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RECEIVED 07 December 2025

REVISED 15 February 2026

ACCEPTED 18 February 2026

PUBLISHED 03 March 2026

CITATION

Zhao Y, Feng Y, Li Z, Zhang Z and
Chen L (2026) Spatiotemporal evolution
and network dynamics of climate
resilience in China's food production.
Front. Sustain. Food Syst. 10:1762349.
doi: 10.3389/fsufs.2026.1762349

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Spatiotemporal evolution and network dynamics of climate resilience in China's food production

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Background: Agriculture and food security are key areas for climate change adaptation efforts. Amid the interplay between climate change and coordinated regional development, revealing the spatiotemporal evolution and network dynamics of China's food production resilience holds significant theoretical and policy implications for synergistically enhancing resilience and promoting regional balance.

Methods: Based on statistical measurements of climate resilience in food production (CRFP), this paper comprehensively analyzes the evolutionary characteristics and driving factors of China's CRFP from the perspectives of spatiotemporal dynamics, regional disparities, and spatial correlation networks.

Results: The research results indicate that China's CRFP showed an overall upward trend from 2000 to 2022, but exhibited fluctuations and regional disparities, along with strong spatial dependence and spillover effects. Since 2006, the eastern region has surpassed other areas in terms of CRFP, and the gap has gradually widened, while the resilience level in the northeastern region is relatively low and more volatile. Additionally, China's CRFP demonstrates extensive spatial correlation network characteristics, with increasingly tighter and more complex. The main driving factors influencing the spatial correlation network of CRFP include spatial geographic location, disparities in economic development levels, differences in industrial structure, and variations in agricultural mechanization levels.

Conclusion: The findings provide a quantitative basis and decision-making support for enhancing China's CRFP and regional coordination, while also offering empirical evidence to advance interdisciplinary research at the intersection of climate change and food security.

KEYWORDS

climate resilience in food production, convergence characteristics, network structure, QAP regression, spatial correlation network

1 Introduction

Food security is not only a crucial factor influencing national livelihoods, national security, and the stability of economic and social development, but also a fundamental cornerstone for achieving Chinese-style modernization. Since the 18th National Congress of the Communist Party of China, food security has been elevated to a paramount concern in national governance.

China has introduced a novel approach to food security, advocating for “ensuring basic self-sufficiency in grain and absolute security in staple foods”. The 14th Five-Year Plan outlines specific measures for food security, emphasizing the need to stabilize acreage, increase yield per unit, enhance quality, and consolidate and improve food production capacity. The 2023 Government Work Report emphasizes anchoring the goal of building an agricultural powerhouse, promoting a broader view of agriculture and food, and advancing the construction of national food security industrial belts. Food production security forms the critical foundation of overall food security. However, the uncertainties surrounding global food production security have significantly increased. In particular, as global warming intensifies and extreme weather and climate events happen frequently, risks from climate change have turned into a key factor impacting global food production security (Mirón et al., 2023; Gyamerah et al., 2023). The Food and Agriculture Organization (FAO) points out that extreme weather events brought about by climate change, such as rising temperatures and changing precipitation patterns, are threatening the stability of global food production. Many countries around the world, especially those that are heavily reliant on agriculture, face a series of challenges such as declining crop yields, increasing production uncertainty, and rising food security risks. As the largest developing country and a major grain producer, China has increasingly experienced the impact of extreme climate change on agricultural production in recent years, including extreme heatwaves, prolonged droughts, and severe flooding. These climatic factors not only directly affect crop yields but also indirectly impact the stability of agricultural ecosystems. This gives rise to a sequence of issues including soil degradation, shortages of water resources, and frequent pest and disease outbreaks. Moreover, climate change has exacerbated regional imbalances in food production, particularly in areas that have long relied on agriculture, where the impact of climate change is particularly pronounced. This spatiotemporal evolution not only influences the distribution of food production in China but also heightens regional risks to food supply. In this context, the “National Strategy for Climate Change Adaptation 2035” introduced by China in 2022, designates agriculture and food security as one of the priority areas for climate change adaptation. However, a pressing empirical question remains: amid intensifying climate change, do food production systems across different regions of China possess comparable climate adaptive capacity? If significant regional disparities exist, are they becoming entrenched, widening, or converging? More importantly, does the CRFP evolve independently across provinces, or does it exhibit spatial interdependence? Balancing resilience-building with the narrowing of regional disparities is both a strategic imperative for ensuring medium- to long-term food security and a practical entry point for advancing sustainable agricultural development. The complexity of this issue lies not only in the multi-dimensional nature of resilience, but also in the spatial correlation characteristics of interregional interdependence, risk transmission, and adaptive synergy. Answering these questions can provide quantitative evidence to support the optimization of national governance frameworks for climate adaptation in food security, and to facilitate the transition of the *National Strategy for Climate Change Adaptation 2035* from macro-level planning toward more targeted implementation.

For the purpose of examining the stability and adaptability of food production amid the growing intensification of climate change, Fang et al. (2024) introduced the concept of the Climate Resilience of Food Production (CRFP), defining it as the capacity of food production to accommodate climate change impacts. However, research on the

spatiotemporal analysis of China’s CRFP remains limited. In light of this, this paper employs diverse methodologies from assorted angles to carry out a thorough examination and explanation of how China’s CRFP evolves across time and space. The findings are of significant importance for understanding the vulnerable links in the food production system, optimizing food production layouts, and enhancing the accuracy and applicability of policy-making.

There are two main categories of existing research closely related to this study. The first category focuses on the measurement and analysis of food production resilience. In terms of constructing statistical measurement indicator systems, current research mainly focuses on three aspects: resistance, adaptability, and recovery. However, there are differences in the focus of the indicator systems developed by different scholars. For instance, Ge et al. (2017); Zampieri et al. (2020); Fang et al. (2024); Li et al. (2024); and Wang et al. (2024) have measured and analyzed food production resilience from different perspectives and using various methods. Regarding the measurement results, conclusions from different studies still show discrepancies. For example, Ge et al. (2017) conducted an analysis to pinpoint the adaptability issues of China’s food production system through the lens of spatial resilience, and discovered that the resilience inherent in China’s food production system not only depends on changes in agricultural technology and policies but is also closely related to the distribution of resources, climate conditions, and socioeconomic factors across regions. The measurement results of Zheng H. et al. (2024) and Zheng J. et al. (2024) indicate that the overall degree of China’s CRFP has seen a yearly upward trend, even though the growth rate has decelerated in recent years. Research by Zuo and Ye (2024) found that food production resilience in China exhibits imbalance, but there is a regional convergence trend. The above studies suggest that, under different shock conditions, the measurement results of food production resilience will show variability. This also indicates that food production is highly sensitive to external shocks, and any change in external production conditions can bring about impacts and disruptions to food production. Therefore, improving food production resilience requires a comprehensive consideration of multiple factors. The second category of literature centers on how climate change impacts food production. The findings of these studies indicate that climate change, especially extreme weather events, has serious adverse effects on food systems. It not only causes crop yields to drop but also disrupts the stability of food industry and supply chains. Research by Mirón et al. (2023) found that extreme weather increases the uncertainty of food production, while studies by Subedi et al. (2023) and Gomez-Zavaglia et al. (2020) suggest that climate change harms food production and food security through channels such as rising temperatures, changing precipitation patterns, water resource shortages, and soil degradation. The cumulative evidence establishes climate change as the predominant determinant influencing agricultural productivity. Fang et al. (2024) introduced the concept of food production climate resilience, offering new perspectives and methods for exploring food production security issues within the framework of the new economic development pattern.

Drawing on the aforementioned analysis, it is evident that current research primarily has following deficiencies: First, it primarily focuses on the measurement and analysis of food production resilience, with a lack of research on CRFP. Second, when examining how climate change affects food systems, many studies explore the extent and mechanisms of climate change’s impact on crop yields and food security. However, there is a lack of comprehensive measurement studies on food

production climate resilience and analysis of its spatiotemporal differences. In light of this, this paper takes CRFP as the research subject and specifically analyzes and discusses the following aspects: First, a comprehensive statistical evaluation indicator system incorporating climate change factors is constructed to statistically measure China's CRFP. Second, using methods such as Kernel density estimation, σ -convergence, Dagum Gini coefficient, Markov chain, and β -convergence, a comprehensive analysis is conducted on the trends, characteristics, causes of variation, spatial distribution features, and regional disparities of China's CRFP in both temporal and spatial dimensions. Furthermore, QAP regression is adopted to identify and test the core driving factors of spatial correlation networks. The aim is to provide more information for comprehending the spatial and dynamic evolutionary traits of China's CRFP. The research objectives and marginal contributions of this paper are as follows: on one hand, this research provides a basis for formulating differentiated agricultural adaptation policies for different regions, helping local governments develop more scientific and effective agricultural policies in response to climate change, thereby improving regional CRFP. On the other hand, it offers strong empirical support for ensuring food production security, reducing ecological and environmental issues caused by climate change, and achieving sustainable development goals. In addition, the research results can also offer China's experience for devising and enforcing international climate policies, contributing wisdom to global food production systems' responses to climate change.

2 Theoretical analyses

2.1 Theoretical analysis and indicator construction of CRFP

In economics, "resilience" typically denotes the ability of an economy to withstand shocks and restore itself to its previous growth trajectory or explore new growth paths through its self-regulation and recovery mechanisms when faced with disruptions in economic growth. Wang et al. (2025a,b) introduced resilience into the study of

sustainable development in the construction industry and expanded the boundaries of resilience theory and its methodologies. These research methods and findings deepen the theory of sustainable development and provide theoretical insights for the study of cross-regional collaborative governance in the economic field. Hodbod and Eakin (2015) introduced the concept of "resilience" into food production systems, defining food production resilience as "the capacity of the food production system to react, adjust, and ensure continuity in the face of risk shocks." Fang et al. (2024) incorporated climate factors into the food production resilience framework and proposed the concept of climate resilience in food production, summarizing it as the ability of food production to adapt to climate change. To evaluate the spatio-temporal evolution trends and spatial correlation network characteristics of CRFP in China, this paper incorporates climate conditions and related climatic factors as important input and output components within the food production system based on the analytical framework proposed by Fang et al. (2024). On this basis, a theoretical framework for the analysis of CRFP is constructed (depicted in Figure 1). This study focuses on climate resilience, that is, the ability of the food production system to maintain and restore stable output under climate shocks, rather than the capacity to achieve maximum output from given inputs. In other words, the design of the CRFP indicators in this paper emphasizes capturing the adaptive capacity of the system, rather than simply measuring food production efficiency.

