

Complexity

Spatial Pattern, Complexity and Resilience of Urban Network Structure 2022

Lead Guest Editor: Jing-Hu Pan

Guest Editors: Miao Zhang, Xiuliang Yuan, and Liang Zhou





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Research Article

Spatial Identification and Distribution Pattern of the Complexity of Rural Poverty in China Using Multisource Spatial Data

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Regional poverty is one of the most serious challenges facing the world today. Poverty, antipoverty, and poverty alleviation are the focus of the attention of scholars and the public. This paper takes China's counties as the research unit, selects the influencing factors of poverty from natural and socio-economic factors, establishes an evaluation index system, simulates the natural poverty index and socio-economic poverty eradication index of each county, and clarifies the distribution characteristics of spatial poverty using GIS spatial analysis and BP artificial neural network. The results indicate that natural factors are the main cause of poverty in Chinese counties, with 710 counties having a high natural poverty index, accounting for nearly 30% of the total number of counties in the country. The national county-level natural poverty index shows a clear strip distribution pattern along latitude and longitude, with a strip distribution from north to south and from west to east; socio-economic factors have played a certain role in poverty alleviation, with as many as 1521 counties with low socio-economic poverty alleviation indices, accounting for approximately 64% of the total number of counties in the country. The spatial distribution of the county-level socio-economic poverty alleviation index is relatively fragmented. Through spatial scanning statistics, a total of 44 county poverty pressure index risk clusters reached a statistical significance level, involving 243 counties and districts. In poverty reduction practice, the internal counties and districts of contiguous poverty-stricken areas should strengthen cooperation and exchange. In the process of poverty alleviation and development, targeted poverty alleviation and economic development should be carried out based on the poverty-dominant type and self-development ability of the county, in order to improve efficiency. Regions that are relatively prosperous and have taken the lead in poverty reduction should play a leading and exemplary role in strengthening the radiation power of regional central cities. The prominent feature of this study is the comprehensive utilization of multisource data and the use of new spatial analysis methods (flexible spatial scanning method is widely used in the field of infectious disease prevention and control research). By constructing a multidimensional poverty measurement system that includes natural and social factors, it distinguishes the differences between the factors that cause poverty and the factors that eliminate poverty in regional poverty. At the same time, the flexible spatial scanning detection method was used to detect the differentiation mechanism of poverty spatial patterns.

1. Introduction

Regional poverty is one of the most serious challenges facing the world today. Poverty, antipoverty, and poverty alleviation are the focus of attention of scholars and the public [1]. Since the reform and opening up, the Chinese government has implemented a series of policies to reduce poverty. The number of poor people in rural areas is rapidly decreasing.

However, the epidemic is still raging around the world since the beginning of 2020. The epidemic of SARS-CoV-2 has closed borders in many countries around the world, suspended flights, disrupted traffic, closed factories, and closed stores. The global economy has experienced the largest negative growth in decades. And the impact on the world is far from over. Agence France-Presse reported in October epidemic of SARS-CoV-2 has hit the American middle class

hard and has pushed 8 million people back into poverty. According to a study released in March 2021 by the Pew Research Center [2], an independent polling agency in the United States, the epidemic of SARS-CoV-2 has caused at least 32 million middle-class Indians to return to poverty. According to the estimates of the United Nations Economic Commission for Latin America (CEPAL), the poverty rate in Latin America will increase by 4.4 percentage points to 33.7% in 2020, and the number of poor people will increase by 28.7 million. The extreme poverty rate rose by 2.5 percentage points to 13.5%. The number of people living in extreme poverty increased by 16 million, and nearly 83.4 million people faced food crisis. While the poverty rate has risen, social stratification has accelerated [3]. The epidemic has had a greater impact on socially disadvantaged groups. On the one hand, due to poor health and hygiene protection conditions, these groups are more vulnerable to the epidemic; on the other hand, unemployment and income decline have a greater negative impact on life. Although the epidemic is basically under control in China, it still occurs frequently in some areas, and the prevention and control situation is still very severe. Preventing the pressure from returning to poverty due to the epidemic has also become a major task of China's national governance in the next stage; at the same time, the identification of poor areas has been questioned and criticized by scholars and the public due to the lack of scientific and reasonable identification methods. According to different targeting scales, poverty identification can be divided into two types, respectively, family or individual identification and geographic identification. Geographic identification refers to poverty identification carried out by geographic units of different scales. At this stage, China's poverty is still very large, and the remaining poor population is spatially distributed. It has obvious regional characteristics, which inevitably determines that in the long-term future, the targeting of poverty alleviation projects must still be based on regional targeting. The identification of the traditional poor areas is mainly based on a single indicator, but it only depends on a single indicator cannot accurately identify poverty areas and their characteristics, failing to achieve the goal of "precision poverty alleviation" in space, causing the phenomenon of "there is no assistance". If we simply measure poverty based on statistical data such as income, we often lack a geospatial perspective and cannot intuitively clarify the regional characteristics that caused poverty and the influencing mechanism of spatial geography on poverty. Under the background of the country's vigorous promotion of "precision poverty alleviation", it is of great theoretical value and profound realistic significance to identify poor areas from a spatial perspective and multiple dimensions, and to classify them and propose differentiated countermeasures for poverty alleviation.

Since the 1990s, more and more attention has been paid to the research and application of the results of spatial poverty in the world. From the perspective of social, economic, ecological environment, and other multidimensional space, exploring the endowment of geographical resources, regional spatial characteristics, spatial trap, spatial

dependence of poverty, and so on have become hot topics in the field of poverty research at home and abroad. At the research scale, with the application of GIS and remote sensing technology, the development of statistical methods, and the enrichment of micro data, the study of poverty geography is being developed by focusing on the formation mechanism of the macro-level poverty trap and the combination of low-level equilibrium shifting to multiple scale combination including micro, meso, and macro. In research methods, attach importance to regional poverty appraisal, and quantitative analysis of regional poverty influencing factors. In the research content, pay close attention to the identification of spatial poverty traps, research on the coupling relationship between multidimensional geographic factors and rural poverty, regional poverty appraisal, regional targeting, assessment, and so on. In the formulation of poverty alleviation policies, it is often difficult for policy makers to observe and obtain the real attribute characteristics of poor families, which will restrict the effectiveness of the precision poverty alleviation policy to a certain extent [4]. Due to the nesting, correlation, and influence of different spatial scales, individual or family poverty on the micro-scale is often affected by economic result on the medium and macro-scale. Therefore, it is still necessary to carry out research on poverty space from the perspective of meso- and macro-scale. At present, most of the related research studies take provincial or prefecture-level cities as the research object, and it is rare to target more detailed nationwide research on the regional unit [5].

Based on this, this paper takes the county as the basic unit, abandons the traditional method of relying solely on statistical data for poverty measurement, and uses GIS, artificial neural network, and multisource spatial data to obtain the spatial complexity distribution of the natural poverty index, socioeconomic poverty reduction index, and poverty pressure index at the county level in China. For the first time in the field of poverty research, the Flexible spatial scanning detection method was used to identify deeply impoverished counties. Quantitative analysis was conducted on the impact of natural poverty factors and socioeconomic poverty reduction factors on county poverty. Simulate the relationship between county environmental conditions and the occurrence of poverty and its spatial pattern, and explore the main factors leading to poverty in deeply impoverished counties, aiming to find out the current situation of poverty in the country, and providing scientific references for proposing differentiated poverty reduction suggestions and improving the regional accuracy of poverty alleviation policies. From a multidimensional perspective, this paper abandons the traditional method of simply relying on statistical data such as income to measure poverty. By using GIS, artificial neural network, and multisource spatial data, this paper quantitatively analyzes the impact of natural poverty causing factors and social and economic poverty alleviation factors on regional poverty, and simulates the relationship between regional environmental conditions and the occurrence of poverty and its spatial pattern, which can help to understand the current situation of poverty. Improve the precision of regional targeting of poverty alleviation

policies to provide scientific reference. The findings of this study could provide valuable implications for formulating China's poverty alleviation strategy after 2020, thereby contributing to global poverty alleviation and development.

2. Related Work

The famous British economist Rountree first proposed the concept of poverty at the beginning of the 20th century. He explained poverty from the perspective of the most basic living needs of human beings. He believed poverty is a state in which the total income of a family cannot meet the most basic living needs of the family members [6]. Since only the single indicator of minimum living security expenditure is used as the basis for dividing poverty, it is called single-dimensional poverty. Based on the definition of single-dimensional poverty, the World Bank proposes to use the criteria of "1.25 US dollars per day" and "1 US dollars per day" as the basis for determining the international poverty status [6]. There are three poverty line standards in China, namely "1984 standard", "2008 standard", and "2010 standard", and the corresponding poverty lines are 200 yuan, 865 yuan, and 2300 yuan, respectively. As far as the current domestic scholars' research on poverty is concerned, the meaning of single-dimensional poverty mainly refers to income poverty, that is, under certain environmental conditions, the overall income of individuals, families, and social groups cannot meet the minimum requirements of people's basic living needs and resources, so they are classified as poor.

In the 1980s, the research on poverty was further extended and expanded, and scholars' understanding of poverty gradually developed from one dimension to multidimensional, from simple income poverty to multiple dimensions of material, rights, and abilities. The theory of multidimensional poverty originated from Amartya Sen, who won the Nobel Prize in Economics in 1998. He believed that poverty is the deprivation of basic feasible capabilities of human beings [7]. The problem of human poverty is not only the poverty of economic income, but also the poverty of infrastructure and public services, as well as the poverty of subjective feelings of social welfare. The definition of multidimensional poverty is thus come.

In the 1950s, space economists Harris [8] and Myrdal [9] proposed that the social and economic development of backward areas has a certain relationship with the local geographical location. By the 1990s, the research and application of the theory of spatial poverty had received extensive attention from researchers, and the understanding of geographic capital also appeared in the study of spatial poverty. Geographical capital is the collection of natural, social, and economic capital formed by the agglomeration of natural, social, and economic capital in a certain geographical location. The lack of geographic capital in a certain area leads to the formation of a spatial poverty trap, which leads to spatial poverty; that is, spatial poverty is the regional poverty caused by the lack of natural environment, social economy, and other geographical capital. The research on spatial poverty is mainly to reveal

the degree of influence of geographic capital on the spatial distribution of poverty.

Usually, poverty is divided into absolute poverty and relative poverty. Under the influence of the concept of single-dimensional poverty, many scholars have carried out research on the accuracy of identifying individuals with income poverty by formulating different poverty lines, and proposed many methods, such as the Engel Coefficient Method, the Income Ratio Method, the Martin Method, the Linear Expenditure System Model Method, and so on. Domestic scholars compared the poverty line measurement methods proposed by foreign scholars, and believed that the method suitable for China's actual poverty measurement was the Martin Method.

Economic growth is an important guarantee for poverty eradication. Although the economically developed areas have strong financial support and a sound social public service system [10], a sound social public service system will automatically allow higher-income groups to drive the development of low-income groups by providing jobs and increasing consumption through the "trickle-down effect", thereby establishing an environment where social groups can enjoy benefits fairly [11]. However, more and more studies have shown that income can only reflect one aspect of human development and poverty, and cannot fully reflect poverty in other dimensions besides income. With the proposal of the conception of multidimensional poverty, many scholars have correspondingly conducted research on the identification and measurement of poverty from the perspective of multidimensional and multiindicators. Hagenaars [12] added the dimension of leisure on the basis of single-dimensional poverty, and identified and measured poverty from the two aspects of leisure and income, which laid the foundation for subsequent scholars' related research. Nussbaum [13] used 10 dimensions such as physical health, life, thought, real perception, interpersonal relationship, and environmental awareness to explore the problem of ability poverty in issues such as social justice and human rights. Watts proposed the first distribution-sensitive poverty index, which is called the Watts index. After that, Charkravarty [14] extended the Watts index to the Watts multidimensional poverty index based on axiomatic conditions, and was widely used in countries around the world. Callander et al. [15] constructed a multidimensional poverty measurement index system from three dimensions of income, health, and education, and identified the poverty-stricken individuals at different stages in the central area, the transition area between the city center and the suburbs, and the three suburban areas in Australia. Luzzi and others [16] used the principal component analysis method to determine the optimal dimension for measuring poverty, and eliminated the multicollinearity effects between indicators of different dimensions and between indicators of the same dimension, and used cluster analysis to explore the impact of each dimension on the unbalanced effects among different groups.

Among the research studies on poverty in the world, Chinese scholars' research on multidimensional poverty not only compares foreign multidimensional poverty

measurement methods, but also measures China's poverty from multiple dimensions. Li [17] firstly measured and analyzed the poverty situation in rural China from multiple dimensions. Wang and Alkire [18–20] used the AF method to measure and identify China's multidimensional poverty, and further studied the decomposition of regions, dimensions, and urban and rural areas. Zou and Fang [21] studied the fuzzy set method for measuring average ability deprivation, the efficiency method, and the measurement method based on the input-output theory, and discussed the existing problems and future development trends of multidimensional poverty measurement.

In the 1990s, Jalan and Ravallion [22] conducted a survey on farmers in four southern provinces, including Guangxi and Guangdong, and the results showed that spatial differences in factors such as topography, medical care, education, and road network density would cause some areas to fall into persistent poverty. Ravallion and Lokshin [23] found through their research on poverty in Bangladesh that geographical factors have a great influence on poverty, and location environment is the decisive factor leading to poverty. Minot et al. [24], Epprecht et al. [25], and others studied the distribution of spatial poverty in Vietnam and found that the poor are mainly concentrated in inland mountainous areas, and terrain and road density are the main influencing factors of spatial poverty. Curtis et al. [26] and others found that the high incidence of child poverty in the United States is concentrated in the southern Appalachian Mountains, remote areas, and northern plains Indian aboriginal agglomeration areas, and race and employment are the main factors causing poverty.

