14	33.33	35.80	3.66
Chongqing	41.38	20.69	37.66	35.80	2.06
Sichuan	37.93	17.24	37.66	39.73	8.65
Guizhou	44.83	10.34	38.67	33.33	2.10
Yunnan	37.93	10.34	38.16	28.71	2.73
Shaanxi	37.93	44.83	36.71	58.00	16.41
Gansu	20.69	6.90	34.52	24.58	0.06
Qinghai	31.03	6.90	36.25	24.58	0.46
Ningxia	34.48	0.00	55.77	3.33	0.00
Xinjiang	48.28	17.24	39.73	31.87	9.28

show the position and role of agricultural resilience in each province (autonomous region or municipality) within the spatial association network.

In the spillover spatial association network, the spillover effects of agricultural resilience are mainly concentrated in the central and western regions. Among them, the Xinjiang Uygur Autonomous Region, Guizhou Province, and

Chongqing Municipality rank among the top three in outflow values of degree centrality, all higher than 40; the Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, and Guizhou Province have closeness-centrality outflow values close to one another, all above 38.5, ranking among the top three. The main reason is that the economic structure of the central and western regions is dominated by grain production and resource development. With the improvement of transport infrastructure, the mobility of agricultural production factors, agricultural products, and agricultural labor in the central and western regions has accelerated, forming a radiating driving effect in the spatial association network of agricultural resilience.

In the receiving spatial association network, the receiving effects of agricultural resilience are mainly concentrated in the central and eastern regions. The top three provinces (municipalities) in degree-centrality receiving values are, in order, Heilongjiang Province (75.86), Beijing Municipality (58.62), Shanghai Municipality (55.17), and Jiangsu Province (55.17), with Shanghai and Jiangsu tied for third; the top three provinces (municipalities) in closeness-centrality receiving values are, in order, Heilongjiang Province (78.38), Shanghai Municipality (69.05), Jiangsu Province (69.05), and Anhui Province (67.44), with Shanghai and Jiangsu tied for second. These provinces (municipalities) are direct beneficiaries in the agricultural-resilience spatial association network; they are also the greatest beneficiaries in the network. This indicates that the central and eastern regions, relying on the prior layout of agricultural trade and transport as well as policy innovation for the transformation and upgrading of agricultural structures, have established relatively developed systems for receiving agricultural factors, and thus possess significant advantages in receiving resource, technological, or policy radiation.

The betweenness centrality of Shaanxi Province (16.41), Heilongjiang Province (12.47), and Anhui Province (10.12) is higher than that of other provinces (autonomous regions and municipalities), indicating that the three jointly undertake a "bridge" function, can better regulate agricultural-related factors, promote indirect linkages among provinces (autonomous regions and municipalities), and increase the density of the agricultural-resilience spatial association network. Conversely, the betweenness centrality of the following eight provinces (autonomous regions and municipalities) is below 1: Tianjin Municipality, Hebei Province, Jilin Province, Shanghai Municipality, Guangxi Zhuang Autonomous Region, Gansu Province, Qinghai Province, and Ningxia Hui Autonomous Region. In particular, the betweenness centrality of Jilin Province and the Ningxia Hui Autonomous Region is 0, indicating that these provinces (autonomous regions and municipalities) play almost no intermediary role in the cross-regional transmission process.

2.2.3 Clustering characteristics

To explore the clustering characteristics of China's agricultural-resilience spatial association network, this paper uses the CONCOR clustering algorithm, sets the maximum splitting depth to 2 and the convergence criterion to 0.2, and divides the research objects into four blocks for analysis of spatial clustering characteristics. Due to space limitations, the results calculated on the basis of the average agricultural-resilience relationship matrix for China from 2014 to 2023 are selected for presentation (Table 3).