Specifically, climate conditions, as key input factors affecting the food production system, include various aspects such as temperature, humidity, and drought and flood conditions. Referring to the study by Fang et al. (2024), this paper selects environmental input indicators, including maximum temperature, minimum temperature, extreme high temperature, extreme low temperature, rainfall, rainfall intensity, number of drought days, and forest cover. Among these, temperature significantly influences the production cycle, photosynthesis, pest and disease occurrence, pollination rate, and grain setting rate of food crops. Suitable temperatures can promote photosynthesis in food crops and improve pollination and grain setting rates. However, extreme high or low temperatures can affect normal crop production and reduce food yield. Extreme high temperatures may accelerate the crop production cycle, causing early heading and

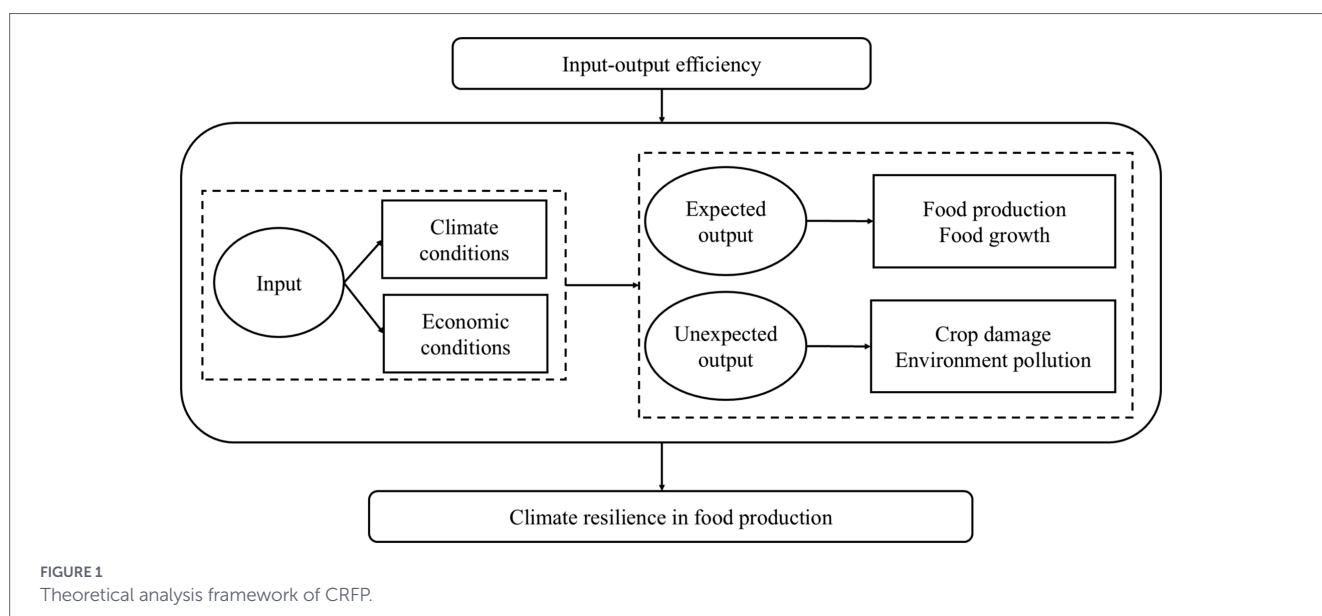


FIGURE 1
Theoretical analysis framework of CRFP.

flowering, leading to insufficient fruit development and reduced yields; it might likewise generate advantageous circumstances for the proliferation of pests and pathogens, elevating the likelihood of crop impairment (Lesk et al., 2016; Kumar et al., 2022). Extreme low temperatures suppress photosynthesis, respiration, and other physiological activities, thereby affecting the growth rate and yield of crops. It may even lead to a slowdown or stagnation in the development of some crops, causing irreversible damage to them (Thakur et al., 2010). Furthermore, suitable rainfall is also a necessary condition for crop growth (Shortridge, 2019). Water is a key factor in essential physiological processes such as photosynthesis, nutrient transport, and cell expansion in crops. Appropriate rainfall can meet the water requirements of crops. Rainfall is also an important factor affecting soil moisture. Adequate rainfall helps maintain the soil's optimal moisture levels, which is beneficial for crop root systems to absorb water and nutrients, promoting crop growth and ensuring yield. However, extreme rainfall (flooding) or extreme drought (lack of rainfall) will harm the normal growth of crops and reduce yields. Flooding disasters have a direct impact on food production by submerging crops, while their indirect effects include the onset of pests and diseases, damage to agricultural infrastructure, and even long-term soil pollution. Droughts also have a devastating impact on food production (Begna, 2021), directly preventing crops from obtaining sufficient water and simultaneously reducing the solubility of soil nutrients, which hinders crops from effectively absorbing essential nutrients such as nitrogen, phosphorus, and potassium. In addition, forest cover is a major indirect factor affecting food production (Yamamoto et al., 2019). Forests influence food production by regulating temperature and humidity, protecting soil structure, and maintaining biodiversity. The economic conditions of food production include various aspects such as land, seeds, fertilizers, agricultural machinery, and energy. Based on Fang et al. (2024), this paper selects crop planting density as an economic input indicator. An appropriate crop planting density benefits crops by ensuring sufficient sunlight, adequate soil nutrients, and water, reducing spatial competition between crops, and ultimately increasing crop yield.

The direct expected output of food production is yield. The level of crop yield not only reflects the overall production efficiency of crops but also serves as a crucial guarantee for achieving the expected economic returns. Additionally, the growth rate of crop yield is an important component of expected output. An increase in crop yield reflects the improvement of agricultural input–output efficiency, and it is of significant importance for food security, social stability, and sustainable development. The non-expected outputs of food production include crop damage and environmental pollution. Crop damage not only leads to a reduction in food yield and economic losses but also affects food quality. For example, pests and diseases can infect crops, causing a decline in quality and impacting the nutritional value and safety of the food, thereby posing further risks to consumer health. Based on Fang et al. (2024), this paper uses the proportion of crops affected by disasters as an indicator to measure the severity of crop damage. Pollutant emissions are an important component of unintended outputs in food production, including carbon dioxide, methane, nitrogen compounds, phosphorus compounds, particulate matter (such as PM_{2.5} and PM₁₀), and organic pollutants. The emission of these pollutants exacerbates environmental pollution, harms human health, and is detrimental to sustainable development. This paper, referencing Lu et al. (2020), uses carbon emissions as a measure of environmental pollution output.

2.2 Theoretical analysis of the dynamic evolution of CRFP

As global climate change issues become increasingly prominent, such as global warming, air pollution, soil degradation, and water resource scarcity, the frequency of extreme weather and climate events is gradually increasing. This poses varying degrees of impact on food production. For instance, in 2003, the European heatwave caused a sharp decline in crop yields, especially wheat and corn (Ciais et al., 2005). In 2008, rare low temperatures, snowfall, and freezing weather in southern China caused severe damage to crops, fruit trees, and livestock (Feng et al., 2021), especially in areas including Guangdong, Guangxi, Hunan, and Guizhou. Economic crops like citrus and tea were affected by frost, and livestock died in large numbers due to insufficient feed supply and cold weather. The abnormal heatwaves and droughts in Russia and Eastern Europe in 2010 resulted in a drastic decline in Russia's grain output (Hunt et al., 2021). This highlights that the impact of extreme weather and climate events will affect the dynamic trend of CRFP. Furthermore, the continuous advancement of technological innovation in the agricultural sector has not merely boosted agricultural production efficiency yet also strengthened the capacity of food production systems to forecast and cope with climate risks (Popescu et al., 2022). For example, agricultural meteorological early warning systems can utilize modern meteorological satellites, sensors, and data processing systems to predict future extreme weather patterns and propose response strategies, thereby minimizing the risks to agricultural production. The development and application of smart agriculture information platforms can integrate data from multiple sources, such as meteorology, soil, crops, and markets, providing farmers with personalized production advice, improving production efficiency, and offering decision support during extreme weather events. Precision agriculture leverages advanced sensors and automation control systems to monitor soil moisture, crop growth status, and nutrient requirements in real time. It allows for the timely identification of issues such as pest and disease outbreaks, and water shortages, enabling precise irrigation and fertilization, reducing water waste, and improving crop yield and resource utilization efficiency. Crop varieties developed via genetic engineering and modern molecular breeding technologies, which exhibit enhanced tolerance to abiotic and biotic stresses including drought, flooding, pests, and saline-alkaline soils, can enhance food production's ability to adapt to extreme weather, thereby increasing crop yields. This demonstrates that scientific and technological advancements are another important factor influencing the dynamic trend of CRFP.

Furthermore, according to the first law of geography, all geographical phenomena are interrelated in their spatial distribution (Klippel et al., 2011). Wang et al. (2023, 2025c) demonstrated in their research on the sustainable development of the construction industry that spatial correlation is a crucial factor influencing cross-regional collaborative policy formulation and the promotion of the circular economy. Therefore, the level of CRFP in one region will also impact the CRFP in other regions, especially neighboring areas. The flow of production factors is more likely to occur between neighboring regions. For example, when a region has well-developed agricultural infrastructure and a high level of smart agriculture technology, its CRFP will be enhanced. Meanwhile, since the technology and experience from this region are more likely to spread to neighboring areas, it can subsequently promote the improvement of CRFP in those neighboring regions. There are interactions between ecosystems. Food production

TABLE 1 Evaluation index system for CRFP.

Indicator type	Indicators	Description	Unit
Input	Maximum temperature	Daily maximum temperature in a year	°C
	Minimum temperature	Daily minimum temperature in a Year	°C
	Extreme high temperature days	Annual count of days when daily maximum temperature > 35 °C	d
	Extreme low temperature days	Annual count of days when daily minimum temperature < 0 °C	d
	Annual precipitation	Annual total precipitation > 1 mm	mm
	Precipitation intensity	Annual total precipitation/the number of days with daily precipitation > 1 mm	mm/d
	Extreme rainfall days	Annual count of days when daily precipitation > 25 mm	d
	Drought days	Maximum number of consecutive days with daily precipitation < 1 mm	d
	Forest coverage rate	Forest area/administrative area	ratio
	Crop seeding density	Grain sowing area/administrative area	ratio
Expected output	Grain yield per unit area	Total grain yield/grain sowing area	tons/hectare
	Grain yield growth rate	(Total grain yield in this year - Average of total grain yield over the previous 6 years)/average of total grain yield over the previous 6 years	ratio
Unexceeded output	Proportion of crops affected by disasters	Crop disaster-damaged area/crop sowing area	ratio
	Agricultural carbon emissions	Agricultural carbon emissions	10,000 tons

is closely related to the health and stability of ecosystems, and cross-regional ecosystems such as water systems, forests, and land resources can jointly influence food production. Changes in the ecosystem status of one region can exert a cascading impact on agricultural production in neighboring areas. In other words, the CRFP in one region is closely linked to the ecological environment of neighboring regions. Additionally, the diffusion of policies and ideologies is another important factor contributing to the spatial correlation of CRFP. At the same time, due to differences in geographic locations, there are significant disparities in technology levels, resource endowments, ecological environments, and agricultural production conditions between regions, resulting in spatial heterogeneity in CRFP.

In summary, under the influence of multiple factors, the CRFP in China will exhibit volatility and heterogeneity across different time periods and spatial locations. Therefore, exploring the trends, characteristics, and causes of the spatiotemporal evolution of CRFP is of significant importance for predicting changes in the development of CRFP and for enhancing its resilience.

3 Methods and materials

3.1 Methods

3.1.1 Measurement of CRFP based on the super-EBM model

The measurement method for climate resilience in food production used in this study is the Super-EBM model, which takes into account undesirable outputs. The model integrates two key components: the radial distance from actual inputs to the production frontier, and non-radial input slack variables, which collectively enhance measurement precision. And it allows for the incorporation of undesirable outputs (Li et al., 2022; Zheng H. et al., 2024; Zheng J. et al.,

2024). Meanwhile, this study employs the Super-EBM model to measure CRFP, aiming to leverage the comparative advantages of this method in multi-input and multi-output scenarios to quantify the capacity of the food production system to maintain its output under these constraints. In addition, based on the theoretical analysis above, the evaluation index system for climate resilience in food production established in this study is shown in Table 1.

3.1.2 Spatiotemporal evolution analysis method

3.1.2.1 Kernel density estimation

Kernel density estimation is a non-parametric technique used to describe the distribution characteristics of a variable using a smooth density curve (Chen, 2017). Its functional structure is given by Equation 1:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{x_i - \bar{x}}{h}\right) \quad (1)$$

Here, N indicates the sample size, x_i denotes the observed data points assumed to be independent and identically distributed, \bar{x} stands for the sample mean, and $K(\cdot)$ is the kernel density function. For this research, the Gaussian kernel is used, which is

$$\text{expressed as } K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right).$$

3.1.2.2 Dagum Gini coefficient and decomposition

The Dagum Gini coefficient not only fully considers the distribution of sub-sample data but also effectively addresses the issue of cross-overlap between sub-sample data, making it a key method for analyzing the spatial differences and sources of a variable. With reference to Zhang H. et al. (2022) and Zhang L. et al. (2022), this

study decomposes the overall Gini coefficient of climate resilience in food production into within-regional differences (within-group differences), between-regional differences (between-group differences), and super-variable density. The model structure is given by Equations 2, 3:

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |x_{ji} - x_{hr}|}{2n^2\bar{x}} \tag{2}$$

$$G = G_w + G_{nb} + G_t \tag{3}$$

Where G represents the overall Gini coefficient, k denotes the number of regions, x_{ji} (x_{hr}) refers to the climate resilience in food production of province i (r) within region j (h), \bar{x} is the mean climate resilience in food production across provinces, n represents the total number of provinces, and n_j (n_h) indicates the number of provinces in region j (h). G_w , G_{nb} , G_t represent the contributions of within-group differences, between-group differences, and super-variable density, respectively.