In summary, there are many studies on spatial poverty by domestic and foreign scholars. In their research, the measurement objects include both the impoverished population and administrative units, and the research scale includes both macro and relative micro levels. The research methods are also different. However, the rural impoverished population in China exhibits a wide range and relatively concentrated spatial distribution pattern, with a multilevel organizational structure and spatial agglomeration distribution pattern of impoverished households, impoverished villages, impoverished counties, and impoverished areas. With the deepening of China's poverty alleviation work, the complexity and difficulty of rural poverty problems continue to emerge, and the promotion of precision poverty alleviation strategy is facing unprecedented pressure and challenges. Therefore, in the formulation of poverty reduction and elimination policies, decision-makers often find it difficult to observe and obtain the true characteristics of impoverished families, which can to some extent constrain the effectiveness of precision poverty alleviation policies. However, traditional methods for identifying poverty-stricken areas and calculating the number of impoverished people mainly focus on single factors such as income, which is often unable to accurately identify impoverished individuals and their poverty characteristics, and rarely consider geographical factors. Therefore, there is a lack of geographical spatial perspective, which cannot intuitively clarify the regional characteristics of poverty and

the impact mechanism of spatial geography on poverty. The results obtained are often not well matched with other spatial data. There is currently no relevant research on using flexible spatial scanning detection to identify poverty risks in impoverished areas.

There are not many studies on the mechanism of spatial differentiation of poverty. Minot and Baulch [27] and others studied the spatial distribution of poverty in Vietnam using the small-area estimation method, and put forward corresponding poverty reduction policy recommendations. Katsitadze [28] studied the causes of poverty and the distribution of spatial poverty in Georgia in the post-Soviet era and proposed corresponding poverty reduction methods. Li et al. [29] and others used household survey data from 22 counties in 13 provinces to study how to implement targeted poverty reduction methods.

In this paper, two research methods are used: artificial neural networks and spatial scan metrology. Artificial neural network (ANN) is a network that is widely interconnected by a large number of neurons. It is an abstraction, simplification, and simulation of the human brain neuron network from the perspective of information processing. It reflects the basic characteristics of the human brain. Its research began in the early 1940s. The psychologist McCulloch and the mathematical logician Pitts established a neural network and mathematical model, referred to as the MP model, and the development process was from the initial development climax to 1969. The book "Perceptron" in 2009 proposed that perceptrons cannot solve the problem of higher-order predicates, which greatly affected the research on artificial neural networks. There was a low tide period until the BP algorithm was proposed in 1986, which marked the artificial neural network. Another research climax is coming. The research content includes theoretical research, technical research, and applied research. This paper focuses on applied research.

In the past ten years, the research work of artificial neural networks has become more and more in-depth, and great progress has been made in practical applications. For example, in the fields of automation, prediction, and estimation, biology, medicine, and economics, many practical problems that modern computers cannot solve have been very successfully solved. At present, there are many models of artificial neural networks, and learning algorithms are emerging one after another. However, from the perspective of its application, there are only more than ten kinds of research studies, among which BP (back propagation) neural network is the most representative [30]. Its applications are involved in various fields. In the research on poverty identification and measurement; on the whole, there are few studies using the BP neural network method to analyze spatial poverty.

Identifying spatial agglomerations has always been the core goal of space science and spatial statistics. Currently, there are three methods: general, focused, and agglomeration identification [31] to identify and test the existence of spatial agglomerations. Global Moran's I and Local Moran's I are the most widely used general and focused identification test methods, respectively. The non-random geographic

process produces spatial agglomeration. Compared with the former two, the agglomeration identification test uses the likelihood ratio test [32] to evaluate the spatial agglomeration situation of geographical phenomena without prior knowledge or assumptions. Naus and Naus [33] first proposed the scanning statistic model in 1965. This agglomeration detection test can not only detect whether a phenomenon or event exists in a certain area, but also can accurately locate and determine the size of the aggregation area [34]. Before 1995, researchers generally used scanning windows of fixed shape and size, but due to the different regional population densities and the indeterminacy of the distribution scale of geographical events, the identification results were far from the actual situation. In 1995, Kulldorff and Nagarwalla [32] and others proposed a generalized mathematical model based on likelihood ratio test, which corrects for nonuniform population density and uses variable-sized circular or elliptical scanning windows [35], but it cannot detect irregularly shaped agglomerations; in 2005, Tango and Takahashi [36, 37] and others proposed a flexible spatial scanning measurement method on the basis of circular scanning measurement. A collection of geographically connected regions, different regions are scanned with a dynamically changing irregular scanning window, and the scanned region is limited to a smaller neighborhood of the starting region.

This method can not only detect whether a phenomenon or event is clustered in a certain area, but also can accurately locate and determine the scale of the cluster area, which is mostly used for risk prediction and assessment of diseases, but the related research on spatial poverty has not been seen, so this paper uses this method to detect the risk of poverty in poor areas.

3. Methods and Data Sources

3.1. Methods

3.1.1. BP (Back Propagation) Neural Network. To evaluate the poverty status of a region, multiple indicators need to be considered at the same time to form a comprehensive evaluation index system. The problem of spatial poverty is generally characterized by spatiality, nonlinearity and uncertainty due to the simultaneous interaction of natural and socioeconomic factors. So it is not possible to use a simple linear method for causal analysis. BP (back propagation) neural network is a multilayer feedforward artificial neural network using an error back propagation algorithm, with the advantages of simple model construction and a rich training algorithm. This paper uses the BP neural network to simulate the natural impoverishing poverty index (NII) and social economic poverty alleviation index (SEPAI) in MATLAB R2012b. Take each natural and social economic factor (Table 1) as the input layer, NII and SEPAI as the output layer, and the number of nodes in the hidden layer is determined by the formula $n = \sqrt{n_i + n_o} + a$ (n is the number of nodes in the hidden layer. n_i and n_o are the number of nodes in the input layer and output layer, respectively. In this paper, n_i and n_o are 6 and 1, respectively,

and a are constants between 1 and 10). Finally, the number of nodes in the hidden layer is determined according to the above formula through many experiments. After repeated tests, it is finally determined that the number of nodes in the implicit layer of NII and SEPAI in the simulation process is 5. Traditional BP algorithm (such as traingdx) has a slow convergence speed and is easy to fall into local minimum, while L-M optimization algorithm (Levenberg–Marquardt) uses the derivative of error to replace the derivative of mean square error of traditional BP algorithm, and uses batch processing in the training process, which greatly improves the convergence speed and convergence, so the training function used in this paper is L-M optimization trainlm algorithm function. Finally, the Poverty Pressure Index (PPI) is put forward. According to NII and SEAPI, the PPI of the study area is determined. The expression is

$$PPI = NII * (1 - 0.2 * SEAPI). \quad (1)$$

In the formula: 0.2 is social economic poverty alleviation coefficient, which means that 20% SEPAI is used to eliminate or alleviate local poverty.

3.1.2. Flexscan Measurement Method. The purpose of using the Flexscanning measurement method in this paper is to detect poverty-stricken counties with a high risk of poverty, and to further identify and determine the deep-poor counties that need to be focused on in the future. The key to the Flexscanning statistics of the average risk is to detect the abnormal situation of poverty occurrence at the three scales of province, city, and county, that is, to detect whether the poverty pressure index at the three scales of province, city, and county has a statistical significance of aggregation, its precise location and the magnitude of poverty risk. Currently, there are two methods for Flexscanning statistics, SaTScan, and Flexible. The former uses a dynamic circular or elliptical scanning window to analyze the risk of poverty. The size and position of the scanning window are dynamically changed, which can avoid the subjective influence caused by human selection; the latter mainly uses the dynamic irregular scanning window to analyze the size of the risk of poverty occurrence. Based on the irregularity of the boundaries of administrative divisions at all levels, this paper adopts Flexible. The theoretical poverty pressure index is calculated according to the Poisson distribution, and then the log-likelihood ratio test statistic (Log Likelihood Ratio Test Statistic) (LLR for short) is constructed using the actual poverty pressure index and the theoretical poverty pressure index. Finally, the scanning window with the largest LLR is selected as the high-poverty aggregation window [36], the provinces, cities, and counties included in the window are determined, the relative risk of the corresponding study area is calculated, respectively, and the Monte Carlo method is used. Calculate the P value of the LLR to determine whether it is statistically significant.

Assuming that the Flexscan statistics S is the largest likelihood ratio among all possible scan windows Z , then [34]

TABLE 1: Appraisalment index system of rural spatial poverty.

First-level index	Second-level index	Unit	Data type
Natural environment	Net primary productivity (NPP) X_1	gc/m ²	Raster data
	Catchment index X_2	—	Observation data
	Terrain fragmentation X_3	m	Spatial grid
	Average height X_4	m	Spatial grid
	Average slope X_5	—	Spatial grid
	Vegetation Humidity Index (GVMI) X_6	—	Raster data
Social economy	Per capita public financial revenue X_7	Yuan/person	Statistics data
	Per capita household savings balance X_8	Yuan/person	Statistics data
	Per capita net income of farmers X_9	Yuan/person	Statistics data
	Illiteracy rate X_{10}	%	Statistics data
	Bed number per 10000 of health institutions X_{11}	Bed	Statistics data
	Average nighttime light X_{12}	—	Raster data

$$S = \frac{(\max(Z)\{L(Z)\})}{L_0} \quad (2)$$

$$= \frac{\max}{Z} \left\{ \frac{L(Z)}{L_0} \right\}.$$

In the formula (2): $L(Z)$ is the likelihood function value of the scan window Z , and L_0 is the likelihood function value obtained based on the null hypothesis [34].

The likelihood ratio of the Poisson model is

$$\text{LLR} = \frac{L(Z)}{L_0}$$

$$= \frac{[n(Z)/u(Z)]^{n(Z)} [N - n(Z)/u(G) - u(Z)]^{n(G)-n(Z)}}{[N/u(G)]^{n(G)}}. \quad (3)$$

In the formula: $n(Z)$ is the actual poverty pressure index in the scanning window Z ; $\mu(Z)$ is the ideal value of the poverty pressure index in the scanning window Z obtained according to the null hypothesis; N is the poverty pressure index in the research area; $\mu(G)$ is the ideal value of the poverty pressure index in the research area obtained according to the null hypothesis, and $\mu(G) = N$.

3.2. Data

3.2.1. Administrative Boundary Vector Diagram. As this paper mainly studies rural poverty, for the convenience of research, if there are several municipal districts in a city, it is necessary to combine all municipal districts and name them as “urban areas”, and then conduct statistical analysis as a unit. Thus, a total of 2,389 county-level research units were obtained nationwide. Data of Taiwan Province, Hong Kong, and Macao SAR are temporarily unavailable and are not included in the scope of study.

3.2.2. Digital Elevation Model. The DEM grid resolution is 90 m (Figure 1). Using DEM in ArcGIS software, the relevant data and the county administrative boundary vector map are superposed to obtain the terrain fragmentation, average elevation, average slope, and composite terrain index of each county.

3.2.3. NPP Data. NPP data obtained from NASA’s MODIS product website (<https://ladsweb.nascom.nasa.gov>). It is a synthetic product of MOD17A3 with 1 km resolution in 2013. The MOD09A1 product used to calculate GVMI is also downloaded from this website.

3.2.4. Precipitation Data. The precipitation data in 2013 is taken from China Meteorological Data Network (<https://data.cma.cn/>).

3.2.5. Nighttime Light Data. The night light data in 2013 is from NOAA’s National Geographic Data Center (<https://ngdc.noaa.gov/eog/download.html>), which is a stable lighting product.

3.2.6. Social-Economy Statistical Data. The social-economy statistical data were collected from the China Regional Economic Statistics Yearbook published in 2014, and some missing data were obtained from the 2014 statistical yearbooks of provinces and cities (2013 data). The Digital Elevation Model (DEM) data was obtained from the United States Geological Survey (USGS) website (<https://lta.cr.usgs.gov/HYDRO1K>). The grid resolution is 90 meters (Figure 1). Using the DEM in the ArcGIS software, the relevant data is superimposed with the vector diagram of county administrative boundaries, and the terrain fragmentation, average elevation, average slope, and synthetic terrain index of each county are statistically obtained. The sources of the data are shown in Table 2.

3.3. Index System of County Poverty Appraisalment. A comprehensive and in-depth analysis of regional poverty appraisalment needs to start from the perspectives of economy, society, nature, and ecological environment, and systematically characterize regional poverty manifestations (economic status and hard status), livelihood capabilities (social status and soft status), and sustainable development capabilities (natural environment and potential state). When selecting an indicator, it is necessary to comprehensively consider the basic principles of comprehensiveness, scientificity, conciseness, rationality, and operability of the indicator. It can meet the poverty alleviation requirements of

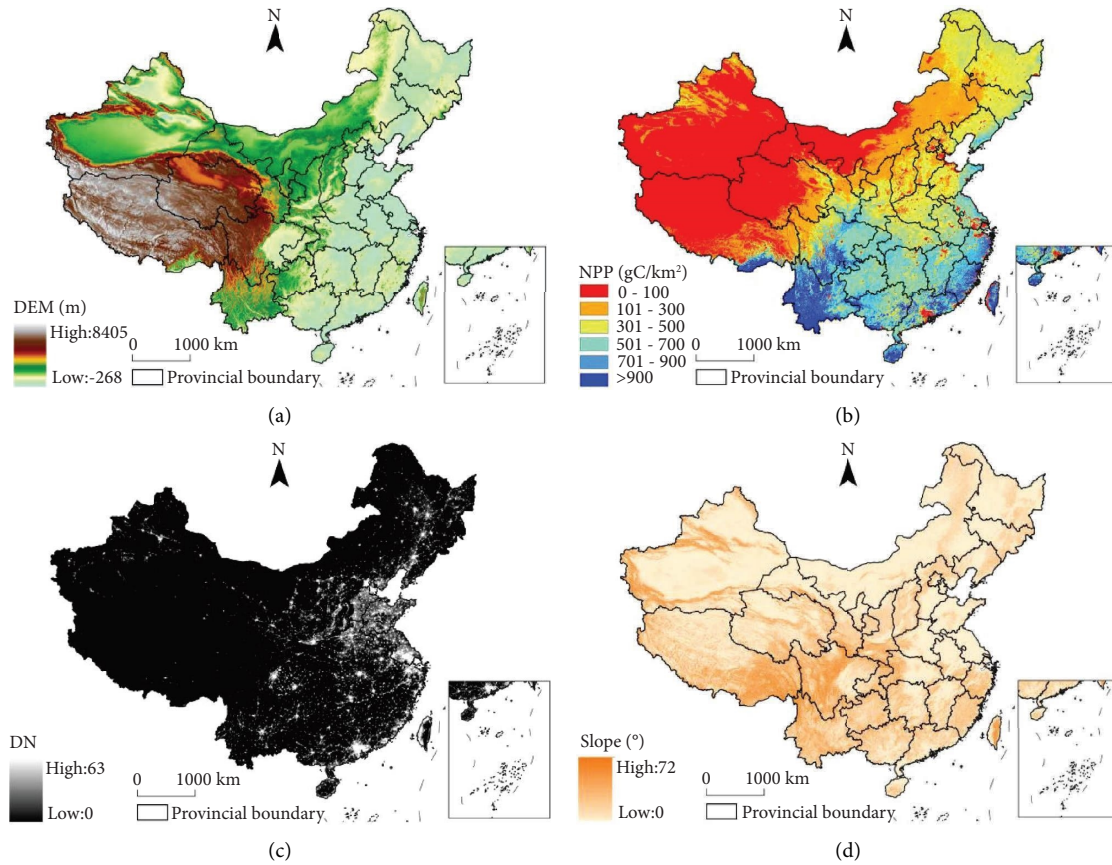


FIGURE 1: Spatial distribution of some rasterization index. (a) DEM. (b) NPP. (c) Nighttime light. (d) Slope grade.