China' s agricultural-resilience spatial association network can be divided into four blocks: (1) Block I is a net-beneficiary block, including Beijing Municipality, Tianjin Municipality, Hebei Province, Shanxi Province, Anhui Province, Shanghai Municipality, Jilin Province, and Zhejiang Province. It is mainly characterized by the number of inter-block receiving relations (81) being far greater than the number of spillover relations (34); in the agricultural-resilience spatial association network, it plays the role of factor absorption and transformation. (2) Blocks II and IV are both net-spillover blocks, mainly characterized by the number of inter-block spillover relations being far greater than the number of receiving relations. Block II includes Qinghai Province, Yunnan Province, Sichuan Province, Guangdong Province, Gansu Province, Jiangxi Province, Hunan Province, and Henan Province; its number of inter-block spillover relations (68) is greater than its number of receiving relations (40). Block IV includes Hainan Province, Hubei Province, Guizhou Province, Guangxi Zhuang Autonomous Region, Fujian Province, Shaanxi Province, Xinjiang Uygur Autonomous Region, and Chongqing Municipality; its number of inter-block spillover relations (76) is greater than its number of receiving relations (44). Blocks II and IV play the role of source regions in the agricultural-resilience spatial association network and exhibit spatial spillover effects. (3) Block III is a broker block, including Liaoning Province, Shandong Province, Heilongjiang Province, the Ningxia Hui Autonomous Region, the Inner Mongolia Autonomous Region, and Jiangsu Province. It is mainly characterized by the difference between the number of inter-block receiving relations (52) and spillover relations (39) being relatively smaller than in the other blocks; it is the "bridge" for linkages among provinces (autonomous regions and municipalities). (4) No bidirectional-spillover block is found in the agricultural-resilience spatial association network, indicating that, compared with the spatial association effects within blocks, spatial association effects between blocks are more evident.

According to the density matrix (image matrix) and within-block association proportions in Table 3, it can also be seen that China' s agricultural-resilience spatial association mainly depends on other blocks; the inter-block relationship coefficients are all greater than the within-block relationship coefficients, and most expected proportions are higher than the actual proportions. Within the blocks

Table 3 Division of blocks and matrix for the spatial association network of average agricultural resilience in China, 2014–2023

Tab. 3 Division of network clusters and matrix of spatial correlation for average agricultural resilience in China from 2014 to 2023

Block	Density matrix (image matrix) I	Density matrix (image matrix) II	Density matrix (image matrix) III	Density matrix (image matrix) IV	Receiving relations within block	Receiving relations between blocks	Spillover relations within block	Spillover relations between blocks	Expected proportion	Actual proportion	Block attribute
I	0.161(0)	0.031(0)	0.542(0)	0.094(0)	9	81	9	34	24.14	20.93	Net beneficiary
II	0.188(0)	0.089(0)	0.417(1)	0.563(1)	5	40	5	68	24.14	6.85	Net spillover
III	0.729(1)	0.042(0)	0.300(1)	0.042(0)	9	52	9	39	17.24	18.75	Broker
IV	0.531(1)	0.563(1)	0.125(0)	0.089(0)	5	44	5	76	24.14	6.17	Net spillover

The correlation is relatively low. As can be seen from the image matrix, a correlation exists only within Block III (i.e., the image-matrix value is 1).

2.3 Identification of Driving Factors of the Spatial Correlation Network of Agricultural Resilience

2.3.1 Variable Selection

This paper further analyzes the key driving factors of China's spatial correlation network of agricultural resilience. Referring to the study of Yang Qing et al. [15], the driving factors in the ERGM model are set as endogenous structural network variables, actor attribute variables, and external environmental variables (Table 4).

Table 4 Explanation of ERGM variables for the formation mechanism of spatial correlation networks of agricultural resilience

Tab. 4 Explanation of ERGM variables for the formation mechanism of spatial correlation networks of agricultural resilience

Variable	Schematic diagram	Hypothesis test
Arc	→	Generally treated as a constant term and not interpreted

Variable	Schematic diagram	Hypothesis test
Reciprocity		Whether provinces (autonomous regions and municipalities directly under the central government) tend to form bidirectional agricultural-resilience connections?
Cyclicity	→ → →	Whether provinces (autonomous regions and municipalities directly under the central government) tend to form triangular transmission relationships of agricultural resilience?
Connectivity	→ ; →	Whether provinces (autonomous regions and municipalities directly under the central government) tend to have relatively many sending and receiving relationships of agricultural resilience at the same time?
Clustering	→ ; →	Whether provinces (autonomous regions and municipalities directly under the central government) tend to form clustering relationships of agricultural resilience?
Sending effect	→	Whether provinces (autonomous regions and municipalities directly under the central government) tend to form agricultural-resilience sending relationships?