3.1.2.3 σ -convergence

σ -convergence is a key method for analyzing how a variable converges to its mean over time, that is, it measures the trend of decreasing deviation from the mean as time progresses. In this study, the coefficient of variation is used to measure the σ -convergence characteristics of climate resilience in food production. Its calculation method is given by Equation 4:

$$\sigma = \frac{\sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N}}}{\bar{x}} \tag{4}$$

3.1.2.4 β -convergence

Absolute β -convergence analysis is a method to test whether a variable converges to a steady-state equilibrium value, i.e., to study whether lagging regions exhibit a “catch-up effect” relative to more developed regions. If $\beta < 0$, the presence of absolute β -convergence is indicated, and the smaller the coefficient, the faster the convergence rate. Conditional β -convergence adds control variables to the absolute β -convergence, analyzing whether convergence exists for a given economic variable while considering external conditions. Referring to Lin and Zhu (2021), this study constructs the model structures for absolute β -convergence and conditional β -convergence, represented by Equations 5, 6, respectively.

$$\ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) = \alpha + \beta \ln(CRFP_{it}) + \mu_i + \eta_t + \varepsilon_{it} \tag{5}$$

$$\ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) = \alpha + \beta \ln(CRFP_{it}) + \lambda control_{i,t+1} + \mu_i + \eta_t + \varepsilon_{it} \tag{6}$$

Where $i = 1, 2, \dots, N$ represents regions and $t = 1, 2, \dots, T$ represents years. $CRFP_{i,t+1}$ and $CRFP_{it}$ represent the CRFP of region i in years t and $t + 1$, respectively, and $\ln(CRFP_{i,t+1} / CRFP_{it})$ represents the annual growth rate of CRFP for region i . β is convergence coefficient. μ_i , η_t , ε_{it} are individual fixed effects, time fixed effects, and random disturbances, respectively. $Control_{i,t+1}$ refers to the control variables affecting CRFP. Referring to Huang et al. (2022) and Baig et al. (2023), this study selects fiscal support for agriculture (FSA), urbanization level (URB), and technological innovation level (TIN) as control variables. Among them, FSA is measured by the ratio of local fiscal expenditure on agriculture, forestry, and water affairs to local fiscal general budget expenditure, URB is quantified as the ratio of urban residents relative to the overall population, and TIN is assessed based on the annual count of approved domestic patent applications (units: items).

To account for the influence of spatial dependence on the convergence of climate resilience in food production, this study introduces the spatial Durbin model to construct the spatial absolute β -convergence model and the spatial conditional β -convergence model. The model structures are represented by Equations 7, 8, respectively.

$$\ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) = \alpha + \beta \ln(CRFP_{it}) + \rho \sum_{j=1}^n W_{ij} \ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) + \theta \sum_{j=1}^n W_{ij} \ln(CRFP_{jt}) + \mu_i + \eta_t + \varepsilon_{it} \tag{7}$$

$$\ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) = \alpha + \beta \ln(CRFP_{it}) + \rho \sum_{j=1}^n W_{ij} \ln\left(\frac{CRFP_{i,t+1}}{CRFP_{it}}\right) + \lambda control_{i,t+1} + \theta \sum_{j=1}^n W_{ij} \ln(CRFP_{jt}) + \tau \sum_{j=1}^n W_{ij} Control_{i,t+1} + \mu_i + \eta_t + \varepsilon_{it} \tag{8}$$

Where W_{ij} is the spatial weight matrix, ρ is the spatial autoregressive coefficient, and θ is the spatial interaction coefficient.

3.1.2.5 Markov chain

The conventional Markov chain employs stochastic process theory to analyze system dynamics through state transition probability matrix. In this process, it is assumed that the event exhibits “no aftereffect,” meaning that the historical state prior to the current period does not influence the prediction of the future. Referring to Fan et al. (2022), this study uses the conventional Markov chain to construct an $N \times N$ transition probability matrix, where the probability of the climate resilience in food production of sample provinces transitioning from level E_i in year t to level E_j in year $t + 1$ is given by Equation 9:

$$P_{ij}(E_i \rightarrow E_j) = \frac{n_{ij}}{n_i} \tag{9}$$

Where n_{ij} counts all observed cases where provinces shifted from state i in year t to state j in year $t + 1$, and n_i denotes the number of provinces that were in state i during the sample observation period.

The spatial Markov chain extends the conventional Markov chain by incorporating geographical interdependencies, allowing it to reveal the intrinsic connection between the spatiotemporal evolution of economic phenomena and regional spatial positions. Its conditions on the spatial lag type of a region in the initial year and decomposes the traditional Markov chain into N conditional transition probability matrices of size $N \times N$. The detailed model structure can be found in Kerkouch et al. (2024).

3.1.3 Spatial correlation analysis method

3.1.3.1 Spatial correlation network structure

① Modified gravity model.

This study employs a modified gravity model to construct a spatial correlation network of CRFP, with the calculation formula given by Equation 10 (Zhou and Wen, 2024):

$$F_{ij} = \frac{x_i}{x_i + x_j} \times \frac{\sqrt[3]{p_i g_i x_i} \sqrt[3]{p_j g_j x_j}}{\left(\frac{d_{ij}}{G_i - G_j} \right)^2} \quad (10)$$

Where F_{ij} is the spatial correlation intensity of CRFP between regions i and j ; x_i and x_j represent the CRFP for regions i and j ; d_{ij} is the geographical distance between regions i and j ; p_i, g_i, p_j, g_j indicate the annual resident population and gross domestic product (GDP) of regions i and j ; G_i and G_j correspond to the per capita GDP of regions i and j .

② Social network analysis.

Social Network Analysis (SNA) quantitatively examines the relationships between individuals or groups to reveal the structural characteristics of network connections. By analyzing topological features of the network graph, nodal relationship strength, network density, and other metrics, this method elucidates spatial correlations among study subjects. With reference to Chen et al. (2022), this paper employs network density, network connectedness, network hierarchy, and network efficiency to characterize the whole network features, while selecting degree-centrality, closeness-centrality, and betweenness-centrality to analyze individual network characteristics.

3.1.3.2 Quadratic assignment procedure (QAP) analysis

The QAP method represents a non-parametric approach for examining determinant factors in correlation network. This paper adopts QAP regression to identify the key drivers shaping the spatial correlation network of CRFP. Given that spatial geographical location, economic development level, industrial structure, and agricultural mechanization level are key factors affecting the CRFP (Hu et al., 2022; Yang et al., 2025; Zhang H. et al., 2022; Zhang L. et al., 2022; Fang et al., 2024). The difference matrices of the above indicators and the spatial matrix of CRFP passed the QAP correlation test, therefore this paper constructs the QAP regression model given by Equation 11:

$$FG = f(DS, EC, IS, MC) \quad (11)$$

Where FG represents the spatial correlation matrix of CRFP; DS denotes the spatial adjacency matrix; EC is the economic development

level difference matrix, measured by regional GDP; IS stands for the industrial structure difference matrix, using the proportion of tertiary industry value-added to GDP as a proxy variable for industrial structure; MC indicates the agricultural mechanization level difference matrix, measured by total agricultural machinery power.

3.2 Materials

This study utilizes climate variables (temperature and precipitation) obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center. The agricultural carbon emission data refer to the estimates provided by Liu et al. (2023). Data on forest coverage, food production, planted area, and crop disaster-affected area are obtained from the *China Statistical Yearbook* and the *China Agricultural Statistical Yearbook*. Considering the availability and comprehensiveness of the data, the study sample includes 31 provinces in China (excluding Hong Kong, Macau, and Taiwan), with a time range from 2000 to 2022. Furthermore, to further analyze the distribution and evolution characteristics of climate resilience in food production across different geographical regions, the 31 provinces in the study sample are divided into four regions: Eastern, Central, Western, and Northeastern China.

4 Results

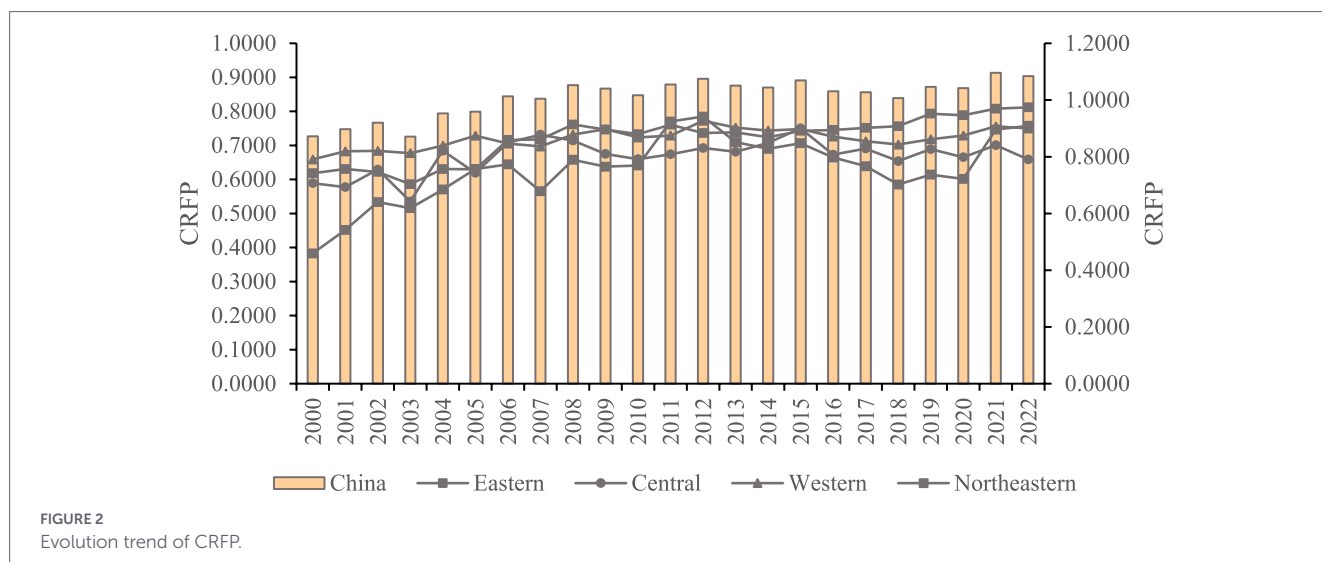
4.1 Spatiotemporal evolution characteristics of CRFP

4.1.1 Temporal evolution and regional disparities

4.1.1.1 The overall level and changing trend of CRFP

The average CRFP in China and its four regions from 2000 to 2022 was computed (Figure 2). The CRFP in China has followed a rising pattern over the entire sample period, climbing from 0.7267 in 2000 to 0.9035 in 2022, representing an increase of 24.33%. This indicates that the adaptability of China's food production to climate change has been continuously improving. Specifically, the CRFP shows some volatility. The period from 2000 to 2012 was a phase of rapid increase, with an increase of 23.29%. During this stage, China made significant efforts to promote agricultural technological innovation and the building of agricultural infrastructure. For example, the promotion of drought-resistant, waterlogged-tolerant, and pest-resistant crop varieties improved the agricultural sector's ability to adapt to extreme weather conditions. Additionally, the strengthening of irrigation systems reduced the dependence of food production on precipitation and enhanced drought resistance. Notably, carrying out the South-to-North Water Diversion Project enhanced the supply of water resource in arid regions, effectively enhancing production resilience. In addition, policy support was also a key factor contributing to the improvement of CRFP during this phase. Policies such as the minimum grain purchase price, agricultural subsidies, land reforms, and the establishment of climate early warning systems enhanced the economic resilience of farmers when confronting climate change. These measures promoted the stability and sustainability of agricultural production.