TABLE 2: The sources of the data.

Data set name	Data source
The administrative boundary vector diagram	The 1:4,000,000 database of National Geographic Center for Basic Data (https://www.ngcc.cn/ngcc/html/1/index.html)
Digital elevation model (DEM) data	U.S. Geological survey (USGS) website (https://lta.cr.usgs.gov/HYDRO1K)
NPP data	NASA's MODIS product website (https://ladsweb.nascom.nasa.gov)
The data of the amount of precipitation	China Meteorological Data Network (http://data.cma.cn/)
The nighttime light data	National Geophysical Data Center of the U.S. National Oceanic and Atmospheric Administration (https://ngdc.noaa.gov/eog/download.html)
Social-economy statistical data	The China Regional Economic Statistics Yearbook published in 2014

multidimensional comprehensiveness and fairness of spatial poverty identification, the pertinence of research objects, policy relevance, and availability of evaluation data on the national scale at the same time. By referring to relevant literature [38] and the actual situation of poverty-stricken counties in China, and taking into account the monitoring needs of the core indicators of the current national comprehensive poverty alleviation strategy, this paper is guided by the theory of spatial poverty and the theory of man-land relationship, and takes the county-level administrative division as the research object. Meanwhile, it combines objective factors such as the natural ecological environment to alleviate poverty and the dynamic relationship of mutual effect between poverty and the natural environment, ecology, resources, society, economy, and other factors to

establish a candidate set of multidimensional poverty appraisal index systems including natural, ecological environment, socioeconomic, and other indicators. On this basis, candidate indicators are screened according to the relevance and discrimination of the indicators, and factors that a variance expansion factor VIF greater than 10 are eliminated, and the impact of multicollinearity is reduced. The appraisal index system shown in Table 1 is finally obtained.

To study the spatial distribution pattern of rural poverty at county level in China, firstly we must identify the factors causing poverty and poverty alleviation, as well as the degree of each factor's impact on spatial poverty. In this paper, we use correlation analysis to identify the factors that cause poverty and eliminate poverty. The cause of poverty is the

factor that leads to poverty. The factors caused poverty are negatively related to the degree of poverty. The greater the numerical value of the indicators that caused poverty, the more severe the degree of poverty. There is a positive correlation between poverty alleviation factors and the degree of poverty. The higher the value of poverty alleviation indicators, the lower the degree of poverty. Correlation analysis is performed on each selected indicator and per capita GDP to measure the factors that caused poverty and poverty alleviation factors that affect the spatial distribution of rural poverty in the county. Judging the factors causing poverty and poverty alleviation factors according to the results of related analysis, the size of the numerical value indicates the degree of poverty.

The NPP in the indicator system is used to reflect the strength of the productivity of the county ecosystem. The terrain fragmentation is characterized by the standard deviation of the high average at different points in each county. The compound Topographic Index (CTI) is a function of the upstream confluence area (FA) and landscape slope (slope). The calculation formula is [38]

$$CTI = \ln\left(\frac{FA}{\tan(slope)}\right). \quad (4)$$

The catchment index is introduced to represent the availability of water resources in a county. The calculation formula is

$$AW = \frac{(CTI * AP)}{10000}. \quad (5)$$

In this formula, AW is the catchment index; and AP is the annual precipitation. If a county has flat terrain, large catchment area and abundant rainfall, its AW will be large. On the contrary, if the terrain slope is large or the catchment area is small, and the precipitation is scarce, then the AW is small.

The Global Vegetation Moisture Index (GVMI) can reflect the information of vegetation and soil moisture comprehensively, and indicate the good or bad of the ecological environment of the county. The calculation formula is [39]

$$GVMI = \frac{(NIR + 0.1) - (SWIR + 0.02)}{(NIR + 0.1) + (SWIR + 0.02)}. \quad (6)$$

In the formula, NIR and SWIR are, respectively, the near infrared band (Band 2) and short infrared band (Band 6) of MODIS data product MOD09A1. The spatial resolution of MOD09A1 data product is 500 m, and the temporal resolution is 8 d synthesis. The spatial resolution of 500 m is resampled to 1 km, and the corresponding GVMI of 8d is obtained according to formula (3), and then the monthly GVMI is obtained by using the maximum synthesis method (MVC), and finally the annual average value is obtained.

The nighttime light remote sensing data adopts NPP-VIIRS data with high spatial resolution, and adopts invariant target area method [40] and neighborhood filtering method to eliminate the abnormal values in the original NPP-VIIRS nighttime light image. All the spatial data use the Albers

equivalent conical projection coordinate system, and the spatial resolution is resampled to 1 km, which is convenient for calculation and analysis. The spatial distribution is shown in Figure 1.

The flowchart of this paper is shown in Figure 2.

4. Results

4.1. Correlation Analysis of Poverty Influencing Factors. In order to obtain the degree of impact of selected indicators on poverty pressure at county level, some scholars do a correlation analysis on each factor and per capita GDP or farmers' per capita net income. Considering that per capita GDP is the most important indicator for measuring the socio-economic development status. This paper uses Person correlation analysis. On the one hand, further understand the main influencing factors of the degree of poverty in the study area, determine the linear correlation between each variate and per capita GDP, and judge whether each indicator is the impoverishing poverty factor or a poverty alleviation factor, and the nature of the impact of each indicator on poverty; on the other hand, ensure the accuracy of training and simulation of BP neural networks. Due to the large number of samples, this paper adopted a sampling method, and selected 200 samples at equal intervals for analysis after ranking GDP per capita of all county-level. Table 3 shows the influence of all factors selected in this paper on county-level spatial poverty. A negative correlation coefficient indicates that the factor is an impoverishing poverty factor; otherwise, it is a poverty alleviation factor. From the significant level test results, it can be seen that each factor having a significant impact on regional poverty. Except for the significance level of the catchment index X_2 and illiteracy rate X_{10} , which is greater than 0.01, the others are less than 0.05.

There is a negative correlation between the net primary productivity of vegetation in natural factors, degree of terrain fragmentation, average slope, average elevation, vegetation humidity index, and per capita GDP. Socio-economic factors are positively correlated with per capita GDP. Among them, average slope, per capita public financial income, per capita savings balance, per capita net income of farmers, the number of beds per 10,000 people in the health institutions, and the average nighttime light index showed a significant correlation.

4.2. Simulation and Analysis of Natural Impoverishing Index. Natural Impoverishing Index (NII) refers to the degree of impact of natural geographic elements on poverty. In this paper, the degree of terrain fragmentation, elevation, average slope, NPP, GVMI, and catchment index are used as the input layer, and NII is used as the output layer to build a BP neural network. The number of input layer nodes is 6 and the number of hidden layer nodes is 5 and the number of output layer nodes is 1. A $6 \times 5 \times 1$ network topology is constructed. The reasonableness of the training samples directly affects the quality of the neural network training results. Therefore, the training level is of great importance.

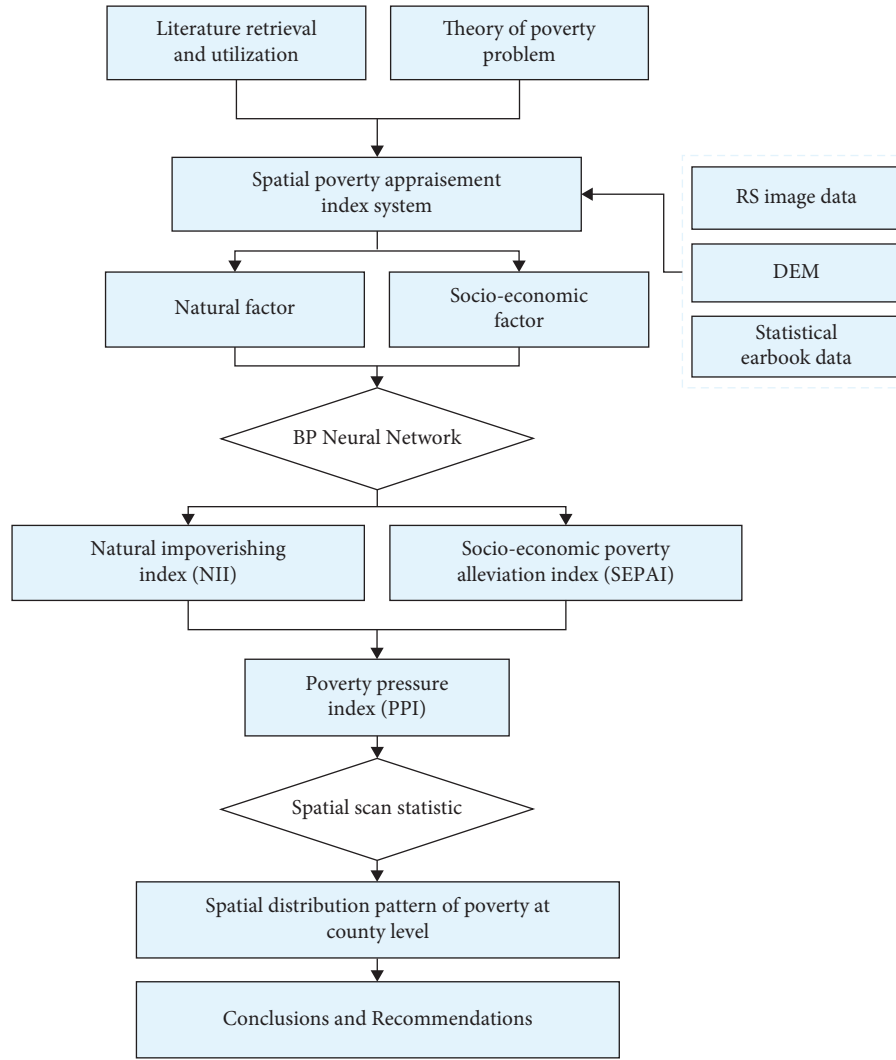


FIGURE 2: The flowchart.

TABLE 3: Results of correlation analysis.

	X_1	X_2	X_3	X_4	X_5	X_6
Correlation coefficient	-0.086	0.050	-0.155	-0.176	-0.279	-0.145
Significance level	0.004	0.243	0.015	0.006	0.000	0.021
	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Correlation coefficient	0.890	0.727	0.764	0.020	0.501	0.421
Significance level	0.000	0.000	0.000	0.388	0.000	0.000

According to the maximum and minimum ranges of all sample data, and the distribution characteristics of the data, this paper uses the natural breakpoint method to classify. The advantage is that the variance between classes is the largest and the variance within the class is the smallest. Finally, NII is divided into 5 levels. The degree of poverty in the order of levels 1 to 5 is low, lower, average, high, and higher, and the specific evaluation criteria are shown in

Table 4. The neural network is constructed and trained according to the above determined evaluation level criteria. The output layer neuron uses a purelin transfer function, and the training function uses the optimized L-M algorithm trainlm function. The basic parameters of network training are: the learning rate is 0.01, the maximum time of training is 10,000, and the minimum error is 0.001.

According to the above network and evaluation criteria, the data of the samples to be analyzed in each county input trained network, and is simulated 7 times by the BP neural network to reach the preset accuracy with an error of 0.09%. The BP neural network was trained well. After the network was run, the results of simulating Natural Impoverishing Index of each county were obtained. Using breakpoint method in ArcGIS to display the results spatially, obtains the spatial distribution pattern of the natural impoverishing poverty index NII (Figure 3). As can be seen from Figure 3, if you draw a straight line from Yingjiang, Yunnan to Gaizhou, Liaoning, the Natural Impoverishing Index NII happens to be bounded by this line, and is divided into two parts that are very different. The counties with lower NII are almost all

TABLE 4: Evaluation standard of natural impoverishing index.