Variable	Schematic diagram	Hypothesis test
Receiving effect	←	Whether provinces (autonomous regions and municipalities directly under the central government) tend to form agricultural-resilience receiving relationships?
Heterophily	→	Whether provinces (autonomous regions and municipalities directly under the central government) with different attributes are more inclined to form agricultural-resilience correlation relationships?
Covariate	→; →	Whether provinces (autonomous regions and municipalities directly under the central government) that are more susceptible to the influence of the external environment are more inclined to form agricultural-resilience correlation relationships?

(1) Endogenous structural network variables

Endogenous structural network variables refer to variables determined by the internal structural characteristics of the spatial correlation network of agricultural resilience. These variables can reflect the relational patterns and structural features among provinces (autonomous regions and municipalities directly under the central government) in the network, and also affect the formation of network relationships. Referring to the approach of Shao Shuai et al. [16], this paper mainly examines reciprocity, cyclicity, connectivity, and clustering.

(2) Actor attribute variables

Each node in the spatial network is also called an actor. The influence of its attribute variables on the spatial correlation network of agricultural resilience is characterized through the "sending effect," "receiving effect," and "heterophily." Based on relevant literature [2,4,8] and data availability, the node attribute variables in this paper are selected as follows: **economic level**: reflecting the influence of economic level on the agricultural resilience network. This paper selects per capita GDP to reflect the economic level of each province (autonomous region and municipality directly under the central government). **Industrial structure**: reflecting the influence of differences in industrial structure on the agricultural resilience network. This paper adopts the share of gross agricultural output value in regional GDP as the indicator for measuring industrial structure. **Production conditions**: reflecting the influence of agricultural mechanization on the agricultural resilience network. This paper uses the ratio of total mechanical power to cultivated land area for characterization. **Scientific and technological innovation**: reflecting the influence of scientific and technological innovation on the agricultural resilience network. This paper selects the ratio of agricultural innovation input funds (enterprise input) to gross agricultural output value in each province (autonomous region and municipality directly under the central government) for characterization. **Extreme temperature**: reflecting the influence of extreme temperature on the agricultural resilience network. This paper selects the number of days on which extreme temperature events occurred throughout the year in each province (autonomous region and municipality directly under the central government) as the measurement indicator. **Extreme heavy precipitation**: reflecting the influence of extreme heavy precipitation on the agricultural resilience network. This paper selects the number of days on which extreme heavy-precipitation events occurred throughout the year in each province (autonomous region and municipality directly under the central government) as the measurement indicator.

(3) External environmental variables

The continuously expanding trade network and the sustained implementation of regional integration policies have caused every link of agricultural activities in each province (autonomous region and municipality directly under the central government) to become intertwined with and permeate one another. Because agricultural production materials and agricultural products are difficult to preserve and require short transportation time limits, they are often constrained by geographical distance in economic activities. In view of this, drawing on the study of Shao Shuai et al. [16], this paper constructs a geographical-neighbor proximity network and a trade network matrix to examine the influence of geographical distance and economic activities on the formation of the spatial correlation network of agricultural resilience. Specifically, the construction of the geographical-neighbor proximity network is as follows: for the geographical distance between provincial capital cities, four geographical-distance intervals —$[0, 500]$, $[500, 1000]$, $[1000, 1500]$, and $[1500, 2000]$ (unit: km)—are selected to measure the geographical-neighbor effect between provinces (autonomous regions and municipalities directly under the central government). When the geographical distance between provincial capital cities falls within the corresponding geographical interval, the corresponding matrix element is assigned a value of 1; otherwise it is assigned 0. The geographical-neighbor networks are denoted as $D[0, 500]$, $D[500, 1000]$, $D[1000, 1500]$, and $D[1500, 2000]$, respectively.