However, from 2012 to 2018, the CRFP experienced a slight decline, dropping by approximately 6.63%. The primary cause was the



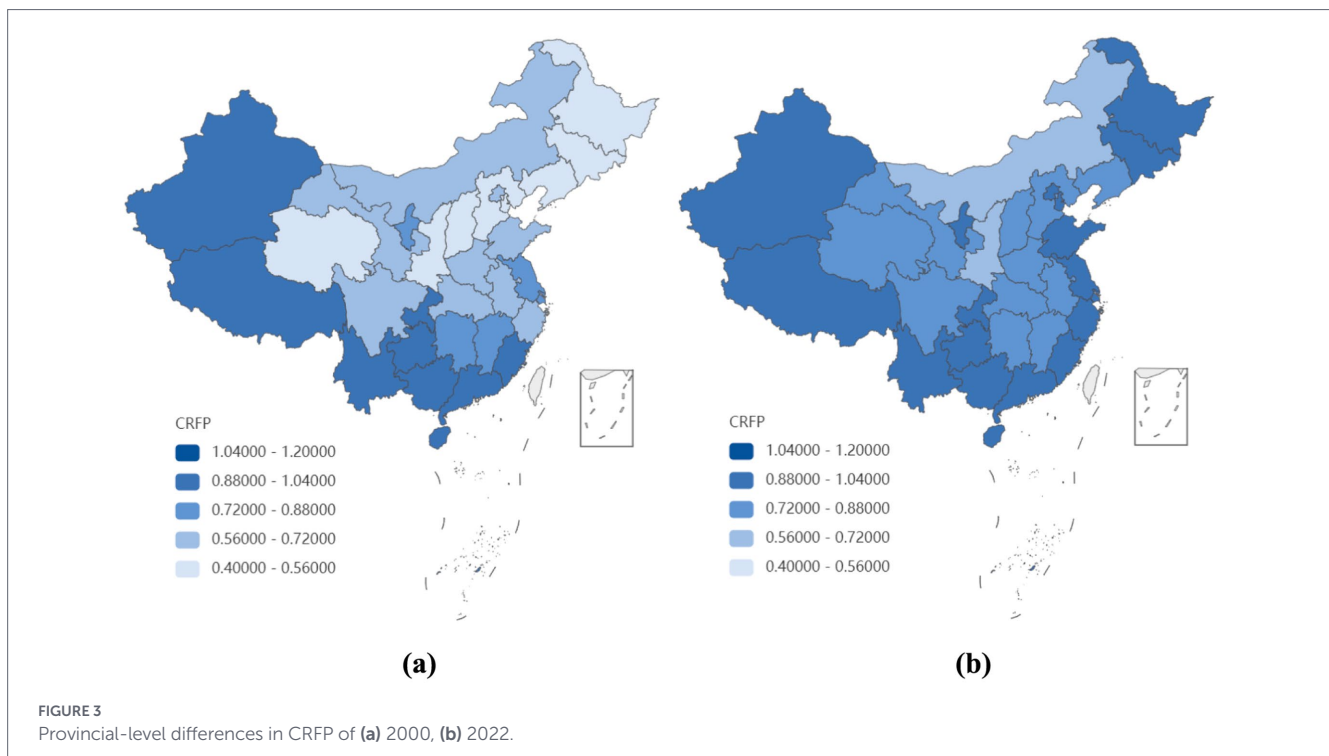
increase in extreme weather events. In particular, the El Niño phenomenon from 2014 to 2016 and the La Niña phenomenon from 2016 to 2018 had a significant impact, leading to frequent extreme weather events in China. These included the drought and flood disasters in 2013, severe flooding in the middle and lower reaches of the Yangtze River in 2016, and extreme heatwaves during the summers of 2013 and 2017. These events introduced greater uncertainty into agricultural production and resulted in a decrease in crop yields. Additionally, factors such as soil degradation and rising agricultural production costs also contributed to the decline in CRFP. From 2018 to 2022, the CRFP showed an upward trend, although at a relatively slow pace, with an increase of 7.69%. After 2018, the adoption of advanced technologies like big data and artificial intelligence in farming enabled both agricultural productivity and the ability to cope with climate change improved significantly. The promotion of ecological environmental governance in agriculture facilitated soil improvement, as well as structural adjustments and diversification in food production. The development of ecological and green agriculture received broader support, and measures such as crop rotation and the reduction of chemical fertilizers and pesticides improved soil health and water conservation. These efforts promoted enduring ecological balance and strengthened resilience to climate shifts in agricultural systems.

When viewed from regional, the CRFP in the western region ranked the highest from 2000 to 2005. However, after 2006, the eastern region overtook the western region, and the gap between these regions steadily widened. Especially after 2016, the CRFP in the eastern region far exceeded all other regions. In 2022, the CRFP in the eastern region was 0.9741, which was 1.23 times higher than in the central region, while exceeding the western and northeastern regions by 8 and 7%, respectively. The eastern region was the first to launch the widespread application of smart agriculture, precision farming, and big data agriculture (Zheng, 2024). Technologies such as smart irrigation systems, drone-based pest control, and intelligent greenhouse systems not only helped farmers improve production efficiency but also enhanced their ability to respond to climate change risks. Farmers in the eastern region have a relatively high adaptability to new technologies and market changes. Additionally, concentrated government policy support and a more diversified food production structure have further strengthened the overall resilience of agriculture in this region.

The CRFP in the northeastern region has consistently been relatively low, with considerable volatility. Between 2000 and 2012, it increased by 105%, but then declined by 25.43% from 2012 to 2018, and rising again by 29.45% from 2018 to 2022. The agricultural production structure in the northeastern region is relatively simple, with food production mainly focused on crops such as corn and soybeans. This monocultural farming structure weakens its ability to cope with risks posed by climate change. The relatively slow pace of technological development also plays a key role in the fluctuating CRFP levels observed in this region. Although there have been notable enhancements in farming technologies in recent years, the adoption and implementation of contemporary agricultural technologies remain limited when contrasted with China's developed eastern and southern regions. Many farmers lack the economic and technical reserves to cope with climate risks. In particular, smallholder farmers, due to their low agricultural incomes, find it difficult to afford high-tech agricultural equipment or disaster prevention measures. The increase in CRFP after 2018 can be attributed to the enactment of the Rural Revitalization Strategy. This strategy provided a clearer development plan for agricultural production in the northeastern region. At the same time, the government increased investments in food production infrastructure in the northeast, such as improving water conservancy facilities and enhancing food storage capacity. These initiatives have successfully strengthened climate resilience in agricultural output by boosting grain storage capabilities.

As shown in Figure 3, the differences in CRFP at the provincial level are more pronounced. In 2000, the highest CRFP (in Yunnan) was 2.42 times that of the lowest (in Liaoning). By 2022, the highest (in Shanghai) was 1.50 times that of the lowest (in Inner Mongolia). Although the gap has narrowed, it remains significant. Specifically, in the early years of the sample period, Yunnan and Chongqing had relatively high CRFP, while Shanghai and Zhejiang exhibited relatively high resilience at the end of the sample period. In contrast, Liaoning, Heilongjiang, and Hebei had relatively low resilience, consistent with the regional differences observed earlier. From the perspective of changing trends, Jiangsu showed the largest increase in CRFP during the sample period, with an increase of 104.04%. Meanwhile, Guizhou, Xizang, and Yunnan experienced declines to varying degrees.

The evolution of CRFP in China exhibits significant temporal and spatial heterogeneity. Exploring its evolutionary characteristics and



driving factors is crucial for formulating more precise measures to enhance the CRFP.

4.1.1.2 Kernel density analysis

This paper uses Kernel density estimation to explore the dynamic evolution patterns of CRFP across China (Figure 4). Except for the eastern region, other regions and the national CRFP distributions initially demonstrate a pattern of shifting rightward first and then leftward, with the leftward shift occurring in 2020. This indicates that the CRFP in most regions of China increased between 2000 and 2020, but began to decline in 2020. This decline may have been influenced by the impact of the COVID-19 pandemic. During the COVID-19 pandemic, agricultural activities in some regions were disrupted, and the instability of agricultural input supply chains increased. Key agricultural supplies, such as fertilizers and seeds, were either insufficient or not delivered on time, which significantly affected food production activities (Pan et al., 2020). The kernel density curve of CRFP in the eastern region shows a rightward shift throughout the sample period, indicating a continuous improvement in climate resilience. This improvement is primarily attributed to the high level of smart agriculture development in the eastern region. Supported by agricultural technology, the eastern region has achieved higher agricultural productivity and greater stability in agricultural supply chains (Zhu et al., 2024). These advancements have enhanced the ability of food production to cope with extreme weather events.

The distribution patterns reveal a decreasing peak amplitude in the national CRFP density plot, indicating that the regional disparity in CRFP is widening. Figure 4 illustrates distinct regional trajectories: the eastern region's primary density peak initially decreased before rebounding, while central and western areas exhibited an inverse pattern of initial growth followed by reduction. The northeastern region showed a "decline-rise-decline" pattern for its main peak. Compared to the early years of the sample period, the internal disparity in CRFP

has become more pronounced in the eastern and northeastern regions by the end of the period. These patterns primarily stem from several factors: First, significant differences in climate conditions, agricultural resource endowments, and levels of technological innovation across different regions of China have resulted in regional characteristics in CRFP. Second, there are differences in the level of policy support among regions. For example, post-disaster recovery and agricultural technology promotion measures have been implemented relatively slowly in some areas, affecting the local ability to recover food production and further exacerbating regional disparities.

Analyzing polarization trends, the CRFP density distributions at the national and regional levels show multiple main peaks, with the most notable example being the central region. This indicates a regional polarization phenomenon in China's CRFP, meaning that there are "leading" provinces with higher climate resilience in both the national and regional contexts. On one hand, this polarization can be attributed to differences in natural resource endowments. Regions with favorable natural conditions, such as climate, soil, precipitation, and topography, generally have stronger agricultural production capacity and are better able to withstand the impacts of climate change. On the other hand, it is also due to disparities in technological levels and application scopes. Some regions have strong momentum for technological innovation, which has promoted the broader application of new technologies in agriculture. This not only improved agricultural productivity but also enhanced the resilience of food production to risks.