NPP	Catchment index	Degree of terrain fragmentation	Elevation	Average slope	GVMi	Classification
1	1	0.0656	0.0520	0.0792	1	1 (low)
0.5530	0.5609	0.1564	0.1500	0.1860	0.7457	2 (lower)
0.4005	0.3681	0.2887	0.2992	0.3194	0.5780	3 (average)
0.2785	0.2441	0.5460	0.5632	0.5308	0.4508	4 (high)
0.1579	0.1423	1	1	1	0.2937	5 (higher)

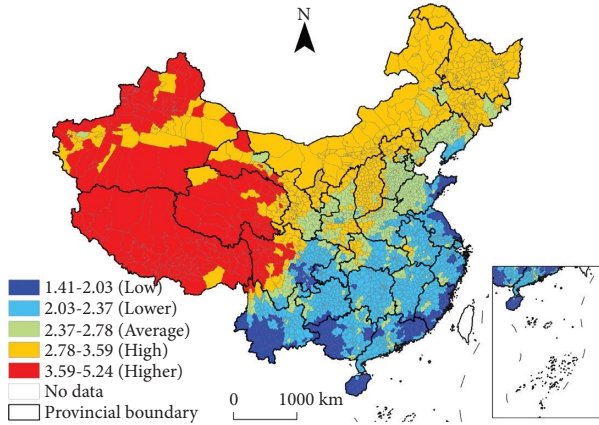


FIGURE 3: Spatial distribution of natural impoverishing index.

located on the east side of the Yingjiang-Gaizhou line, while the counties with higher NII are distributed in the west of the line. On the whole, the distribution of NII in counties across the country shows a clear pattern of zonal distribution with latitude and longitude: NII is arranged in a stripe pattern from north to south and from west to east. There are 278 counties with lower NII ($NII < 2.03$), mostly distributed in provinces and regions south of 26° north latitude; there are as many as 780 counties with lower NII ($2.37 \leq NII < 3.59$), except for some counties in the Bohai Rim, all of them are located south of 35° north latitude. The above-mentioned counties and districts have lower elevations, high vegetation coverage, superior natural conditions, and ample rainfall, which is beneficial to the development of agriculture. At the same time, the vegetation productivity is high, and is rich in products. There are 539 counties with higher NII ($3.59 \leq NII < 5.24$), concentrated in areas north of 33° north latitude; among them, there are 171 counties with higher NII ($NII > 3.59$), all of which are located in the northwest and southwest areas west of 104° east longitude; the county with the highest NII is Yecheng County, Xinjiang, with a value of 5.238. The counties with high and higher NII are concentrated on the first and second steps of China's terrain, in which the landform undulates terribly, and the climate is arid or alpine, and the natural environment is harsh as well as the vegetation coverage is low and geological disasters are frequent, and the soil is barren.

Statistics show (see Table 5) that the average natural poverty index of 680 poverty-stricken districts and counties in 14 contiguous areas of dire poverty determined by the Outline of Poverty Alleviation and Development in China's

Rural Areas (2011–2020) issued by Central Committee of the Communist Party of China and the State Council of the People's Republic of China is 2.83, which is higher than the average natural poverty index (2.56) of all 2389 districts and counties across the country. In terms of the divided area (Table 5), in 14 contiguous areas of dire poverty, Tibet has the highest natural poverty index (4.34), followed by the Kashgar region, Khotan region, and Kizilsu Kirgiz Autonomous Prefecture in the southern Xinjiang, namely 3.66, and the Tibetan areas (3.61) in Gansu Province, Qinghai Province, Sichuan Province, and Yunnan Province. The mountain area in western Yunnan has the lowest natural poverty index (1.99). The natural poverty index in southern regions such as Wuling Mountain, Wumeng Mountain, desertification region in Yunnan Province, Guizhou Province, Guangxi Zhuang Autonomous Region, Luoxiao Mountain, and so on is generally lower than the national average, while the natural poverty index in northern regions such as Liupan Mountain, the southern foot of Daxing'an Mountains, Yanshan Taihang Mountain, Lvliang Mountain, Qinba Mountain, and so on is generally lower than the national average.

In terms of provinces, the average NII value of all counties in Hainan Province is the lowest, only 1.77, and the provinces with a smaller average NII value include Fujian (2.05), Guangxi (2.09), Zhejiang (2.09), and Yunnan (2.10). Tibet has the highest average NII value in all counties, and provinces with an average NII value > 3 also include Xinjiang (3.74), Qinghai (3.67), and Heilongjiang (3.05). In terms of the coefficients of variation of the NII values of every province, Sichuan has the largest coefficient of variation (0.22), followed by Xinjiang (0.18) and Yunnan (0.17), indicating that each county within the jurisdiction of the provinces has huge differences in natural impoverishing condition, and the distribution is the most uneven. The coefficient of variation of the NII value in Heilongjiang Province is the smallest, only 0.04, followed by Ningxia and Inner Mongolia, whose coefficients of variation are 0.05.

4.3. Simulation and Analysis of Socio-Economic Poverty Alleviation Index. The Socio-Economic Poverty Alleviation Index (SEPAI) refers to the extent to which socio-economic factors influence poverty reduction. This paper selects six indicators, respectively, per capita public financial income, per capita household savings, farmers' per capita net income, illiteracy rate, the number of beds per 10,000 people in the health institution and the average light intensity of nighttime

TABLE 5: Poverty indices of 14 contiguous specially poor areas of China.

Poverty index	NII	SEPAI	PPI
Liupan Mountains area	2.82	0.82	2.64
Qinba Mountains area	2.72	1.06	2.68
Wuling Mountain area	2.29	0.94	2.26
Wumeng Mountain area	2.33	0.60	2.95
Stony desertification area in Yunnan, Guangxi, and Guizhou	2.10	0.67	2.26
Mountain area in western Yunnan	1.99	0.86	2.82
South Foothills of the Greater Khingan Range	2.99	0.79	2.09
Yanshan-Taihang Mountains area	2.91	1.02	2.44
Lvliang Mountains area	2.84	0.94	2.33
Dabie Mountain area	2.39	0.68	1.95
Luoxiao Mountain area	2.29	0.87	2.01
Tibetan areas of Sichuan	3.61	0.92	3.15
Kashgar, Khotan, and Kizilsu Kirgiz in southern Xinjiang	3.66	0.99	3.00
Tibet	4.34	—	—

light to be used as the input layer, and SEPAI is used as the output layer to construct the BP neural network. The number of nodes in the input layer is six, and the number of nodes in the hidden layer is five, and the number of points in the output layer is 1. Construct a $6 \times 5 \times 1$ Network Topology. According to the maximum and minimum ranges of all sample data and the distribution characteristics of the data, the natural breakpoint method is used to classify. SEPAI is divided into 5 levels, and the degree of poverty alleviation is low, lower, average, high, and higher in the order of level 1 to level 5 (see Table 6). The neural network construction and training method is the same as the simulation method of NII.

According to the above network and evaluation standards, the sample data of each county to be analyzed was input into the trained network, and the BP neural network was simulated 9 times to achieve a preset accuracy with an error of 0.08%. After the network operation, the results of simulated social and economic impoverishing index of each county were obtained. After spatializing the results using the natural breakpoint method in ArcGIS, the spatial distribution pattern of the socio-economic impoverishing index is obtained (Figure 4). As can be seen from Figure 4, compared with more regular spatial distribution of natural impoverishing index in county areas, the spatial distribution of the socio-economic impoverishing index is more fragmented and chaotic, and the regularity is not strong. There are only 172 counties with higher SEPAI ($\text{SEPAI} > 3.04$), which are mainly concentrated in the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei, Liaodong Peninsula, Shandong Peninsula, and other places. The highest SEPAI is in municipal district of Shanghai Beijing and Shenzhen, and Ordos Dongsheng District, with SEPAI of 4.679, 4.272, 4.227, and 4.220, respectively. There are 236 counties with higher SEPAI ($3.04 \geq \text{SEPAI} > 2.09$), which are mainly distributed in the periphery of high-level SEPAI counties. There are as many as 687 counties with very low SEPAI ($\text{SEPAI} < 0.81$), which is distributed nearly approximating in space to the shape of “ π ”. There are 834 counties with lower SEPAI ($0.81 \leq \text{SEPAI} < 1.34$) and with the largest number, which distributed throughout the country.

Statistics show that the average socio-economic poverty alleviation index of 680 poverty-stricken districts and counties in 14 contiguous poor areas with special difficulties identified by the state is 0.83, which is far lower than the average socio-economic poverty alleviation index of all 2389 districts and counties throughout the country (1.35). In terms of the divided area, among the 14 contiguous poverty-stricken areas, the socio-economic poverty alleviation index in the Wumeng Mountains area is the lowest (0.60), followed by stony desertification area in Yunnan, Guangxi, and Guizhou (0.67) and the Dabie Mountains area (0.68). Qinba Mountain area (1.06) and Yanshan-Taihang Mountain area (1.02) have the highest socio-economic poverty alleviation index, but they are still far below the national average level. In terms of provinces, Guizhou Province has the lowest average SEPAI value in each county, and Zhejiang Province has the highest average SEPAI value. From the perspective of the coefficients of variation in the SEPAI values of each province, Guangdong and Ningxia have the largest coefficients of variation, followed by Henan and Guizhou, indicating that the socio-economic development conditions of the counties and districts governed by these provinces are very different and the distribution is the most uneven. Zhejiang province has the smallest coefficient of variation in SEPAI values, followed by Inner Mongolia and Shanxi. Compared with the coefficient of variation of NII, the coefficient of variation of SEPAI in each province is much higher than the coefficient of variation of NII, even in Zhejiang province with the smallest coefficient of variation in SEPAI. It is as high as 0.41, which indicates that the differences in the socio-economic poverty alleviation index among counties in China are much larger than the differences in a natural impoverishing index.

4.4. Analysis of Poverty Stress Index. Using the natural impoverishing index and the socio-economic poverty alleviation index, the poverty pressure index of each county is calculated according to formula (4), and comprehensive consideration of natural and socio-economic factors can better reflect the regional poverty status and spatial distribution characteristics. The natural breakpoint method was

TABLE 6: Evaluation standards socio-economic poverty alleviation index.

Per capita public financial income	Per capita household savings	Farmers' per capita net income	Illiteracy rate	The number of beds per 10,000 people in the health institution	Average light intensity of nighttime light	Level
0.0364	0.0531	0.0453	0.1834	0.0845	0.0254	1 (low)
0.0951	0.1118	0.0964	0.2473	0.1443	0.0873	2 (lower)
0.1925	0.2094	0.2021	0.3262	0.2358	0.1986	3 (average)
0.5077	0.3902	0.4310	0.5363	0.4052	0.4509	4 (high)
1	1	1	1	1	1	5 (higher)

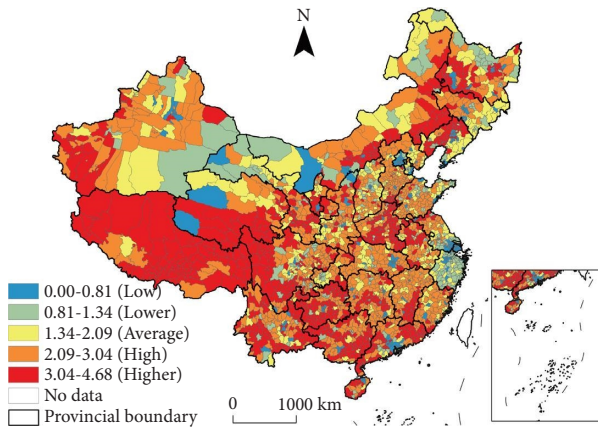


FIGURE 4: Spatial distribution of socio-economic poverty alleviation index.

used to classify the results spatially, and the spatial distribution pattern of the poverty pressure index was obtained (Figure 5). From Figure 5, it can be seen that the national poverty pressure index PPI is bounded by the “Heihe-Baise” line, and is divided into different east and west parts. The counties with lower PPI are almost all located on the east side of the “Heihe-Baise” line, while the counties with higher PPI are located on the west side of the line. Overall, the poverty pressure index shows a spatial distribution pattern “large dispersion, small aggregation” and there is a significant differences between east, middle, and west. There are 80, 85, and 308 counties with extremely high, high, and higher PPI, respectively, accounting for 20% of the total counties; counties with $PPI > 2$ have a total of 873 Counties, accounting for 37% of the total counties and these counties should be the key counties for poverty alleviation and poverty alleviation work. Due to the lack of statistical data, there are 28 counties and counties with no data.

Statistics show that the average poverty pressure index of 680 poverty-stricken counties in 14 contiguous poor areas with special difficulties is 2.64, which is much higher than the average poverty pressure index (1.95) of all 2,361 districts and counties in the country. In terms of the divided area, the poverty pressure index of the three regions in southern Xinjiang is the highest among the 14 contiguous special hardship areas (3.00), followed by the Wumeng Mountains area (2.95) and the western Yunnan border mountains area

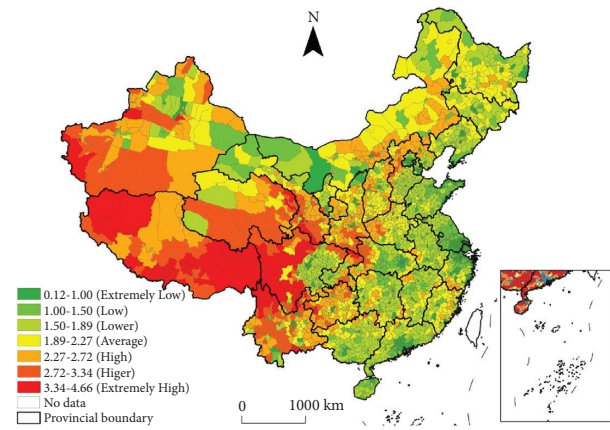


FIGURE 5: Spatial distribution of poverty pressure index.

(2.82); Dabie Mountain area (1.95) and Luoxiao Mountain area (2.01) have the lowest poverty pressure index, which is the same as or slightly higher than the national average level. In terms of provinces, Qinghai Province has the highest average PPI of 2.79. The provinces with higher average PPI also include Yunnan (2.52), Gansu (2.47), Xinjiang (2.47), Sichuan, and Guizhou (2.35). The county's PPI average is the lowest in all counties of Jiangsu Province (1.18), and the provinces with an average PPI is less than 1.5 also include Zhejiang (1.42), Guangdong, and Hainan (1.47). From the coefficient of variation of the PPI value of each province, Zhejiang has the largest coefficient of variation of 0.40, followed by Chongqing (0.37) and Guangdong (0.35). Although Zhejiang and Guangdong have the highest levels of economic development in the country, the degree of poverty pressure in the counties and districts in the province is quite different. The development level of Chongqing's urban function core area, developing area, and new areas is high, which is very different from northeast Chongqing and southeast Chongqing. The coefficient of variation of the PPI value was the smallest, only 0.17, followed by Guizhou and Hainan, with coefficients of variation of 0.18 and 0.19, respectively.