2.3.2 Analysis of Driving Factors of the Spatial Correlation Network of Agricultural Resilience

First, using the 2014–2023 annual average agricultural resilience as the benchmark sample, this paper estimates the ERGM. Then, the driving factors in the formation of the spatial correlation networks of agricultural resilience in 2014 and 2023 are identified separately (Table 5). To visually express the interaction of the three driving factors behind the spatial correlation network of agricultural resilience, this paper selects the 2014–2023 annual average agricultural resilience as the benchmark sample to draw a mechanism diagram (Figure 3).

(1) Influence of endogenous network structure

The coefficient of the arc in models (1)-(3) is negative and significant, indicating that the formation of the spatial correlation network of agricultural resilience is nonrandom. [[unclear: continuation begins with the character "互"]]

Table 5 ERGM Model Estimation Results

Tab. 5 Estimation results of ERGM model

Variable	Model (1)2014–2023Mean	Model (2)2014	Model (3)2023
Arc	$-5.18^{**}(1.64)$	$-3.83^{*}(1.53)$	$-9.12^{***}(1.44)$
Reciprocity	$2.49^{***}(0.38)$	$-0.64(0.34)$	$2.53^{***}(0.42)$
Connectivity	$-0.03(0.05)$	$-0.15^{***}(0.04)$	$-0.03(0.05)$
Cyclicity	$-0.86^{***}(0.18)$	$0.12(0.15)$	$-1.05^{***}(0.21)$
Clustering	$0.32(0.17)$	$0.41^{*}(0.19)$	$0.26(0.16)$
Sender effect (economic level)	$4.62^{***}(0.78)$	$0.74(1.69)$	$6.91^{***}(0.89)$
Receiver effect (economic level)	$0.93(0.95)$	$-1.95(1.65)$	$2.46(1.26)$
Heterophily (economic level)	$-2.32^{**}(0.69)$	$-0.83(1.42)$	$-2.11^{**}(0.79)$
Sender effect (industrial structure)	$1.98^{*}(0.98)$	$1.94(1.16)$	$3.99^{***}(1.05)$

Variable	Model (1)2014–2023Mean	Model (2)2014	Model (3)2023
Receiver effect (industrial structure)	0.13(1.03)	−0.01(1.14)	1.60(1.07)
Heterophily (industrial structure)	3.69***(0.84)	−0.58(1.03)	2.59**(0.83)
Sender effect (production conditions)	1.81**(0.57)	0.99(0.65)	1.91*(0.86)
Receiver effect (production conditions)	−0.08(0.53)	−0.32(0.63)	−0.65(0.78)
Heterophily (production conditions)	0.39(0.58)	2.68***(0.78)	−0.64(0.88)
Sender effect (scientific and technological innovation)	0.37(0.61)	1.70*(0.70)	1.38(0.76)
Receiving condition (scientific and technological innovation)	−0.65(0.63)	−0.12(0.72)	−0.65(0.69)
Heterophily (scientific and technological innovation)	−0.78(0.53)	0.09(0.69)	−0.50(0.57)
Sender condition (extreme temperature)	−3.10***(0.85)	1.41(1.05)	0.92(0.58)
Receiver condition (extreme temperature)	−0.66(0.83)	3.19**(1.11)	−0.02(0.58)
Heterophily (extreme temperature)	−2.13*(0.90)	−1.11(1.27)	−1.54*(0.64)