4.1.2 Sources of regional disparities

Figure 5a reveals a consistent downward trajectory in China's CRFP, decreasing from 0.150 in 2000 to 0.068 in 2022, a decline of 54.67%. This indicates that the climate adaptability and agricultural risk resistance capabilities across different regions of China have gradually become more balanced. Since 2000, China has vigorously

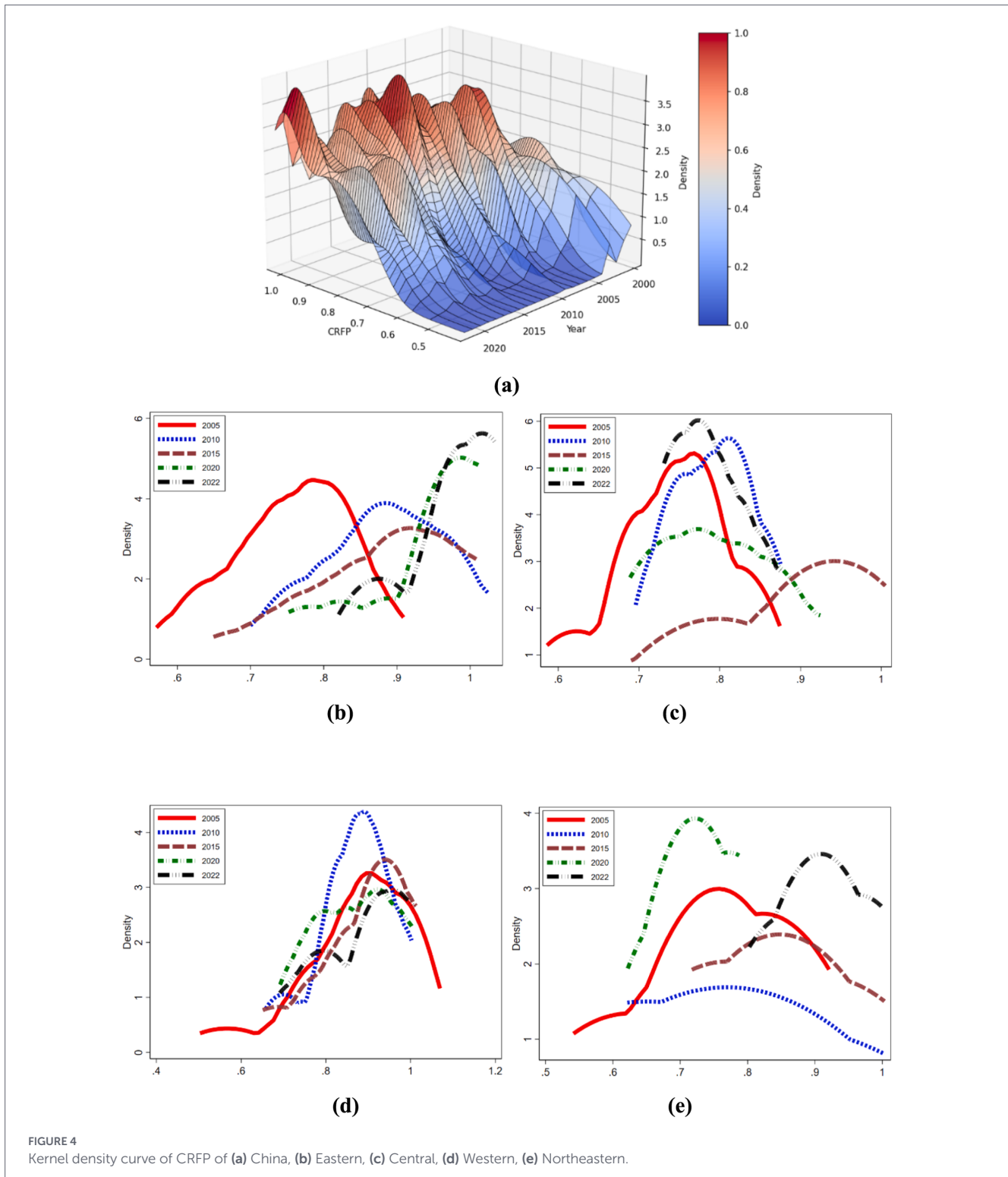
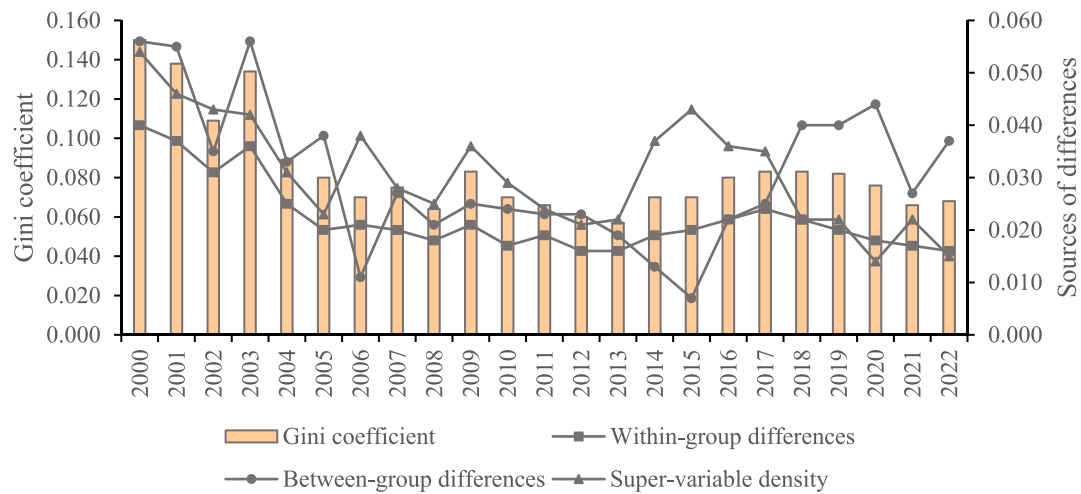


FIGURE 4 Kernel density curve of CRFP of (a) China, (b) Eastern, (c) Central, (d) Western, (e) Northeastern.

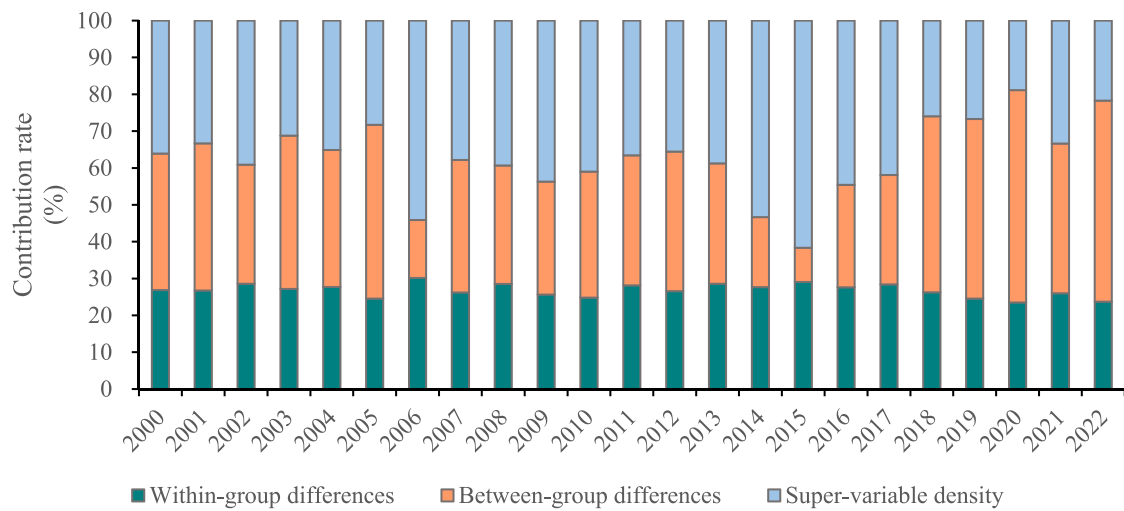
promoted food security and agricultural modernization, especially in the main grain-producing areas of the central and western regions, where investments in farmland infrastructure, technology promotion, and disaster resilience have been increased. The widespread application of agricultural technologies has contributed to enhancing overall CRFP. However, between 2012 and 2018, there was a slight increase, with a rise of 38.33%. Apart from the impact of extreme weather events, agricultural structural adjustment is also an important influencing factor. The period from 2012 to 2018 was a critical phase for

agricultural structural adjustment in China. Some traditional major grain-producing regions converted part of their arable land to the cultivation of high-value crops. These economic crops may have a relatively lower capacity for adapting to climate change, resulting in a decline in CRFP in some regions. Meanwhile, other regions, supported by modern agricultural technologies and policies, maintained a relatively high level of CRFP.

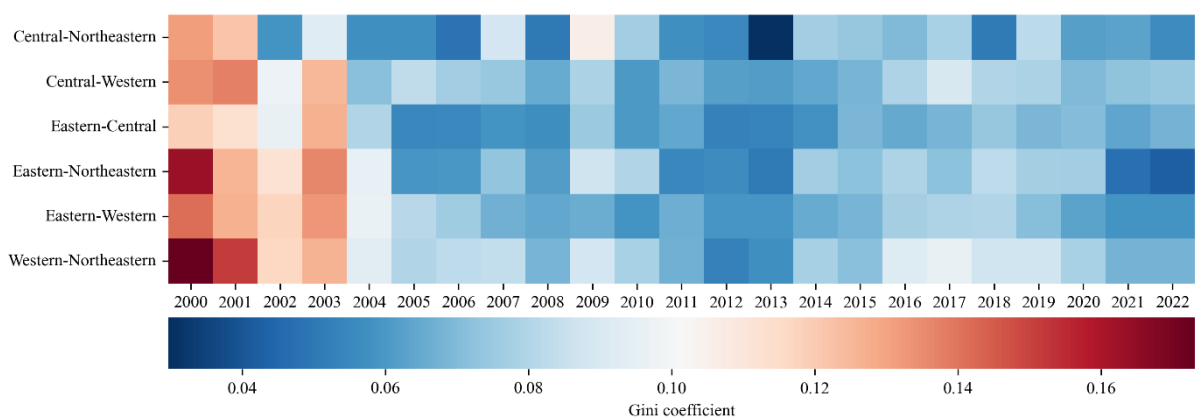
As shown in Figure 5b, the contribution rate of within-group differences to the overall Gini coefficient is relatively high and has



(a)



(b)



(c)

FIGURE 5 Gini coefficient of CRFP of (a) Gini coefficient of CRFP, (b) decomposition of Gini coefficient of CRFP, (c) decomposition of the within-group differences in CRFP.

shown an upward trend during the sample period, with an increase of 47.23%. Particularly after 2018, within-group differences emerged as the dominant contributor, and surpassed that of the other two factors. This indicates that within-group differences constitute the principal element leading to the imbalance of CRFP. This is primarily due to the significant differences in agricultural production models across different regions. Each region has developed a distinct agricultural production model, shaped by variations in agricultural history, culture, and economic structure. Some regions rely on intensive agricultural production methods, which allow for the faster adoption of modern agricultural technologies and enhance adaptability to climate change, while other regions still depend on traditional small-scale farming methods, which have relatively weaker climate resilience. Additionally, marked discrepancies exist in the economic development levels, scientific and technological capabilities, and market and trade conditions across different regions of China. These factors also contribute significantly to the higher within-group differences in CRFP.

As shown in Figure 5c, during initial observations, the within-group differences between the eastern-northeastern and the western-northeastern were the largest. By the end of the sample period, the within-group differences between the central-western and western-northeastern became relatively larger. In terms of trend, the within-group differences between different regions showed a narrowing tendency, particularly the eastern-northeastern, where the within-group Gini coefficient decreased by 74.2%. Conversely, the within-group Gini coefficient in the eastern-central saw the smallest decline, with a decrease of 43.09%. Some advanced agricultural technologies, climate adaptation strategies, and management experiences from the eastern region have gradually been transferred to the northeastern region through regional cooperation, thereby enhancing the CRFP in the northeast and narrowing the gap with the eastern region. Although the central region has favorable climate conditions, it is more susceptible to extreme weather events such as floods and droughts. Some areas also face relative water scarcity, which limits the improvement of CRFP. Particularly in comparison with the eastern region, the agricultural industry chain in the central region is still not sufficiently complete, and risk management mechanisms are not yet fully developed, which slows down the rate at which the gap in CRFP between the central and eastern regions is narrowing.

4.1.3 Dynamic evolution analysis

4.1.3.1 σ -convergence analysis

The coefficient of variation was used to further analyze the σ -convergence characteristics of CRFP (Figure 6). The coefficient of variation of national CRFP decreased by 53.3% during the sample period, indicating that the overall disparity in China's CRFP is gradually narrowing, exhibiting significant σ -convergence characteristics. The advancement of agricultural modernization, including the widespread application of technologies such as drought-resistant crops, precision irrigation, and intelligent weather early warning systems, has provided technological support for reducing the gap in CRFP. Analysis reveals decreasing variation coefficients across eastern, central, and western regions, with the most substantial reduction occurring in the east (69.91%), followed by central (54.49%) and western (48.33%). In contrast, northeastern territories displayed an opposite trajectory, with an increase of 37.59%. This is consistent with the analysis above, further indicating that the volatility of CRFP in the northeastern region is relatively large, and it does not exhibit σ -convergence characteristics.