The corresponding spatial weight matrix was constructed using the Rook standard. The global Moran's I value of the poverty pressure index in China's counties was calculated to be 0.33 with the support of GeoDA software. It passed a 1% significance test, indicating that the poverty

pressure index in China's counties has a higher agglomeration effect in space. Counties and districts with higher PPI have higher PPI in the surrounding counties; counties and districts with lower PPI have lower PPI. According to the spatial autocorrelation of districts and counties with neighboring districts and counties, at 5% level of significance, the districts and counties throughout the country are divided into 4 types, as shown in Figure 6: high-high agglomeration (HH), low-low aggregation (LL), low-high agglomeration (LH), and high-low agglomeration (HL). As can be seen from Figure 6, the significant number of each type is $LL (565) > HH (475) > LH (49) > HL (48)$. The pressure of self-poverty is high and HH-type counties with high poverty pressure in the surrounding counties accounted for 20% of the country's total counties, which indicates that the distribution of poverty in China's counties is still very wide, and can be called "poverty-type" counties. HH-type contiguous large area is distributed in the Northwest and Southwest. The number of LL-type counties that the pressure of self-poverty is small and the poverty pressure in surrounding counties is also small accounts for about 23.9% of the total. It is not as continuous as the HH-type in space, and can be called "rich" counties. However, LH-type districts and counties with high poverty pressures in the surrounding counties are often embedded in HH-type distributions and fill in the blanks, which is called Peach orchards-type County. The HL-type counties that the pressure of self-poverty is high, and the poverty pressure in surrounding counties is small is distributed around LL-type, which is called "shadow-type". These counties are mostly distributed near the economically developed metropolitan areas, covered by the aura of the metropolitan areas, and should be highly concerned.

The problem of spatial poverty in China's counties in the new period is more caused by natural factors, and socio-economic factors can play a certain relief role in spatial poverty in counties. The harsh natural environment in some counties has greatly restricted the regional socio-economic development. Studies have shown that regions with higher poverty pressures have correspondingly higher natural impoverished index. For example, the natural condition of the three regions and states of Xinjiang in the west, the Qinghai-Tibet Plateau, and the Loess Hilly and Gully Areas is harsh, and the terrain is undulating, and the climate is dry or cold, and disasters are frequent; the ecological environment in Yunnan, Guizhou, and Guizhou karst areas is fragile, and rocky desertification is serious, and the area of arable land in rural areas is small, and the lack of water and land resources, which make the contradiction between human and land sharp. Social development level in the above-mentioned area is also relatively backward, and the transportation infrastructure is poor; the industrial structure is often single, and the contrast between economic development and resource advantages is large, lacking regional endogenous growth mechanisms, relying more on foreign aid, and lacking self-blood-making capacity. The low eastern coastal areas, the central plains, and the individual industrial and mining cities in the west have relatively superior natural conditions, good climatic conditions, and relatively abundant water and land resources. The regions have strong self-

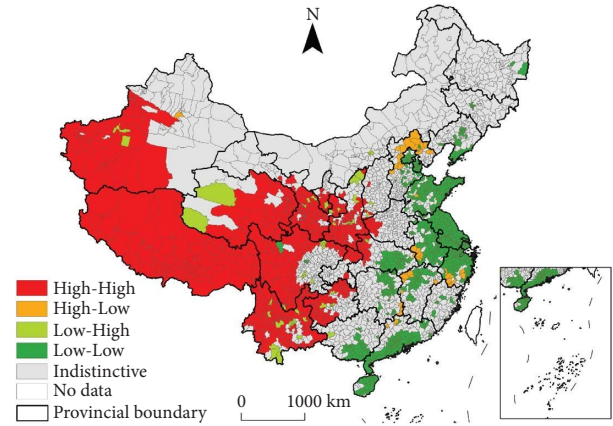


FIGURE 6: The local spatial autocorrelation pattern of poverty pressure index in China.

development capabilities, developed industries and agriculture, and generally have complete industrial chains. The level of third industries is also higher, absorbing labor force employment, and has a significant role in stimulating the development of surrounding areas; moreover, these places have convenient transportation, complete infrastructure, complete social and public services, and a socio-economic poverty alleviation index is naturally high.

In this paper, after the merger of 592 key poverty-stricken counties and 680 counties in 14 contiguous poor areas with special difficulties, duplicate counties were eliminated, and the rest of poverty-stricken counties is 832 in total (hereinafter collectively referred to as national-level impoverished counties). The poverty pressure index calculated in this paper is arranged in order of counties, and 832 counties and districts are also selected for comparison with national-level impoverished counties. In terms of the number of counties and districts, 566 counties identified in this paper are consistent with national-level poverty counties (Figure 7). The provinces with large numbers of differences are mainly Henan, Hunan, Guangxi, and so on. From the perspective of spatial distribution, this paper finds that the districts and counties under higher poverty pressure show a high degree of coupling with ecologically fragile areas, and mountainous areas, plateaus, hills, and restricted development areas have become the areas with the highest concentration of poverty pressure. Compared the districts and counties with high poverty pressure obtained in this paper with national-level poverty counties, we can find that:

- (1) It has a high coincidence in spatial distribution, especially in a large number of poverty-stricken areas such as northwest, southwest, north China, and the contiguous poor areas with special difficulties as well as poverty-stricken districts and counties obtained in this paper are often distributed in the core area of the country's concentrated contiguous poverty-stricken areas.
- (2) From this paper, we can obtain that the spatial distribution characteristics are discrete in the poverty-stricken districts and counties in some

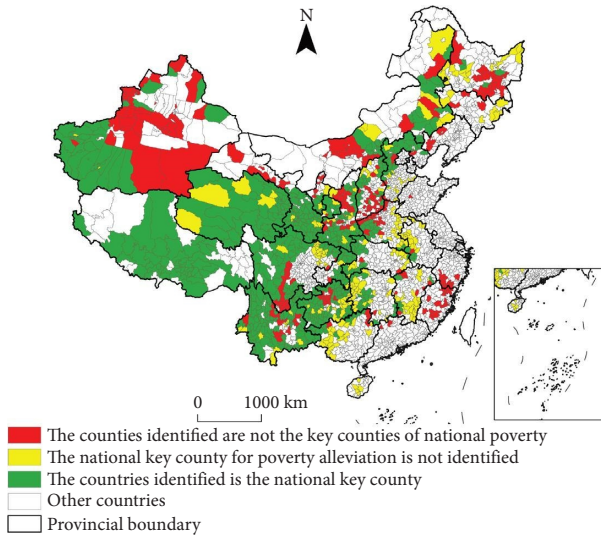


FIGURE 7: Comparison between identified in this study and state-supported impoverished counties.

provinces such as central and northeast China. For example, in Shanxi, Jiangxi, Heilongjiang, and Anhui provinces, according to the spatial distribution of national-level poverty counties, these districts and counties are all concentrated in continuous distribution.

- (3) The poverty-stricken districts and counties have a decreasing trend from west to east and from south to north. Compared with the spatial distribution of national-level poverty counties, the poverty-stricken districts and counties proposed in this paper are concentrated in the southwest and northwest regions. This also shows that these districts and counties are the key and difficult areas for China's poverty alleviation work in the future, and other districts and counties are relatively better. The poverty alleviation pressures in the poor areas and counties located in the plain area are not great, and they have basically reached the level of poverty alleviation.
- (4) Some poverty counties are distributed in the east and the key ecological function areas. In this paper, several poverty counties are identified in the mountainous regions of Zhejiang and Fujian. Some poverty counties are also distributed in important ecological function areas such as the Qilian Mountains area, regions on the middle and upper reaches of the Yellow River, and northern Xinjiang. These are not listed into the list of national poverty counties.

4.5. Analysis of Spatial Scanning Detection. In the research of this chapter, the poverty pressure index of the province, city, and county are obtained, respectively, and the regions with high, high, and extremely high poverty pressure index are divided into the poverty-stricken areas identified in this paper. On this basis, this section will use the spatial scanning measurement method to analyze and study the poverty-

stricken areas identified above under the three scales, and further obtain the areas that are more difficult to reduce poverty in the poverty-stricken areas. Based on the irregularity of the boundaries of administrative division units and the actual situation of the distribution of poverty-stricken areas, this paper first calculates the theoretical poverty pressure index of each scanning window according to the Poisson distribution, and then constructs the logarithm of the test statistic according to the actual and theoretical poverty pressure index. Likelihood Ratio (Log Likelihood Ratio, LLR), LLR is used to evaluate the abnormal degree of poverty pressure index in the scanning window [37]. Generally speaking, the larger the LLR value, the higher the abnormal degree of poverty stress index in this window. Usually, the window with the largest LLR is defined as the window with the highest abnormal degree of poverty stress index, and then the statistical significance level (P) of this window is evaluated.

Since the probability distribution of the scan statistic is extremely complex, this paper uses the Monte Carlo method proposed by Kulldorff and others to calculate the P value of the test statistic. Scanning statistics can be used to evaluate not only the window with the largest LLR, but also other windows with larger LLR for statistical significance, and try to find all outlier regions [36]. In order to avoid the identified poverty risk clusters from being too large and save the scanning time, the LLR with restriction statistical type is selected in this paper. The default Alpha value is 0.2, and the scanning results of poverty risk clusters are visualized by ArcGIS 10.2 software.

According to the above principles, the log-likelihood ratio LLR of the test statistic at the county scale is constructed, and the spatial scanning results are shown in Figure 8.

Through spatial scanning statistics, a total of 44 county-level poverty pressure index risk clusters that reached statistical significance were obtained (Figure 8), with a maximum value of 5.77, a minimum value of 0.00, a mean value of 3.21, and a standard deviation of 1.75. The 44 clusters involved a total of 243 counties and districts. Xinjiang, Tibet, Qinghai, Gansu, Sichuan, Yunnan, and other provinces have many high-risk poverty counties.

According to the list of key counties for national poverty alleviation and development work issued by the State Council Leading Group for Poverty Alleviation and Development, 592 poverty-stricken counties have been identified nationwide. Contiguous areas with special difficulties, a total of 680 counties, are the main battlefields for poverty alleviation in the new stage (Figure 9). In this paper, the duplicate counties and districts are eliminated after merging the two, there are a total of 832 poverty-stricken counties (hereinafter collectively referred to as national-level poverty-stricken counties).

The above 243 high-risk poverty counties are superimposed with 832 national-level poverty-stricken counties, and 208 are both national-level poverty-stricken counties and high-risk poverty-stricken counties identified in this paper, which are called deep poverty counties in this paper. These places should be the areas with the most difficulty in

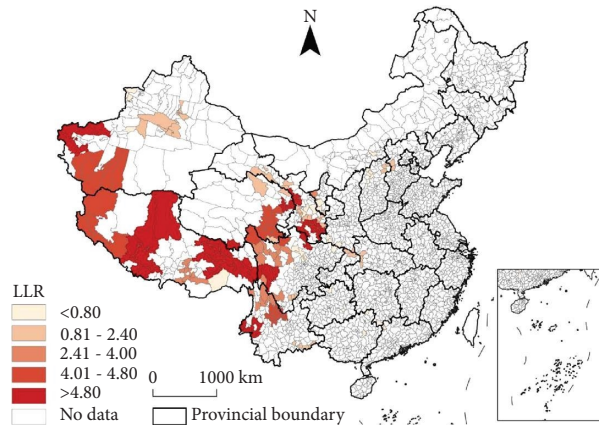


FIGURE 8: The spatial distribution of high risk clusters of poverty at county level.

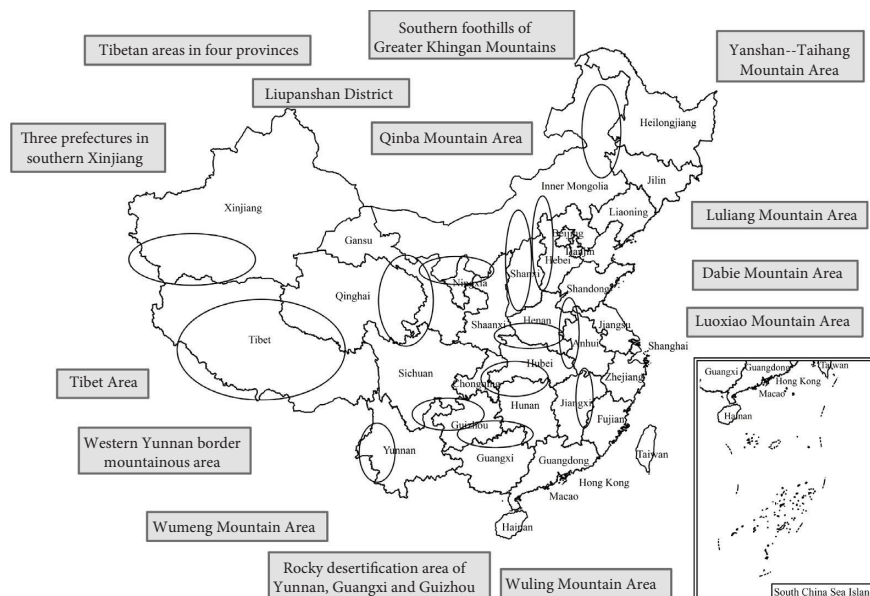


FIGURE 9: The sketchmap of 14 contiguous special poverty-stricken areas of China.

getting rid of poverty in the near future and in the future are also the areas that need to benefit most from poverty alleviation and poverty reduction policies. The spatial distribution of these areas is shown in Figure 10.