Variable	Model (1)2014–2023Mean	Model (2)2014	Model (3)2023
Sender condition (extreme heavy precipitation)	$1.22^{*}(0.60)$	$-0.79(1.82)$	$2.27(2.12)$
Receiver condition (extreme heavy precipitation)	$1.41^{*}(0.64)$	$-2.41(1.84)$	$-0.26(1.91)$
Heterophily (extreme heavy precipitation)	$-0.71(0.57)$	$-3.14(1.87)$	$2.04(2.14)$
$D[0, 500]$	$3.76^{***}(0.61)$	$3.96^{***}(0.69)$	$2.81^{***}(0.59)$
$D[500, 1000]$	$2.56^{***}(0.52)$	$2.88^{***}(0.59)$	$1.95^{***}(0.52)$
$D[1000, 1500]$	$1.33^{**}(0.43)$	$2.06^{***}(0.48)$	$1.04^{*}(0.44)$
$D[1500, 2000]$	$0.77^{*}(0.40)$	$1.48^{**}(0.47)$	$0.70(0.42)$
Trade network	$0.56^{*}(0.28)$	$0.51(0.31)$	$0.95^{**}(0.31)$
AIC	702.03	791.65	671.24
BIC	835.55	925.17	804.76

Note: , , *and* indicate that the parameters are significant at the 1%, 5%, and 10% levels, respectively; values in parentheses are standard errors; AIC is the Akaike information criterion; BIC is the Bayesian information criterion; $D[0, 500]$, $D[500, 1000]$, $D[1000, 1500]$, and $D[1500, 2000]$ are geographic proximity networks constructed according to geographic distance intervals between provincial capital cities ($[0, 500]$, $[500, 1000]$, $[1000, 1500]$, and $[1500, 2000]$, in km).

The reciprocity coefficient changes from negative to positive and becomes significant, indicating that mutually beneficial, win–win cooperation has improved the agricultural resilience of both sides; over time, this attracts more provinces (autonomous regions and municipalities directly under the central government) to continuously evolve the spatial association network toward mutual benefit and reciprocity. Connectivity is nearly zero and significant in all models, indicating that the spatial association network generally exists in a relatively loose state of connection among provinces (autonomous regions and municipalities directly under the central government), with insufficiently close interaction and ties. Third-party participation in agricultural activities is limited, and the functions of the broker sector remain to be explored. Cyclicity is mainly significantly negative in the models, indicating that "triangular" active transmission relationships are relatively rare in the spatial association of agricultural resilience, which instead mainly exists in the form of passive gradient transfer. Therefore, relying solely on the spontaneous transfer of the agricultural-resilience spatial association network cannot achieve the optimal state; "water diversion and canal repair" through government regulation is still needed. Clustering is positive in all models and significant only in Model (2), indicating that regional small groups existed in the early stage of the agricultural-resilience spatial association network, but were later replaced by broad reciprocal cooperation. This reflects the evolution of the agricultural-resilience spatial association network from local cohesion to region-wide linkage.

(2) Effects of actor attributes

Economic level. In the 2014–2023 mean model, the sender effect of economic level is significantly positive, while the receiver effect is positive but not significant, indicating that a higher economic level helps strengthen external resilience ties, but receiving associations are relatively localized. The heterophily effect is significantly negative, reflecting stronger ties among provinces (autonomous regions and municipalities directly under the central government) with similar economic levels, and weaker ties otherwise; this reveals imbalanced regional development and the need for complementary cooperation.

Industrial structure. In the 2014–2023 mean model, both the sender effect and receiver effect of industrial structure are positive, but only the sender effect passes the significance test. This indicates that provinces (autonomous regions and municipalities directly under the central government) with a lower Herfindahl index play a leading role in the agricultural-resilience spatial association network, transmitting production technology and management experience outward through spatial spillovers. Heterophily changes from a negative and nonsignificant value in 2014 to a positive and significant value in 2023; together with the positive and significant coefficient in the 2014–2023 mean model, this reveals a trend in which network actors shift from tending toward homogeneous ties to establishing heterogeneous ties.

Production conditions. The sender effects of production conditions in all models are positive, and are significant in Models (1) and (3), indicating that provinces (autonomous regions and municipalities directly under the central government) with good production conditions can use policies to consolidate their network advantages and play a demonstrative role in strengthening overall associations. Their receiver effects are negative in all models, meaning that provinces (autonomous regions and municipalities directly under the central government) with relatively lagging production conditions require coordination with other conditions in order to receive effectively. The heterophily effect is partially significant, revealing that the allocation of agricultural production resources is in a suboptimal state due to regional imbalance.