4.1.3.2 β -convergence analysis

The β -convergence analysis was used to explore the convergence characteristics of the development trend of CRFP in China, in order to understand whether convergence exists under the condition of external environmental heterogeneity and whether its convergence trend has changed. According to Table 2, the significantly negative coefficients at the 1% level for both national and regional CRFP indicates that a notable β -convergence characteristic in China's CRFP. This suggests that regions with lower CRFP tend to catch up with those with higher resilience. On one hand, this convergence is driven by the demonstration effect and collaborative. Regions with higher climate resilience are more likely to access new technologies and adopt new crop varieties. The successful practices in these regions generate a demonstration effect, promoting the introduction, updating, and dissemination of agricultural technologies in low-resilience areas. This, in turn, helps optimize resource allocation and enhance risk management capabilities, thus improving CRFP in those regions. On the other hand, market forces and governmental interventions jointly drive this process. With increasing societal attention on food security and

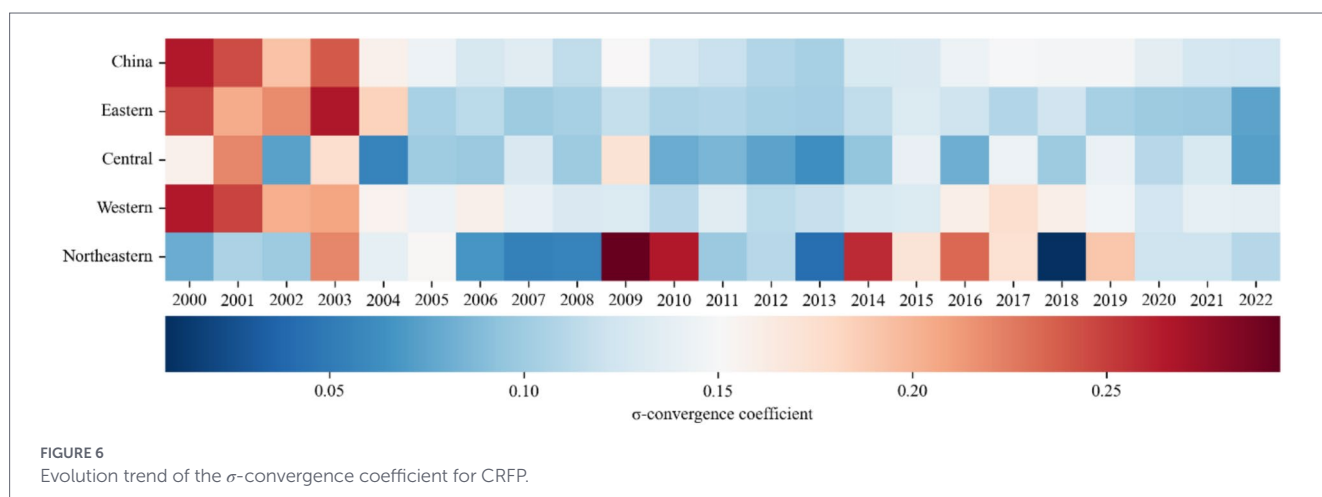


TABLE 2 β -convergence test results for CRFP.

Variable	Absolute β -convergence				
	China	Eastern	Central	Western	Northeastern
β	-0.5468*** (0.0325)	-0.4854*** (0.0535)	-0.7963*** (0.0949)	-0.6425*** (0.0554)	-0.4359*** (0.1294)
α	-0.1601*** (0.0196)	-0.1290*** (0.0292)	-0.3188*** (0.0476)	-0.1348*** (0.0272)	-0.1761 (0.1248)
Individual fixed effects	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y
N	682	220	132	264	66
R ²	0.3914	0.4442	0.6822	0.4238	0.5576

Variable	Conditional β -convergence				
	China	Eastern	Central	Western	Northeastern
β	-0.5658*** (0.0333)	-0.5388*** (0.0563)	-0.7897*** (0.0964)	-0.6462*** (0.0559)	-0.4254*** (0.1407)
α	-0.0731 (0.0915)	-0.3069* (0.1733)	-0.4936 (0.3203)	-0.1488 (0.1626)	1.1892 (1.5707)
Control variables	Y	Y	Y	Y	Y
Individual fixed effects	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y
N	682	220	132	264	66
R ²	0.3974	0.4684	0.6845	0.4270	0.5785

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The values in brackets represent robust standard errors (the same below).

sustainable development, low-resilience regions are able to improve their production methods and strengthen climate adaptation capabilities with the help of stronger policy support. From the comparison of the β coefficients, the convergence speed in the central and western regions is higher than the national level, with the central region exhibiting the fastest convergence, while eastern and northeastern regions lag behind the national level. In recent years, both the central and western regions have increased their investment in agricultural technology, using new technologies and crop varieties to enhance the CRFP. But the northeastern regions are more reliant on traditional agriculture, which has relatively lower flexibility and adaptability in responding to climate change.

After controlling the factors such as fiscal support for agriculture, urbanization level, and technological innovation, the β coefficients for CRFP remains significantly negative at the 1% level at both national and regional scales. This confirms persistent conditional β -convergence characteristic in China's CRFP. From the national perspective, the conditional convergence speed has improved relative to the absolute convergence speed, suggesting that the combined effects of factors such as fiscal support for agriculture, urbanization level, and technological innovation have facilitated the convergence of CRFP across regions. The improvement in fiscal support for agriculture helps promote the updating and dissemination of agricultural technologies, such as the adoption of new technologies and crop varieties, which in turn increases crop diversity and enhances climate adaptability. Urbanization has facilitated the improvement of rural infrastructure, providing comprehensive foundational support for enhancing agricultural climate resilience. Technological innovation has introduced new

technologies and methods to agriculture, effectively increasing crop resistance and production efficiency, as well as improving the early warning and response capabilities of food production to climate risks. Regionally, the conditional convergence speed has also improved in the eastern and western regions, while the conditional convergence speed in the central and northeastern regions has slowed down. The northeastern region suffers from population loss, leading to labor and agricultural talent shortages, which in turn restricts economic and technological innovation development. This has become a significant factor hindering the conditional convergence of CRFP.

To assess spatial interdependence in CRFP convergence patterns, this paper further employs the spatial Durbin model for spatial β -convergence analysis (Table 3). The result reveals significantly negative spatial absolute β coefficients for CRFP at the national and all regions. This indicates that the convergence of CRFP to its steady-state level remains significant across these regions. The significantly positive spatial coefficient ρ at both national and regional scales indicates that there is a notable positive spatial spillover effect in China's CRFP. Neighboring regions exhibit similar climatic conditions and high ecological interconnectivity. Ecological restoration and climate adaptation measures in one region can influence adjacent areas through natural factors such as water systems and soil, thereby enhancing their CRFP. The demonstration effect of agricultural technology management and the interregional transmission mechanism are also key factors driving the positive spatial spillover effect in CRFP. Geographically, the central region demonstrates the strongest spillover, whereas the northeast displays the weakest effects.

TABLE 3 Spatial β -convergence test results for CRFP.

Variable	Spatial absolute β -convergence				
	China	Eastern	Central	Western	Northeastern
β	-0.6042*** (0.0345)	-0.6281*** (0.0587)	-0.6839*** (0.0825)	-0.6724*** (0.0548)	-0.3845*** (0.0973)
ρ	0.4944*** (0.0398)	0.3766*** (0.0555)	0.4565*** (0.0680)	0.3178*** (0.0716)	0.2501** (0.0997)
θ	0.4432*** (0.0477)	0.5196*** (0.0676)	0.2489** (0.1087)	0.3640*** (0.0825)	0.0983 (0.1202)
Individual fixed effects	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y
N	682	220	132	264	66
R ²	0.2992	0.2828	0.3761	0.3605	0.2636

Variable	Spatial conditional β -convergence				
	China	Eastern	Central	Western	Northeastern
β	-0.6093*** (0.0346)	-0.6878*** (0.0589)	-0.7111*** (0.0828)	-0.6772*** (0.0555)	-0.4705*** (0.1081)
ρ	0.4765*** (0.0409)	0.3673*** (0.0569)	0.4242*** (0.0703)	0.3182*** (0.0730)	0.1954* (0.1043)
θ	0.3976*** (0.0552)	0.4952*** (0.0770)	0.1363 (0.1203)	0.3634*** (0.0981)	-0.0855 (0.1405)
Control variables	Y	Y	Y	Y	Y
Individual fixed effects	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y
N	682	220	132	264	66
R ²	0.3172	0.3468	0.4268	0.3613	0.3853

After controlling for variables, the spatial conditional β coefficients for CRFP at the national level and in all four regions remain significantly negative at the 1% level, with an increased convergence speed. This suggests that factors such as financial support for agriculture, urbanization level, and technological innovation also have a significant impact on the spatial convergence of CRFP. Financial support for agriculture not only provides funding for agricultural development but also promotes balanced regional development through policy guidance, enhancing the CRFP in the region while generating spillover effects in neighboring areas. Urbanization helps improve infrastructure such as transportation and communication, enhancing agricultural risk warning and management capabilities. Additionally, through population migration and optimizing resource allocation, urbanization generates spatial spillover effects in the process of improving CRFP. Technological innovation primarily generates spatial spillover effects in the process of improving CRFP through knowledge spillovers and technological diffusion. In terms of the rate of growth, the northeastern region experienced the largest increase in spatial convergence speed compared to absolute convergence speed, while the western region had the smallest increase in growth rate. In the northeast, agricultural production technologies and infrastructure are relatively underdeveloped, leaving considerable room for improvement. As a result, once financial support is provided, agricultural infrastructure conditions can improve more rapidly. During the urbanization

process, the northeast region has witnessed industrial and service sector growth. This has facilitated the modernization of rural areas and infrastructure improvements, thus significantly contributing to the enhancement of CRFP in the northeast. However, the western region lacks effective industrial chains and supporting services, and its ecological environment faces challenges such as water scarcity and soil infertility. These issues increase the difficulty of agricultural production and limit the convergence speed of CRFP. From the perspective of spatial effects, the spatial coefficient ρ at the national level and in all four regions remains significantly positive, demonstrating robust spatial spillover effects in CRFP even after controlling for covariates.

4.1.3.3 Traditional Markov transition probability matrix

The Markov transition matrix was used to deeply analyze the temporal dynamics of CRFP. In this study, CRFP was categorized into four levels based on quartiles: low, medium-low, medium-high, and high. The probabilities of transitioning between these levels after 1 year were calculated (Table 4). The transition probability matrix in Table 4 reveals that the values along the main diagonal are significantly larger than the off-diagonal entries, indicating that the likelihood of maintaining the same state of CRFP is greater. Among these, the probability of remaining in the low-level state is the highest (70.86%), followed by the high-level state (67.07%). The relatively stable natural conditions

TABLE 4 Traditional Markov transition probability matrix of CRFP.

<i>t</i>	<i>n</i>	<i>t</i> + 1			
		Low	Medium-low	Medium-high	High
Low	175	0.7086	0.2400	0.0400	0.0114
Medium-low	170	0.1882	0.5353	0.2294	0.0471
Medium-high	173	0.0173	0.1676	0.5087	0.3064
High	164	0.0183	0.0671	0.2439	0.6707

n denotes the number of provinces at the corresponding level (the same below).

play a significant role. For instance, in regions with low CRFP, the climate and natural conditions are difficult to improve in the short term, making it challenging to rapidly enhance their climate resilience. Even with technological and policy support, these regions are unlikely to achieve a significant increase in resilience levels in the short run. Technological path dependence is another crucial factor. Technology, funding, and human resources are often concentrated in regions with better agricultural infrastructure, forming a path dependence. As a result, regions with high resilience levels are more likely to maintain their advantages, while regions with low resilience levels face difficulties in narrowing the gap quickly.