As can be seen from Figure 10, the overall spatial distribution pattern of the deeply impoverished counties mostly occurs in the border areas of adjacent provinces, such as Xinjiang and Tibet, Tibet and Sichuan, Sichuan and Yunnan, Sichuan and Qinghai, Gansu, and Sichuan, and Gansu and Sichuan. The border areas of Qinghai, Gansu and Ningxia, Shaanxi and Sichuan, Hubei and Chongqing, Shanxi, Hebei, and Inner Mongolia. Regional economies often expand to the periphery around provincial capitals or regional central cities. The junction of administrative regions, especially the inter-provincial junction area, has become the edge of the national, especially the provincial government's regional development strategy. The economic foundation of these places is very weak, and they cannot enjoy the radiation drive of big cities. The gap between the provinces is growing, and

some of them have even become the regions with the most extensive poverty, the deepest poverty, and the most difficult poverty alleviation in their provinces.

From the perspective of the area, the area with the largest number of deeply impoverished counties is Tibet, with 43 counties, accounting for 20.7% of the total number of deeply impoverished counties, followed by Tibetan areas in the four provinces (37), and western Yunnan border mountainous areas (34). Liupan Mountains (26), Wumeng Mountains (15), and Qinba Mountains (12); there are no deeply impoverished counties in the southern foothills of the Daxing'an Mountains, Dabie Mountains, and Luoxiao Mountains, and there are Wuling in a small number of areas: Mountain area (1), Luliang Mountain area (3), and Yanshan Taihang Mountain area (6). Although the three prefectures in southern Xinjiang are not the areas with the largest number of deeply impoverished counties, they are the areas with the greatest poverty risk, with an average risk of 4.93 (see Table 7). The areas with higher poverty risk include

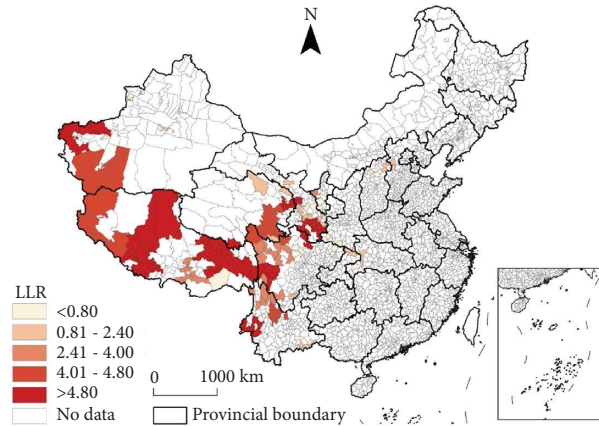


FIGURE 10: The spatial distribution of “Stubborn” poverty-stricken counties.

Tibet (4.50), Tibetan areas in the four provinces (3.99), and mountainous areas in western Yunnan (3.82). The poverty risk in Lvyang Mountain areas was the lowest (0.44), followed by Yunnan- Guangxi-Guizhou rocky desertification area (1.17) and Yanshan Taihang Mountain Areas (1.35).

In terms of provinces (see Table 8), the province with the largest number of deeply impoverished counties is Yunnan, including 45 counties, accounting for 21.6% of the total number of deeply impoverished counties, followed by Tibet (43), Sichuan (30), and Gansu (27); Inner Mongolia and Hunan have the least number, both of which are 1, and Guangxi (2), Chongqing (2), Hubei (2), Ningxia (3), Hebei (3), Shaanxi (4), Guizhou (7), and Shanxi (8). Although Xinjiang is not the province with the largest number, it is the province with the greatest risk, at 4.94. The provinces with higher risk include Qinghai (4.59), Tibet (4.50), Yunnan (3.42), Gansu (3.23), and Sichuan (3.22); Guangxi had the smallest risk at 0.19, followed by Inner Mongolia (0.25), Hunan (0.47), Shaanxi (0.80), Ningxia (0.83), and Shanxi (0.94).

5. Discussion

In recent years, China has successively proposed policy models for poverty alleviation and targeted poverty alleviation in concentrated poverty-stricken areas in terms of poverty alleviation policies. However, from the perspective of implementation effects, the poverty alleviation models in the various concentrated areas are basically similar, or even identical, to policy units, it is too large and lacks targeted, and can be “landed” policy measures [41]. At present, the design concept of precision poverty alleviation is still at a stage suitable for solving the problem of food and clothing for farmers and individuals, and applicable policy units are small, and lack of long-term mechanism for getting rich in rural areas. Under the background of strengthening the top-level design and scientific deployment of national poverty alleviation policies in the new era, it is necessary to innovate and implement policy transformation in poverty alleviation strategies, but the premise of scientifically identifying poor areas is that formulate differentiated poverty alleviation policies.

The analysis results show that there is a high correlation and rationality between the selected indicators and per capita GDP. The poor topography, ecology, climate, and other natural factors are the factors that lead to poverty, while the socio-economic factors are the factors to eliminate and alleviate poverty. Although there is a positive correlation between catchment index and per capita GDP, and it should be determined as poverty alleviation factor, but considering that the smaller the value of catchment index, the more significant the impact on poverty is, it is reasonable to classify it as the impoverishing poverty factor. In this paper, the main factors related to poverty level are selected from natural poverty factor and socio-economic poverty alleviation factors, and regression equation is established. Regression analysis results also show that the poor natural factor as the core of the ecology and terrain is the main impoverishing factor, but social and economic development is the main poverty alleviation factors. Natural factors are not easy to change, and poor ecological environment conditions are often the main factors leading to poverty.

Regarding the relationship between the economy and poverty, it is generally believed that the more economically backward the region, the poorer it is. So the economic factors are classified as the cause of poverty. However, this paper considers that the economic factors are the factors that eliminate or alleviate poverty; it is only in counties with slow economic development. The impact of economic factors on the alleviation or alleviation of poverty is not particularly obvious, which leads to the uneven development of the economy and the subsequent emergence of relative poverty, but its role in alleviating poverty is undeniable. Related scholars [42, 43] believe that the main achievements in poverty alleviation through investigation attributes to the economic growth. The relevant analysis results of this paper also confirm this.

The problem of spatial poverty in China’s counties in the new period is more caused by natural factors, and socio-economic factors can play a certain relief role in spatial poverty in counties. The harsh natural environment in some counties has greatly restricted the regional socio-economic development. Studies have shown that regions with higher

TABLE 7: The number and value of “Stubborn” poverty-stricken counties located in 14 contiguous special poverty-stricken areas of China.

Areas	No.	Risk average	Areas	No.	Risk average
Liupan Mountains	26	2.70	Yanshan and Taihang Mountain area	6	1.35
Qinba Mountains	12	2.86	Lyliang district	3	0.44
Wuling Mountains	1	1.77	Dabie Mountain area	0	0.00
Wumeng Mountains	15	2.14	Luoxiao mountains	0	0.00
Rocky desertification area in Yunnan, Guangxi, and Guizhou	9	1.17	Four provinces Tibetan areas	37	3.99
West Yunnan border mountains	34	3.82	Three prefectures in southern Xinjiang	12	4.93
The mountains at the southern foot of the great	0	0.00	Tibet region	43	4.50

TABLE 8: The number and value of “Stubborn” poverty-stricken counties located in the various provinces and autonomous regions in China.

Provinces	No.	Risk average	Area	No.	Risk average
Hebei	3	1.08	Guizhou	7	1.05
Shanxi	8	0.94	Yunnan	45	3.42
Inner Mongolia	1	0.25	Tibet	43	4.50
Hubei	2	1.77	Shaanxi	4	0.80
Hunan	1	0.47	Gansu	27	3.23
Guangxi	2	0.19	Qinghai	17	4.59
Chongqing	2	1.77	Ningxia	3	0.83
Sichuan	30	3.22	Xinjiang	13	4.94

poverty pressures have correspondingly higher natural impoverished index. For example, the natural condition of the three regions and states of Xinjiang in the west, the Qinghai-Tibet Plateau, and the Loess Hilly and Gully Areas is harsh, and the terrain is undulating, and the climate is dry or cold, and disasters are frequent; the ecological environment in Yunnan, Guizhou, and Guizhou karst areas is fragile, and rocky desertification is serious, and the area of arable land in rural areas is small, and the lack of water and land resources, which make the contradiction between human and land sharp. Social development level in the above-mentioned area is also relatively backward, and the transportation infrastructure is poor; the industrial structure is often single, and the contrast between economic development and resource advantages is large, lacking regional endogenous growth mechanisms, relying more on foreign aid, and lacking self-blood-making capacity. The low eastern coastal areas, the central plains, and the individual industrial and mining cities in the west have relatively superior natural conditions, good climatic conditions, and relatively abundant water and land resources. The regions have strong self-development capabilities, developed industries and agriculture, and generally have complete industrial chains. The level of third industries is also higher, absorbing labor force employment, and has a significant role in stimulating the development of surrounding areas; moreover, these places have convenient transportation, complete infrastructure, complete social and public services, and a socio-economic poverty alleviation index is naturally high.

For the high-risk areas of poverty identified by the spatial scanning at the county scale, the spatial distribution of the three prefectures in southern Xinjiang, Tibet, Qinghai, and Yunnan has a high consistency. The deeply impoverished counties identified at the county scale account for 25% of the total number of impoverished counties, and these counties should be the primary focus in poverty alleviation practice.

In this paper, after the merger of 592 key poverty-stricken counties and 680 counties in 14 contiguous poor areas with special difficulties, duplicate counties were eliminated, and the rest of poverty-stricken counties is 832 in total (hereinafter collectively referred to as national-level impoverished counties). The poverty pressure index calculated in this paper is arranged in order of counties, and 832 counties and districts are also selected for comparison with national-level impoverished counties. In terms of the

number of counties and districts, 566 counties identified in this paper are consistent with national-level poverty counties (Figure 7). The provinces with large numbers of differences are mainly Henan, Hunan, Guangxi, and so on. From the perspective of spatial distribution, this paper finds that the districts and counties under higher poverty pressure show a high degree of coupling with ecologically fragile areas, and mountainous areas, plateaus, hills, and restricted development areas have become the areas with the highest concentration of poverty pressure. Compared the districts and counties with high poverty pressure obtained in this paper with national-level poverty counties, we can find that:

- (1) It has a high coincidence in spatial distribution, especially in a large number of poverty-stricken areas such as northwest, southwest, north China, and the contiguous poor areas with special difficulties as well as poverty-stricken districts and counties obtained in this paper are often distributed in the core area of the country's concentrated contiguous poverty-stricken areas.
- (2) From this paper, we can obtain that the spatial distribution characteristics are discrete in the poverty-stricken districts and counties in some provinces such as central and northeast China. For example, in Shanxi, Jiangxi, Heilongjiang, and Anhui provinces, according to the spatial distribution of national-level poverty counties, these districts and counties are all concentrated continuous distribution.
- (3) The poverty-stricken districts and counties have a decreasing trend from west to east and from south to north. Compared with the spatial distribution of national-level poverty counties, the poverty-stricken districts and counties proposed in this paper are concentrated in the southwest and northwest regions. This also shows that these districts and counties are the key and difficult areas for China's poverty alleviation work in the future, and other districts and counties are relatively better. The poverty alleviation pressures in the poor areas and counties located in the plain area are not great, and they have basically reached the level of poverty alleviation.
- (4) Some poverty counties are distributed in the east and the key ecological function areas. In this paper, several poverty counties are identified in the mountainous regions of Zhejiang and Fujian. Some poverty counties are also distributed in important ecological function areas such as the Qilian Mountains area, regions on the middle and upper reaches of the Yellow River, and northern Xinjiang. These are not listed into the list of national poverty counties.

Existing literature rarely examines the distribution pattern of poverty within the meso-scale region. Chinese scholars' research on spatial differences in poverty at the district and county level is mostly qualitative analysis, and quantitative analysis results are rare. After superimposing

the planning maps of counties and national main functional areas, it is found that the distribution of poor counties is highly consistent with the distribution of important ecological functional areas in China. These poor areas are high in Natural Impoverishing Index and far from regional central cities. It has the characteristics of marginality and closedness, which hinders the input of material and energy outside the zone, and its internal resources and environmental carrying capacity have a smaller space for “potential tapping”. In addition, the socio-economic poverty alleviation index is low, and the infrastructure facilities are lagging behind, and outside the zone, the slow diffusion of advanced technologies has reduced the efficiency of the use of resources and the environment, which made the economy highly dependent on the environmental background of regional resources. For the aforementioned poor counties, they can be further divided into two types: ecologically fragile and ecological conditions to be improved. For the former, in the process of poverty alleviation and development, we must focus on promoting ecological migration, and moderately promote local poverty alleviation in areas with suitable conditions. For the latter, we should continue to improve the local poor production and living conditions, and steadily promote poverty alleviation and development in accordance with the principle of “pointed development and protection on the surface” to improve the quality of people’s livelihood.

The fact that there is a significant spatial correlation in poverty pressure in counties suggests that we are practicing poverty reduction. The internal counties and districts in the successive poverty-stricken areas, should strengthen cooperation and exchanges, and abandon the traditional concepts of “Benefit Oneself at Others’ Expense”; while the phenomenon of large internal differences within the more economically developed provinces has inspired us that we should be targeted to carry out poverty alleviation and economic development to improve efficiency in accordance with the poverty-dominated types and self-development capabilities of counties; areas that are relatively rich and take the lead in reducing poverty should take the lead in demonstration and strengthen the radiative power of regional central cities [44].