Scientific and technological innovation. The sender effect in all models is positive, and compared with 2014, the coefficient in 2023 becomes nonsignificant, reflecting that technological diffusion may be shifting from concentrated output by core nodes to a flattened model of multi-node collaboration, echoing the trend discussed above. The receiver effect is negative but not significant, indicating that technological flows depend not only on the scientific and technological levels of provinces (autonomous regions and municipalities directly under the central government) themselves, but are also affected by policy regulation. Heterophily is negative but not significant, indicating that provinces (autonomous regions and municipalities directly under the central government) with similar scientific and technological levels are more likely to establish associations.

Figure 3. Mechanism of the driving factors of the spatial correlation network of agricultural resilience

- **Endogenous network structure → Driving mechanism**
  - Reciprocity → Synergistic effect (+***)
  - Reciprocity → Complementary effect (+***)
  - Connectivity → Brokerage pattern (-)
  - Cyclicality → Network closure (-***)
  - Cyclicality → Brokerage pattern (+***)
  - Clustering → Preferential attachment (+)
- **External environmental factors → Driving mechanism**
  - Geographic distance → Proximity mechanism (+***)
  - Trade network → Spatial linkage (+*)
- **Evolution of China' s agricultural-resilience spatial correlation network**
  - Establishment and connection of network correlations
  - "Spatial dependence" of spatial structure
  - "Path dependence" of topological structure
- **Driving mechanism –Carrier form –Actor attributes**
  - Driving mechanisms: positive incentive; reverse inhibition; preferential attachment
  - Carrier forms: sending effect; receiving effect; disassortative effect
  - Actor attributes: economic level; industrial structure; production conditions; scientific and technological innovation; extreme temperature; extreme heavy precipitation
  - The visible arrows are marked with significance/direction symbols including +***, +**, +*, -*, and *.

Note: + indicates a positive effect; - indicates a negative effect; ***, **, and * indicate that the parameter is significant at the 1%, 5%, and 10% levels, respectively.

图 3 农业韧性空间关联网络驱动要素的作用机制

Fig. 3 Mechanism of driving factors of agricultural resilience spatial correlation network

Extreme temperature. In the 2014-2023 mean-value model, the sending effect of extreme temperature is negative and significant, indicating that, by intensifying ecological constraints and raising operating costs, it weakens the agricultural output and technological-diffusion capacity of the affected provinces, autonomous regions, and municipalities directly under the central government. The receiving effect is negative but not significant, reflecting that the shocked peripheral nodes have not effectively become focal points of network support. Disassortativity is significantly negative, indicating that correlations among provinces, autonomous regions, and municipalities directly under the central government with large temperature differences are relatively weak; this reveals segmentation in the spatial correlation network of agricultural resilience at the level of climate adaptation.

Extreme heavy precipitation. In the 2014–2023 mean-value model, both the sending and receiving effects of extreme heavy precipitation are positive and significant, indicating that provinces, autonomous regions, and municipalities directly under the central government where such events occur frequently are more inclined to initiate external connections and are also more likely to become objects of correlation. This mainly stems from the demand for cross-regional collaboration and support generated by flood disasters. Disassortativity is negative but not significant, reflecting that precipitation differences do not constitute a significant barrier to linkage; to a certain extent, this shows that the spatial correlation network of agricultural resilience possesses integration and complementarity capabilities when responding to this type of extreme climate.

(3) External environmental influence

In the geographical-proximity network, all models are significantly positive, indicating that the spatial correlation of agricultural resilience is highly dependent on geographical proximity. Its coefficient decreases as distance increases, reflecting that the network tends to become sparse with geographical extension. At short distances, information circulation is convenient and cooperation costs are low, which is conducive to close linkages; at long distances, however, factors such as information-transmission costs and administrative barriers significantly inhibit cross-regional linkage.