Furthermore, the results from the Markov transition probability matrix indicate that the likelihood of moving up one level exceeds the chance of skipping to a more distant level. For example, the probability of transitioning from the low level to the medium-low level is 24%, but the probabilities of jumping directly to the medium-high and high levels gradually decrease. The probability of transitioning from the medium-low level to the medium-high level is 23%, and the probability of transitioning from the medium-high level to the high level is 31%, suggesting that improving CRFP is a gradual process. Moreover, the probability of transitioning from the high to low level is relatively low, indicating that once CRFP improves, it tends to stabilize, with a lower probability of decline.

4.1.3.4 Spatial Markov transition probability matrix

The spatial differences in China's CRFP suggest that spatial distribution may influence the dynamic development process of CRFP. In this study, following the methods of Fan et al. (2022), a geographic adjacency-based spatial weight matrix (Rook first-order contiguity; coded as 1 for contiguous provinces, 0 otherwise) was introduced into the traditional Markov transition probability matrix. This approach was used to further analyze the spatial dynamic evolution characteristics of CRFP (Table 5). Under different adjacency conditions, the transition probability matrix shows significant differences, indicating that the dynamic changes in CRFP are influenced by spatial factors. When the CRFP of neighboring regions is at a high level, the probability of transitioning from low to medium-low level is 44%, which is higher than the probability of transition from low to medium-low level in Table 4 (24%). Similarly, the probability of transitioning from medium-high level to high level is 57%, which is also higher than the probability of transition from medium-high to high level in Table 4 (31%). Regions with higher CRFP can drive the improvement of resilience in their neighboring areas. Regions with higher CRFP are

usually at the forefront in agricultural technology application. These advanced technologies can spread and diffuse to neighboring regions through the demonstration effect, encouraging the gradual adoption of new technologies in those areas. Additionally, regions with high resilience often have well-established meteorological warning systems and information networks. These systems can be transmitted to neighboring regions through regional cooperation mechanisms and information-sharing platforms, helping those regions better cope with extreme weather events, thereby enhancing their CRFP.

4.2 Spatial correlation analysis of CRFP

4.2.1 Spatial correlation network structure

4.2.1.1 Whole network characteristics

Figure 7 reveals that there were extensive spatial correlation characteristics in CRFP across various regions in China. By 2022, the network exhibited denser connecting lines, indicating increasingly stronger interactions and synergistic effects of CRFP. The network center, which was initially represented by cities such as Shanghai and Beijing in 2000, evolved to include Shanghai, Jiangsu, Beijing, and Zhejiang by 2022. This shift suggests a gradual increase in the gravity centers of CRFP. Furthermore, this evolutionary pattern demonstrates that the spatial correlation gravity centers of China's CRFP have progressively concentrated in the eastern coastal regions. These areas exhibit higher efficiency in addressing climate change and ensuring the stability of grain production. Their agricultural sectors have played an increasingly prominent role in radiating and driving surrounding regions, thereby promoting the synergistic enhancement of CRFP across broader areas.

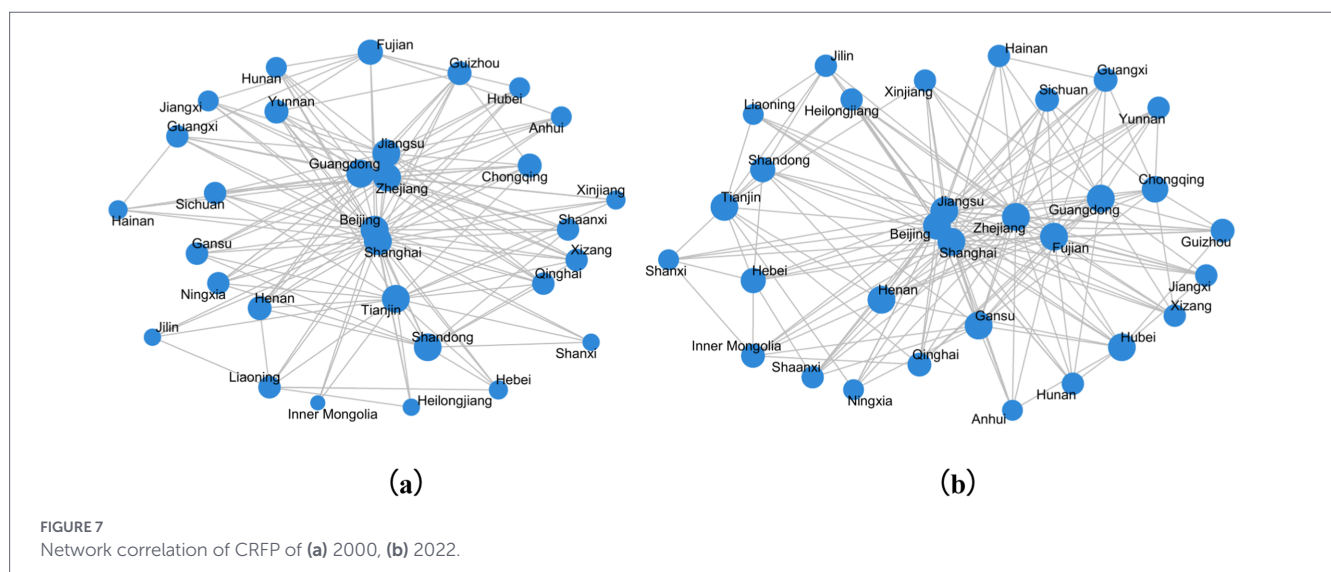
As shown in Figure 8, the network density exhibits a wave-like growth pattern, increasing from 0.1538 to 0.1817. This indicates that the spatial correlation network of CRFP has become increasingly interconnected. The network efficiency displays a fluctuating decline, dropping from 0.7402 to 0.6805, suggesting the spatial correlation network's structural intricacy has steadily increased. This implies that interregional linkages no longer rely solely on single pathways but have evolved into a multi-channel, multi-tiered interaction model. Furthermore, during the entire research period, the network connectness remained at 1, indicating tight interdependence within the spatial correlation network of China's CRFP. The network hierarchy exhibits a fluctuating decline, from 0.6925 to 0.6366, demonstrating that the spatial correlation network of China's CRFP has maintained a fully connected, flat structure. Such a network structure enhances risk resistance capacity, yet vigilance is required against potential disruptions caused by external shocks to network connectivity.

4.2.1.2 Individual network characteristics

As illustrated in Figures 9a,b, between 2000 and 2022, the average degree-centrality rose from 0.31 to 0.36, further indicating a gradual strengthening of spatial connectivity in China's CRFP. Beijing, Jiangsu, Shanghai, and Zhejiang exhibited degree-centrality values significantly higher than the average, and Jiangsu showed a particularly notable growth trend, with an increase of 68.76%. These regions occupy core positions in the network and can significantly influence the CRFP in surrounding regions. Benefiting from well-developed transportation and information networks, these economically

TABLE 5 Spatial Markov transition probability matrix of CRFP.

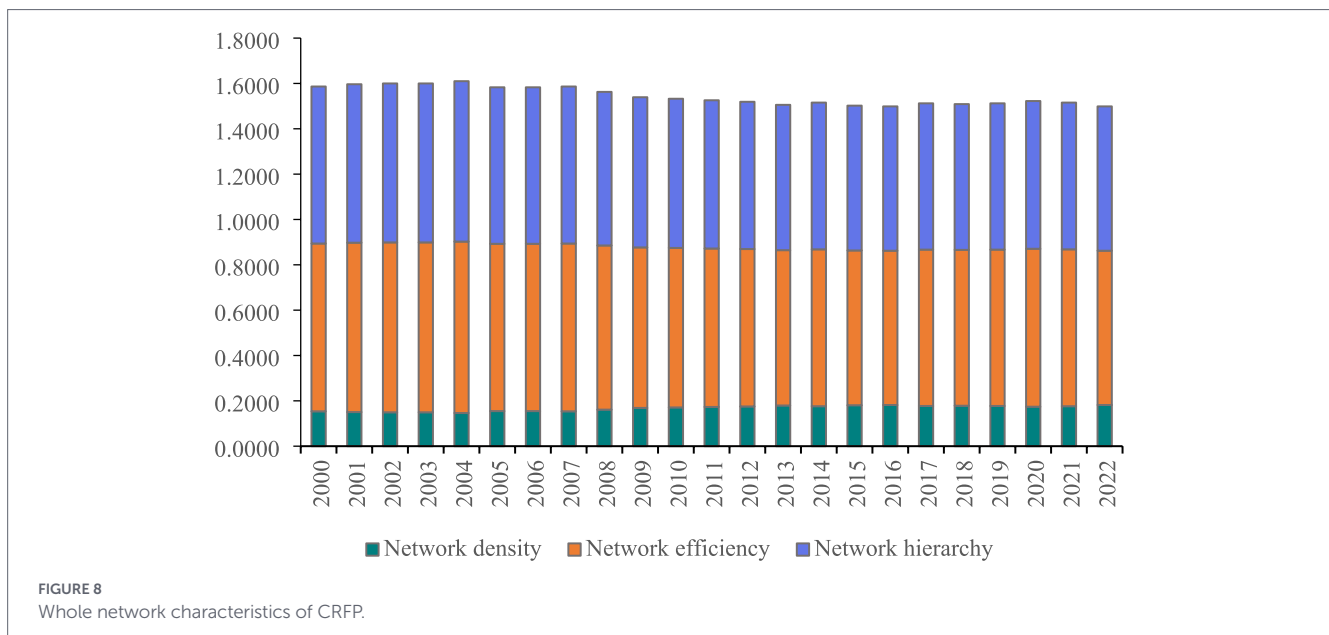
Proximity type	<i>n</i>	<i>t</i>	<i>t</i> + 1			
			Low	Medium-low	Medium-high	High
Low	22	Low	0	0.4545	0.0455	0.5000
	34	Medium-low	0.0294	0.4706	0.1471	0.3529
	14	Medium-high	0.2143	0.0714	0.2143	0.5000
	40	High	0.3500	0.2500	0.1500	0.2500
Medium-low	46	Low	0	0.4565	0.0435	0.5000
	98	Medium-low	0.0102	0.4388	0.1020	0.4490
	30	Medium-high	0.0667	0.1333	0.0667	0.7333
	112	High	0.4018	0.1964	0.1429	0.2589
Medium-high	9	Low	0	0.4444	0.1111	0.4444
	13	Medium-low	0.0769	0.3846	0.1538	0.3846
	7	Medium-high	0.2857	0.1429	0.1429	0.4286
	15	High	0.4000	0.2667	0.0667	0.2667
High	39	Low	0	0.4359	0	0.5641
	90	Medium-low	0	0.5111	0.1000	0.3889
	21	Medium-high	0.1429	0.0476	0.2381	0.5714
	92	High	0.4022	0.3152	0.0978	0.1848



advanced regions can respond swiftly to climate risks and extend their impact to surrounding cities. Jiangsu, in particular, serves as a critical node in the South-to-North Water Diversion Project. Moreover, the continuous advancement of high-standard farmland and digital agriculture platforms has not only accelerated its own agricultural modernization but also strengthened interregional connectivity.

As shown in Figures 9c,d, the average closeness-centrality values for 2000 and 2022 were 51 and 49, respectively. Most cities slightly decreased in closeness-centrality, indicating that the overall compactness of China's spatial correlation network for CRFP has strengthened, and suggesting that the average path length for the flow of information, technology, and resources between different regions has shortened.