Zhou’s study [45–51] reveals that such factors as complex geographical environment, fragile ecological environment, frequent natural disasters, endemic disease prevalence, and aging of social subjects have indeed affected and even aggravated rural poverty in China. There is a high spatial overlap between individual poverty and regional poverty. Poverty causing factors are complex, and there are regional and individual differences. The practice of targeted poverty alleviation in rural areas mainly involves industrial development, resettlement assistance, financial development, education development, medical security, land consolidation and other aspects, and has built an endogenous sustainable mechanism to promote regional development. Du’s study [52] reveals that although the floating population has increased the per capita income of families by 8.5% to 13.1%, the overall impact on poverty is not significant, because most poor people do not migrate. Wang’s study [53–55] made it

clear that the poverty level, type and cause of poverty in each poor village are the premise and guarantee for China to take targeted measures in its poverty alleviation strategy. The main factors affecting the poverty level in China’s rural poor villages include road construction, terrain type, natural disaster frequency, per capital net income, labor force ratio, and labor force cultural quality. Underdeveloped road construction conditions, frequent natural disasters, low income levels, and poor working conditions are the main causes of poverty. Liu’s study [56] Establish multidimensional poverty geographic identification index system and integrated methods to identify rural poverty in China and reveals that In comparison to the income poor and the designated poor counties, the multidimensionally poor counties were not only worse in single-dimensional and composite scores, but also having multiple disadvantages and deprivations. Zhou’s study [57] on the basis of the digital elevation model (DEM) data and geographic information science (GIS) spatial analysis method, it reveals that the complex conditions of the natural topography have a positive driving effect on the spatial distribution of the poverty-stricken counties.

The innovation or research feature of this paper is to comprehensively use data from multiple sources and multiple spatial analysis methods to carry out research from multiple scales. Distinguish the poverty-inducing and poverty-reducing factors (including natural environmental factors, social factors and economic development factors) affecting regional poverty, use an artificial neural network to simulate the spatial pattern of poverty, and use geographic detectors and spatial scanning detection methods to detect the differentiation mechanism of the spatial pattern of poverty. Traditional methods of identifying poor areas and measuring poor populations mainly focus on a single factor such as income, often fail to accurately identify poor individuals and their poverty characteristics, and rarely take into account geographical factors. Therefore, they lack a geographical spatial perspective and cannot intuitively clarify the regional characteristics of poverty and the impact mechanism of spatial geography on poverty. The results obtained often do not match well with other spatial data. This paper focuses on the “spatialization” of poverty, which intuitively reflects the differences in the distribution of poverty in space. In practice, the research method of this paper can provide new ideas and methods for the quantitative and multidimensional measurement of regional poverty in the new era, and the research conclusions can also provide scientific reference for the formulation and implementation of regional poverty reduction policies.

This study is limited by the availability of data. In the construction of the indicator system, some important indicators based on the county scale (such as new rural social endowment insurance, medical insurance, administrative villages connected to the Internet, tap water, and cable TV) are difficult to obtain official data, and may have omissions. As far as the whole country is concerned, there are great differences in the level of social and economic development in the east, middle, and west, and the extent to which social and economic factors alleviate poverty is also different.

When calculating the poverty pressure index in this paper, it is subjective to use 20% of the social and economic poverty reduction index to eliminate or alleviate local poverty on the basis of reference to existing research results.

6. Conclusions

- (1) Natural factors are the main cause of poverty in China's counties at this stage. The distribution of Natural Impoverishing Index in counties across the country shows a clear pattern of zonal distribution with latitude and longitude, and they are arranged in a stripe pattern from north to south, and from west to east. There are 710 counties with higher Natural Poverty Index ($NII > 2.78$), accounting for nearly 30% of the total counties in the country. These counties or areas have large undulations and low-quality cultivated land resources; or low vegetation cover, serious soil erosion; or the cold-dry climate and frequent natural disasters.
- (2) Socio-economic factors play a role in alleviating poverty, and the spatial distribution of the socio-economic poverty alleviation index in counties across the country is relatively fragmented. As many as 1521 counties with lower socio-economic poverty alleviation index ($SEPAI < 1.34$) account for about 64% of the total counties nationwide. These counties have low levels of socio-economic development and the infrastructures, such as transportation and so on, are backward, and social and public services are weak. The coefficients of variation of the socio-economic poverty alleviation index in the counties within each province are much higher than the coefficients of variation of the Natural Poverty Index, indicating that the differences in the socio-economic poverty alleviation index in China's counties are much greater than the difference in the Natural Poverty Index.
- (3) The national poverty pressure index is bounded by the "Heihe-Baise" line, with significant differences between east region and the central and west region, showing a spatial distribution pattern of "large dispersion, small aggregation". The poor counties identified in this paper and the key poverty-relief counties identified by the state have a higher coincidence in spatial terms, and the characteristics of a high degree of coupling with ecologically fragile areas.

Based on the above conclusions, there are several policy suggestion:

- (1) Poverty caused by natural factors can be mainly divided into areas constrained by ecological environment and areas caused by terrain factors. To achieve a win-win situation between regional economic development and ecological environment construction in ecologically constrained poverty-stricken areas, it is necessary to take the path of

green poverty reduction. On the one hand, we will promote comprehensive management projects for mountains, rivers, forests, fields, and lakes in key areas such as the control of sandstorms in Beijing and Tianjin, the control of rocky desertification in karst areas, and the protection of the sources of the Yangtze, Yellow, and Lancang rivers in Qinghai. This will curb the trend of soil desertification and degradation in pastoral areas and poverty-stricken areas where agriculture and animal husbandry are combined, and alleviate land desertification and rocky desertification. On the other hand, exploring the establishment of upstream and downstream ecological compensation mechanisms and increasing ecological compensation efforts is of great significance for synchronously achieving ecological environment protection and poverty alleviation in these regions. According to the needs of ecological environment protection and the characteristics of ecosystems in various regions, we will appropriately expand ecological engineering construction and provide employment opportunities and income for poverty alleviation targets through the use of work as a substitute for relief. Reasonably determine a group of ecological public welfare positions, so that poverty alleviation targets can increase their income by providing ecological public welfare services, and create a beautiful countryside that is livable and suitable for business. For areas that are not suitable for the development of agriculture and have become impoverished due to terrain factors, on the one hand, we can develop standardized animal husbandry at a moderate scale in this type of poverty-stricken area according to local conditions, and strive to explore planting and breeding models that are suitable for local development, such as combining agriculture and animal husbandry, balancing food and grass, and ecological circulation. On the other hand, we should base ourselves on resource endowments, fully utilize local unique natural resources such as land, energy, natural landscapes, and biology, as well as ethnic, cultural, and other cultural resources, develop rural tourism industry according to local conditions, transform resource advantages into industrial and economic advantages, and drive economic development.

- (2) Socio-economic factors leading to poverty are mainly divided into income constrained poverty-stricken areas and areas with inconvenient transportation leading to poverty. Economic income constrained poverty-stricken areas should promote employment poverty alleviation and industrial poverty alleviation based on local conditions. Firstly, we should establish a sound public employment service system that covers both urban and rural areas, conduct large-scale vocational skills training, promote multichannel transfer of employment for migrant workers, and improve the quality of

employment; encourage the establishment of environmentally friendly enterprises in rural areas, achieve rural economic diversification, and provide more employment opportunities; strengthen support and guidance services, implement rural employment and entrepreneurship promotion actions, vigorously develop rural characteristic industries such as culture, technology, tourism, and ecology, and revitalize traditional crafts. This can broaden the channels for farmers to increase their income, not only increasing the economic income of low-income rural residents, but also expanding the income of middle-income rural groups. The overall income level can be improved, and the poverty alleviation plan can be achieved as soon as possible. In areas far from the city center of prefecture level cities with inconvenient transportation conditions that lead to poverty, rural infrastructure and public service facilities are not perfect enough, making it difficult to meet the basic living needs of farmers such as consumption, medical care, and education. On the one hand, we should accelerate the improvement of infrastructure such as rural roads, water and electricity, environmental protection, and information networks, promote major water conservancy projects for water-saving and water supply, and ensure the safety of drinking water; strengthen the construction of rural social security system, improve the unified basic medical insurance system, basic pension insurance system, and minimum social security system for urban and rural residents. In terms of rural public health services, it is necessary to strengthen the construction of the grassroots medical and health service system, and support the improvement of conditions in township health centers and village clinics. On the other hand, by enhancing basic education capabilities, increasing vocational education efforts, and improving the quality of higher education, we can block the intergenerational transmission of poverty, improve the basic cultural quality of the impoverished population, and enhance the labor skills of impoverished families. Finally, for extremely remote areas with harsh terrain and blocked transportation, poverty alleviation through relocation can be adopted. Based on soil and water resources, economic development environment, and urbanization process, relocation and resettlement methods can be selected according to local conditions.

Data Availability

In this paper, the administrative boundary vectors from China national center for basic geography data, Digital Elevation Model (Digital Elevation Model, DEM) data acquisition from the United States geological survey (USGS) website (<https://lta.cr.usgs.gov/HYDRO1K>), NPP data acquisition from NASA's MODIS products website (<https://ladsweb.nascom.nasa.gov>) precipitation According to from

China meteorological data network (<https://data.cma.cn/>). Night light Data from the National Atmospheric and Oceanic Administration of the National Geographic Data Center (NOAA's National Geophysical Data Center, <https://ngdc.noaa.gov/eog/download.html>). The socioeconomic statistics were summarized by the China Regional Economic Statistics Yearbook published in 2014.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Evolution of Urban Resilience from a Multiscale Perspective: Evidence from Five Provinces in Northwest China

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As a new idea of urban risk management, building resilient cities with the ability to resist, eliminate, and adapt to uncertain risks is of great importance to mitigate risk impacts and promote sustainable urban development. Based on the adaptive cycle model and the characteristics of an urban system, this study analyzes the resilience levels of cities, urban agglomerations, and provinces and their adaptive stages. The results show that (1) the comprehensive resilience of cities in the five provinces of northwest China is on the rise and that the differences between cities are gradually narrowing. The development stages of the urban adaptive cycle can be divided into six stages: the rapid exploitation stage, exploitation-conservation stage, stable conservation stage, conservation-release stage, development reorganization stage, and reorganization-exploitation stage. (2) The spatial distribution of the comprehensive resilience of urban agglomerations is “high in the southeast and low in the northwest,” and the development stage of the adaptive cycle is consistent with its central city or central region. (3) The level of resilience varies greatly among provinces, and the development stage of the adaptive cycle is equivalent to the average level of all cities in the province and is closely related to their respective development forces and urban problems. These findings can provide reference for policymakers to formulate scientific resilience building strategies to achieve regional sustainable development.

1. Introduction

Since the 21st century, global extreme climate conditions, which make regional giant systems and cities face a variety of cumulative and sudden risks, have also increased dramatically [1]. According to the 2030 Agenda for Sustainable Development of the United Nations, about half of the world's population lives in cities, and it is expected that, by 2050, the proportion of urban population will reach 75%. Population agglomeration has a serious negative impact on urban infrastructure, education, health, safety, and other living environment and public health. In the face of various disturbances, some cities may adjust their development patterns to adapt to the changes and achieve more long-term progress, while some cities may experience stagnation or even decline due to their weak resistance ability or difficulty in solving urban problems. Therefore, cities must become

resilient and be able to cope with a range of challenges in the process of urban development by resisting shocks and improving adaptive capacity [2].

Resilience Alliance, Rockefeller Foundation, UN-Habitat, UNDRR, and others have stressed the necessity of building resilient cities and applied resilience to the development practice of cities in various countries. In China, the new round of urban master planning emphasizes the need to strengthen the ability to resist risks in order to build a sustainable city [3]. As the largest developing country in the world, China's external shocks and internal pressures interact to form complex feedback and nested relationships, which seriously affect the ability of cities to withstand risk environment. Especially in the northwest, the fragile natural environment and the backward economic development level restrict each other, resulting in the insufficient ability of the city to cope with risks and interference, which limits the

sustainable development of the city. Therefore, it is urgent to clarify the evolution characteristics and measurement methods of urban resilience, which is crucial for enhancing urban resilience and promoting regional sustainable development.

Urban resilience refers to the ability of the urban system to absorb external disturbances and maintain its unique attributes, structures, and main functions [4]. As a new idea of urban risk management, building resilient cities with the ability to resist, eliminate, and adapt to uncertain risks is of great importance to mitigate risk impacts and promote sustainable urban development. In recent years, relevant studies have focused on the concept and connotation of urban resilience [5–8], qualitative analysis, and spatiotemporal patterns [9, 10] and identification of influencing factors and research progress [11, 12]. It involves climate change [13–16], disaster prevention and mitigation [1, 17], urban planning and landscape design [18–20], urban adaptive governance [21–23], and other fields. At present, the research on urban resilience is still at the level of theoretical exploration [24], and its measurement methods have not formed a unified standard [25, 26]. Most of them summarize the characteristics of resilience by establishing models, and from the perspective of research, most of them focus on economic, social, municipal facilities, ecology, and other aspects. Previous studies have also pointed out that the resilience of cities of different scales is different and that there is a cascade effect, which may affect the regional system from point to plane [27]. At the same time, there are corresponding adaptive cycles in the process of urban development, and characteristics of different adaptive stages vary greatly [28–30].

To sum up, most studies on urban resilience are calculated from the dimensions of economy, society, ecology, and facilities and rarely consider the resilience characteristics of the overall urban system, which are often the driving factors for efficient urban development [31] and can effectively promote the improvement of the urban development environment and optimization of the development path. The research scale mainly focuses on a single large scale or rapid economic development of cities and urban agglomerations, and few studies are conducted from multiscale. In addition, the typical adaptive cycle model divides the urban development cycle into four stages: exploitation, conservation, release, and reorganization [32] to explore the future development direction and potential of the city, but it only includes the urban development cycle. In fact, the development of a city is dynamic, and its evolution stage and direction depend on the characteristics of self-organization and learning adaptability that affect the resilience of the system [29, 30, 33]. In general, there are still some challenges and gaps in the research of urban resilience. In particular, it is urgent to investigate the characteristics of and differences in urban resilience and various attributes. How to eliminate this difference between cities? What is the relationship among cities, urban agglomerations, and provinces? How to judge the urban adaptive development cycle? How to put forward corresponding measures at the policy level to enhance urban resilience? Based on the above issues, this study

focuses on the resilience characteristics of the urban system and constructs an index evaluation system of urban resilience from the system attributes. Taking the five provinces in northwest China as the case area, while quantitatively calculating the resilience index, the paper uses the basic characteristics of resilience and the adaptive cycle model to position the development stages of each city and further analyzes the development links from cities to urban agglomerations and from cities to provinces through scale transformation research so as to provide reference for formulating urban sustainable development policies.