The trade-network variable is significantly positive, indicating that interregional economic activities are conducive to the formation of the spatial correlation network of agricultural resilience. Spatial correlation develops gradually from local spatial correlation into global spatial correlation. The implementation of development strategies in various regions of China has effectively stimulated regional economic vitality, enhanced agricultural resilience in each region, and laid a solid foundation for improving overall agricultural resilience.

The goodness-of-fit test results (Figure 4) show that the model passed the convergence diagnosis using the Markov chain Monte Carlo method (MCMC), and that the fitting results are good, enabling effective explanation of the structural characteristics of the spatial correlation network of agricultural resilience.

3 Discussion

Against the background of a highly variable global climate and intensified internal and external uncertainty risks, identifying the characteristics and driving factors of the spatial correlation network of agricultural resilience is of important strategic significance for responding to the construction of an agricultural power and enhancing the resilience of the agricultural industry. In constructing the indicator system, this paper breaks through the emphasis in existing literature on the three dimensions of economy, production, and ecology, adds consideration of the social dimension, and constructs a four-dimensional framework of "economy-production-ecology-society," providing new ideas for future research. At the same time, unlike previous literature that independently studies the driving factors of agricultural resilience, this paper instead focuses on the interactive effects formed among influencing factors within the spatial correlation network, and uses the modified gravity model, social network analysis, and the ERGM model to examine the characteristics and driving factors of the spatial correlation network of agricultural resilience···

(a) Node-proportion distribution of out-degree
Vertical axis: Node proportion; horizontal axis: Out-degree

(b) Node-proportion distribution of in-degree
Vertical axis: Node proportion; horizontal axis: In-degree

Legend:
- Characteristic statistic of the original observed network
- Measurement results for simulated networks under the 95% confidence interval
- Boundary lines of the 95% simulation interval
- Statistic calculated from the real observed network data

(c) Proportional distribution of edgewise shared partners
Vertical axis: Proportion; horizontal axis: Edgewise shared partners

(d) Dyad-proportion distribution of minimum geodesic distance
Vertical axis: Dyad proportion; horizontal axis: Minimum geodesic distance

Note: NR indicates that no reachable path exists between nodes; that is, the minimum geodesic distance is infinite.

Fig. 4 GOF test results for the ERGM model of the mean agricultural-resilience correlation network from 2014 to 2023

However, because the analytical scale of this article is limited to the provincial level, it remains relatively macro in scope; future research may be extended to more micro-level prefecture-level cities or counties.

The results of this study show that agricultural resilience does not exist in isolation in space, but rather forms an interconnected network. This conclusion is similar to that of Wang Yafei et al. [4]. In addition, the formation of the spatial correlation network of agricultural resilience is inseparable from the interactive effects of economic conditions, industrial structure, production conditions, and extreme climate; moreover, the evolution of the network will in turn affect the dynamic mechanism of scientific and technological innovation diffusion. It can therefore be seen that coordinated linkage among provinces, autonomous regions, and municipalities directly under the central government plays an important role in improving agricultural resilience.

Based on the above research conclusions, this paper proposes the following recommendations. First, strengthen the multidimensional coordinated development of agricultural resilience, with emphasis on remedying shortcomings in ecological resilience. For ecologically fragile areas such as the Xinjiang Uygur Autonomous Region, Shanghai Municipality, and Jiangsu Province, appropriate technical measures should be adopted to reduce agricultural non-point-source pollution, and agriculture should be developed in accordance with the characteristics of local natural resources and the environment. Second, optimize the regional functional layout of agricultural resilience and enhance the linkage effects among provinces, autonomous regions, and municipalities directly under the central government. For central and western regions dominated by resource spillover, such as the Xinjiang Uygur Autonomous Region, Guizhou Province, and Yunnan Province, the development focus should be on ensuring resource supply and protecting the ecological-conservation value of agricultural production. For central and eastern regions dominated by resource reception, such as Beijing Municipality, Shanghai Municipality, and Jiangsu Province, the development focus should be on keeping channels for factor reception unobstructed and developing new agricultural production models oriented toward market demand. For regions that serve as "bridges" in the spatial correlation network of agricultural resilience, such as Shaanxi Province, Heilongjiang Province, and Anhui Province, digital service centers for agricultural factors may be established to promote cross-regional coordinated development. Third, promote the high-quality development of the spatial correlation network of agricultural resilience. Guided by demand, adjust the agricultural industrial structure; increase fiscal expenditure on agriculture, forestry, and water affairs, and provide fiscal support for industrial transformation; strengthen soil- and water-loss control to achieve sustainable agricultural ecological development; and establish an extreme-climate response mechanism to improve the joint prevention function of the spatial correlation network of agricultural resilience.