As evidenced in Figures 9e,f, the average betweenness-centrality decreased from 10.39 in 2000 to 9.55 in 2022, indicating a gradual reduction in the network's reliance on a few critical nodes and an increasing structural complexity in its distribution. Beijing, Guangdong, Jiangsu, Shanghai, and Zhejiang exhibited significantly higher betweenness-centrality than the national average, demonstrating their pivotal intermediary roles in the network of CRFP. Beijing maintains its intermediary advantage through policy influence and resource allocation, while Jiangsu and Zhejiang have emerged as key nodes for technology diffusion through agricultural innovation and industrial chain integration. Shanghai and Guangdong leverage their logistics hubs and financial capital to exert substantial influence across the grain production and distribution chains.



4.2.2 QAP regression analysis of driving factors in spatial correlation networks

With 20,000 random permutations selected, the QAP regression analysis was conducted on the driving factor (Table 6). It reveals that the regression coefficients for the spatial geographical location, economic development level difference matrix, industrial structure difference matrix, and agricultural mechanization level difference matrix all achieved statistical significance at the 5% level, indicating that these factors have significant driving effects on the spatial correlation network of CRFP. Among them, spatial geographical location, economic development level differences, and industrial structure differences have significant positive impacts on the spatial correlation of CRFP, while agricultural mechanization level differences exhibit a significant negative effect. Geographically adjacent regions typically share similar climatic conditions and resource endowments, facilitating information sharing and technology diffusion, thereby enhancing interregional linkages in CRFP. Appropriate differences in economic development levels and industrial structures can promote spatial network connectivity of CRFP through resource complementarity. However, significant disparities in agricultural mechanization levels may lead to inconsistent technical standards, hindering cross-regional collaboration and consequently reducing the degree of spatial correlation in CRFP between regions.

5 Discussion and conclusion

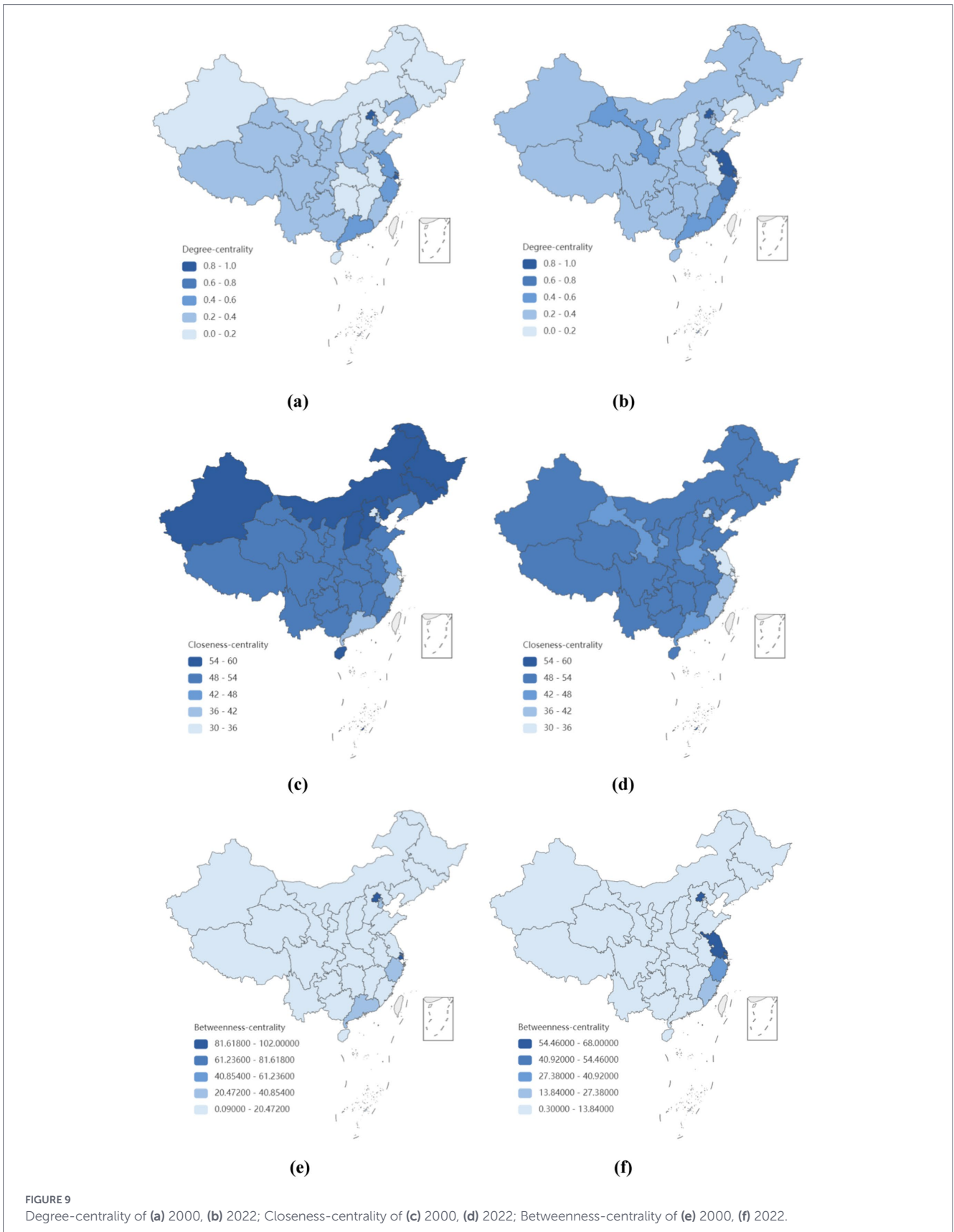
5.1 Discussion

Improving CRFP is of great significance for ensuring food security and achieving high-quality development in food production. Understanding the evolution patterns of CRFP is a crucial prerequisite for enhancing resilience and minimizing the adverse impacts and risks of climate change. This paper employs various methods to explore the spatiotemporal characteristics of the development and changes in

CRFP in China, aiming to provide more valuable insights for improving the CRFP.

In terms of the overall trend, CRFP shows an upward trend but with fluctuations. Specifically, the period from 2000 to 2012 was marked by rapid growth, followed by a decline from 2012 to 2018. After 2018, the upward trend resumed, though at a relatively slower pace. This finding is robustly supported by cross-system validation with existing studies. For example, Cai et al. (2025) found that China's food production resilience exhibited a fluctuating yet overall upward trend from 2010 to 2022, with climate change as a significant factor. Similarly, Lin et al. (2025) reported an overall fluctuating increase in China's agricultural resilience from 2012 to 2022, also identifying climate change as a key determinant. Although these studies differ in conceptualization, measurement, and study periods, they collectively point to a long-term improvement in the adaptive capacity of China's food production system. This cross-study consistency strengthens the robustness and external validity of our measurement results. A key contribution of this study lies in reconceptualizing climate adaptability—from an “exogenous variable” affecting resilience to an “endogenous dimension” embedded within the resilience measurement framework. Thus, the upward trend identified here is not merely a replication of previous findings, but constitutes new evidence specific to the climate adaptation discourse. It indicates that China's food production system has not only become more resilient overall, but also shows measurable progress in its capacity to respond to climate change.

From a regional disparity perspective, significant heterogeneity exists in China's CRFP. Eastern region exhibits relatively high resilience, while the northeastern region shows lower and more volatile resilience. Meanwhile, notable spatial dependence and spillover effects. This regional pattern is consistently corroborated across related studies. For instance, Dong et al. (2025) confirmed uneven regional development and increasing spatial agglomeration in China's food system resilience. Chen et al. (2024) similarly identified persistent regional imbalances in food security resilience, with eastern region significantly outperforming western region, and the northeastern region displaying relatively low resilience with sluggish improvement. Collectively, these studies reveal



pronounced spatial heterogeneity in China’s food resilience. This paper advances the analysis from “how large the disparities are” to “where disparities originate, how they evolve, and who can catch up,” systematically deconstructing the structural sources,

dynamic evolution, and convergence patterns of regional differences.

In terms of spatial correlation network characteristics, China’s CRFP exhibits extensive spatial linkages, with increasing network complexity

TABLE 6 Regression results.

Variable	Unstandardized coefficient	Standardized coefficient	Significance	PA	PB
Intercept	-0.0048	0.1971	0.0027	0.0027	0.9974
DS	0.2431	0.1891	0.0001	0.0001	0.9999
EC	0.0007	0.0329	0.0139	0.0088	0.9913
IS	1.5323	0.0239	0.0415	0.0275	0.9726
MC	-0.0008	-0.0313	0.0151	0.9934	0.0066

PA represents the probability that the regression coefficient generated by random permutation is not less than the observed regression coefficient. PB represents the probability that the random replacement's regression coefficient is not greater than the observed regression coefficient (double-tailed test).

and the gradual formation of multi-channel, multi-tiered interaction patterns. Key drivers include geographic proximity, disparities in economic development and industrial structure, and differences in agricultural mechanization levels. This finding is robustly corroborated across related themes. For instance, Wang et al. (2025) found growing spatial correlations in provincial agricultural economic resilience, while Qu et al. (2022) reported rising complexity in China's agricultural eco-efficiency networks. Although not directly focused on climate resilience in food production, these studies collectively reveal a trend toward structural complexification in China's agricultural spatial networks. Building on their methodological foundations, this study extends the analytical paradigm to the climate resilience in food production. This not only validates the robustness of our network analysis but also demonstrates that spatial synchronization of climate adaptive capacity has emerged as a key feature in the evolution of China's agricultural.

5.2 Conclusion

The main research conclusions of this paper are as follows: (1) CRFP shows an upward trend but with fluctuations. The CRFP in the eastern region has significantly outpaced that of other regions since 2016. In contrast, the northeastern region exhibits lower CRFP, with greater variability. (2) China's CRFP demonstrates notable convergence characteristics, along with spatial dependence and spillover effects. Factors such as financial support for agriculture, urbanization, and technological innovation can accelerate the convergence speed of CRFP. Regional disparities are the primary cause of the differences in CRFP. (3) China's CRFP exhibits extensive spatial interdependence. The complexity of the spatial correlation network structure has gradually increased, with network hubs expanding from cities like Shanghai and Beijing in 2000 to include Shanghai, Jiangsu, Beijing, and Zhejiang by 2022, progressively forming a multi-channel, multi-level interactive pattern. Spatial geographic location, disparities in economic development levels, differences in industrial structure, and variations in agricultural mechanization levels constitute the primary driving factors influencing the spatial correlation network of CRFP.

To further enhance China's CRFP, reduce the disparity in climate change adaptation capabilities across regions, and promote the sustainability of food security under climate change, this paper presents the following policy recommendations based on research findings: (1) Focus on the regional disparities in CRFP and formulate policies to promote coordinated development between regions, such as encouraging regional collaboration and strengthening collaborative governance. Deepening inter-regional cooperation, especially in high-resilience regions through technology transfer and policy alignment, can effectively drive the improvement of neighboring

low-resilience regions. (2) Optimize resource allocation and infrastructure development. Allocate more resources to regions with relatively low climate resilience but with potential for improvement, and strengthen agricultural infrastructure construction according to local conditions. For example, build more early warning facilities in areas prone to extreme weather events, enhance the forecasting and response capabilities of these regions, and achieve an overall improvement in CRFP. (3) Establish a dynamic monitoring mechanism for agricultural climate change. Adjust agricultural and climate policies in a timely manner based on real-time changes in climate and production conditions, improving the flexibility and adaptability of policies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YZ: Data curation, Formal analysis, Funding acquisition, Methodology, Software, Writing – original draft, Writing – review & editing. YF: Formal analysis, Investigation, Supervision, Validation, Writing – review & editing. ZL: Methodology, Writing – review & editing. ZZ: Conceptualization, Data curation, Methodology, Software, Writing – review & editing. LC: Funding acquisition, Methodology, Resources, Visualization, Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This research was supported by the Basic Scientific Research Operating Expenses Project of Heilongjiang Provincial Universities (145409408), National Social Science Foundation of China (24CTJ030), and Hunan Social Science Foundation Project (24ZDB014).

Acknowledgments

The authors are grateful to the editor and the reviewers of this paper.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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