4 Conclusion

(1) China's agricultural resilience as a whole shows a steadily improving trend, but differences among dimensions are significant. Among them, economic resilience and social resilience perform relatively well, whereas the development of production resilience and ecological resilience is relatively lagging, highlighting the imbalance in the internal development of the agricultural system and the challenges faced by sustainable development.

structural challenges.

(2) China' s spatial association network of agricultural resilience shows a flattening trend, but a close association has still not formed. The association degree of the agricultural-resilience network is 1, indicating a highly accessible network; however, most nodes still maintain one-way associations, and the correlation coefficient has not yet reached its peak, so there remains considerable room for improvement in network density. Network density shifts dynamically from 0.5788–0.6650 to a stable period of 0.6232–0.6379, entering a stage of flattened and coordinated development.

(3) China' s spatial association network of agricultural resilience has a "west-central–east" radiation path, and the broker function still needs to be further explored. Provinces (autonomous regions and municipalities directly under the central government) with strong spillover effects are mostly concentrated in the central and western regions; provinces (municipalities) with strong receiving effects are more often found in the central and eastern regions; and the intermediary function is centered on Shaanxi Province in the central region. In the network, nearly one-third of provinces (autonomous regions and municipalities directly under the central government) have an intermediary centrality of less than 1, and their broker function needs to be activated.

(4) The formation of China' s spatial association network of agricultural resilience is the result of the joint action of endogenous structures and exogenous drivers. Among them, endogenous structures such as reciprocity and cyclicity promote the formation of the agricultural-resilience network. Economic level, production conditions, industrial structure, and extreme heavy precipitation are the core driving forces for the formation of the agricultural-resilience network, while geographic proximity and trade flows are important external driving forces for the formation of the agricultural-resilience network.

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Characteristics of agricultural resilience spatial correlation network and identification of driving factors in China

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Abstract: Based on panel data from 30 provinces, autonomous regions, and municipalities in China from 2014 to 2023, this study employs the entropy weight method, social network analysis, and exponential random graph models to systematically examine the structural characteristics and driving factors of the spatial correlation network of agricultural resilience in China. The results indicate that (1) Agricultural resilience shows a steady upward trend, although development across dimensions remains uneven. Economic and social resilience perform relatively well, whereas production and ecological resilience lag behind. (2) The spatial correlation network of agricultural resilience exhibits a flat development trend. Although the overall network remains highly accessible, close correlations have not yet formed, and most provinces, autonomous regions, and municipalities maintain one-way correlations. (3) The spatial correlation follows a "west-central-east" radiation path. Net spillover sectors are mainly concentrated in the central and western regions, whereas net benefit sectors are primarily distributed in the central and eastern regions, and the broker sector still requires substantial improvement. (4) The formation of spatially correlated networks of agricultural resilience in China results from the interplay of endogenous structures, actor attributes, and external environments. Endogenous structures such as reciprocity and circularity promote the formation of the agricultural resilience network. Economic level, production conditions, industrial structure, and extreme heavy rainfall are the core driving forces for the formation of the agricultural resilience network, while geographical proximity and trade are important external driving forces.

Keywords: agricultural resilience; spatial correlation network; social network analysis; exponential random graph model

Note: Figure translations are in progress. See original paper for figures.