2. Theoretical Basis and Research Framework

2.1. Adaptive Cycle Model. The adaptive cycle model is a resilience research model based on complex adaptive system theory (CAS), which evolves the general or linear recovery process when the system responds to interference into a complex nonlinear evolution process of continuous learning, adaptation, and self-adjustment. It explains the development state of the city through four stages of exploitation, conservation, release, and reorganization [32]. At the same time, further refining the characteristics of resilience is helpful to reveal the dynamic direction and development potential of urban development at different stages. The model believes that cities have certain resilience and can adjust themselves to benign development in the face of risky environments. Its purpose is to establish a “safe” urban system, which can not only recover from shocks but also “bounce forward” and continuously improve its performance and adaptability. Therefore, resilience is a process of positive qualitative change occurring in a city or a transformational development process formed by quantitative change accumulation. What stage a city is in and to which stage it is evolving can be determined by comparative analysis of development levels in different periods [34]. Walker et al. [35] and Folke et al. [36] also emphasized that resilience is the ability of a system to resist interference, self-organize, learn, and adapt, with obvious evolutionary characteristics.

2.2. Research Framework. The impact of the risk environment will often destroy the original relative stability of the city and break its original development path, but it will also urge the city to take countermeasures, change or optimize the original development path, change the city from a nonbenign development state to a benign development state, and realize the sustainable transformation of the city.

Urban resilience refers to the ability of the urban system to absorb external disturbance and maintain its unique properties, structures, and main functions, which can be regarded as the collection of various abilities to achieve adaptive development under disturbance. It includes the ability of a city to maintain normal functions when it meets emergencies (such as earthquakes, floods, and emergencies), to resist and quickly recover to a normal state when disturbed, and to adjust and learn to cope with future challenges [37]. Previous studies have pointed out that resilient

cities have four basic characteristics: stability, self-organization, learning adaptability, and transformability [1, 38–44]. Among them, stability is the foundation and the bearing mechanism of urban structures. It can strengthen the development framework of the urban system by continuously accumulating resources and energy and maintain the basic social functions in a certain period of time and has a relatively stable environment in the face of interference. Self-organization is the way, which requires the urban system to achieve the coordination of internal elements through self-adjustment and self-adaptation, and its own governance efficiency is often the driving force of the long-term development of the city. Learning adaptability is fundamental, and it is the innovation mechanism of the urban system. “Human” as constitute is the basic unit of the city, with strong independent initiative and the ability to adapt, be able to predict changes, and take actions according to predetermined goals. This also promotes the city to have strong ability to adapt and restructure and improve its hierarchical structure and function structure. Transformability is the purpose and the dynamic transformation mechanism of the urban system. The purpose of urban development is to improve the quality of people’s life, which also requires that it should aim at “transformation.” When ecological, social, economic, and political conditions are well coupled and developed, the city will naturally evolve towards a higher stage.

In addition, there are four stages of the adaptive cycle of urban development (Figure 1), with differences in resilience and development status in different stages. In the exploitation stage (r), resilience increases rapidly and the city takes the opportunity to accumulate resources, develop rapidly, and improve its competitiveness. The stability and self-organization of the urban structure increase significantly, and learning adaptability and transformability are relatively small. In the conservation stage (K), the urban resilience and attributes of the system increase slowly and even have a trend of decline, and the peak may appear in this stage. At this stage, the city develops slowly, most of the system resources are stored and utilized, and stability, certainty, and resilience are high, but resilience is close to the threshold. The system tends to mature at the current level, and the risks of structural solidification and path locking appear. At the same time, the city uses its internal intellectual capital and innovation capacity to realize adaptive governance and development through research technology, policy formulation, and management optimization so as to prepare for the city’s transformation and development. In the release stage (Ω), urban resilience and all attributes show an obvious downward trend, the system is unstable, and urban problems become prominent. In the reorganization stage (α), urban resilience and various attributes showed an obvious trend of recovery, while self-organization and learning adaptability increased significantly. The system is in the period of innovation and structural adjustment, with great uncertainty.

Therefore, by extending the adaptive cycle model, this paper builds a theoretical framework for urban resilience analysis and emphasizes the role of four characteristics of resilient cities, which contribute to sustainable urban development.

3. Study Area and Methods

3.1. Study Area. The case area is located to the west of the Great Khingan and to the north of the Kunlun Mountain-Altun Mountain-Liupan Mountain in China, involving 52 cities in five provinces of Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang, including Guanzhong Plain urban agglomeration, northern slope of Tianshan Mountain urban agglomeration, Ningxia along Yellow River urban agglomeration, and Lanzhou-Xining urban agglomeration, with an area of 3.079 million square kilometers, accounting for about 1/3 of the national area, but only about 5% of the population. It borders on eight countries, is a strategic frontier of China’s national interests, is of great significance to national security, and is also an important water source for the country. The area has a temperate monsoon climate and temperate continental climate. The terrain is complex, covering plateau, Gobi, desert, grassland, mountain, basin, etc. Precipitation is scarce and decreases from east to west and from south to north. The average annual precipitation in some areas is even less than 50 mm. The natural landscape showed the evolution characteristics of arable land, steppes, desert steppes, deserts, and plateaus. Ecological environment problems such as serious soil erosion and frequent sandstorms were prominent, and the radiation area expanded year by year. As an area rich in natural resources, it provides a solid foundation for China’s energy security. However, the level of social and economic development is low, and there are obvious regional differences. There is growth but no development. At the same time, although it is an open gateway to the west, traffic conditions are still relatively backward, the number of hub stations is small, high-quality medical and educational resources are concentrated in provincial capital cities, and infrastructure needs to be improved. Driven by the “Belt and Road initiative” and the “Silk Road Economic Belt,” the region has an extremely important economic and strategic position with a large number of ethnic groups and rich products. In 2019, the total population of the region was 103,496,800, and the per capita GDP was 52,970.73 yuan, accounting for 74.72% of the national average. Compared with 2010, the increase rate was only 0.44%, lagging behind the national level (Figure 2).

3.2. Research Method

3.2.1. Measurement of Urban Resilience. Different scholars have different standards for measuring urban resilience. Wildavsky [38] proposed six basic characteristics of the resilience system in 1988, and then, scholars decomposed resilience into four characteristic elements of resistance, recovery, adaptation, and transformation under risk shock. At the same time, some studies have also pointed out that urban resilience in the context of the risky environment is the ability of an urban system to pursue its ecological, social, and economic goals, and there is a complex relationship between it and risk factors, including urban stability, self-organization, learning adaptability, and transformability [1, 38–44]. Therefore, urban resilience can be seen as the result of the comprehensive effect of system stability, self-

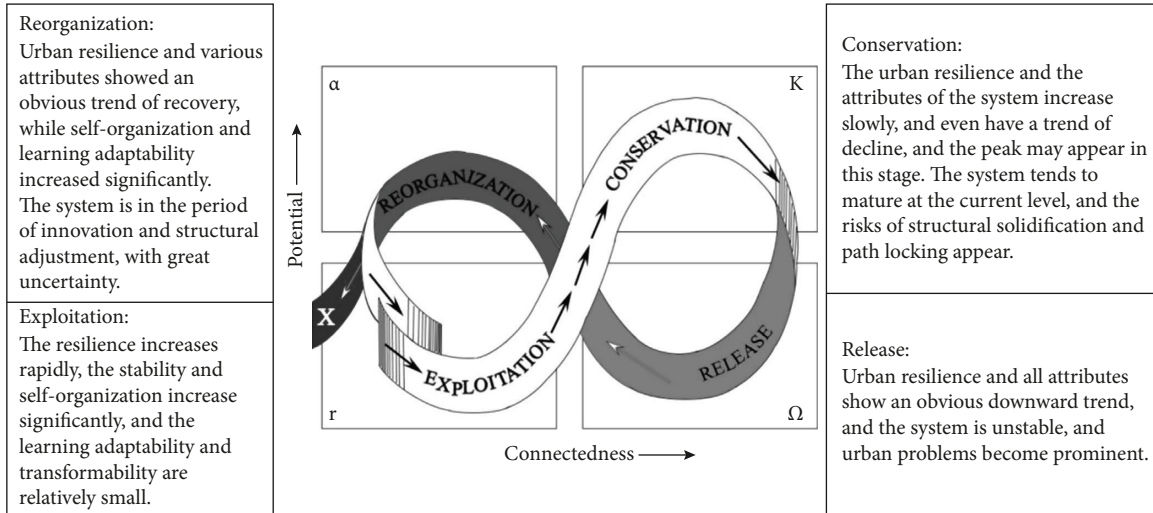


FIGURE 1: Adaptive cycle model.

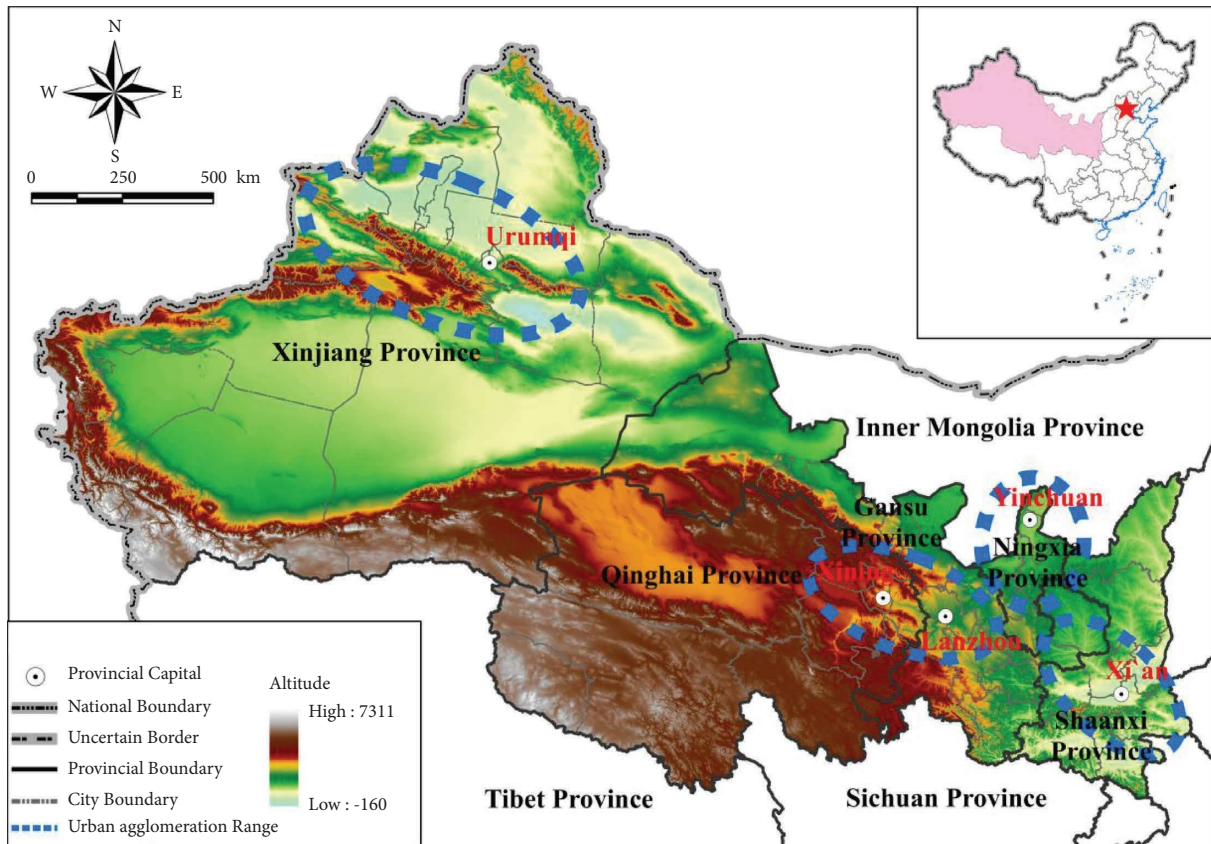


FIGURE 2: Study area.

organization, learning adaptability, and transformability. On the basis of fully considering the development status of cities in the five provinces of northwest China, this paper constructs the evaluation index system of urban resilience according to the urban development objectives of enhancing stability, improving self-organizing ability, strengthening

adaptability, and improving transformation performance (Table 1).

Stability helps the disturbed system maintain its identity, function, and structure and is a solid foundation for urban recovery and development. Drawing on previous scholars' consideration of social ecosystem resilience [45, 46], this

TABLE 1: Urban resilience evaluation index system.

Target layer	Criterion layer	Factor layer	Index layer
Urban resilience	Stability	Society	Hospital beds per 10000 people, Public vehicles per 10000 people, Urbanization rate
			Proportion of the education expenditure in fiscal expenditure Proportion of the public service expenditure in fiscal expenditure and proportions of the urban and rural populations receiving subsistence allowances in the total population
		Economy	Per capita GDP Proportion of the added value of the tertiary industries in the GDP and GDP growth rate
		Environment	Regional vegetation coverage Good weather frequency Urban domestic sewage treatment rate Discharge standard rate of industrial wastewater and comprehensive utilization rate of industrial solid waste
	Self-organization	Population	Population natural growth rate Population density and registered urban unemployment rate Per capita cultivated land area
		Resource	Per capita construction land area and per capita daily domestic water consumption Investment in fixed assets of the whole society
		Capital	Number of mobile phone users and number of Internet users
		Information	College students per 10000 people and full-time teachers in colleges and universities per 10000 people
	Learning adaptability	Technological	Number of R&D personnel in enterprises and internal expenditure in enterprise R&D funds
		Basic environment for innovation	Per capita books in public libraries
			Per capita disposable income of urban residents Per capita disposable income of rural residents and proportion of science and technology expenditure in fiscal expenditure
		Transformability	Regional connectivity
	Urban form		Urban elongation
	Investment and financing level		Density of enterprises above the designated size
	Industrial structure		Advanced index and rationalization index
		Social structure	Employment increment Aging index and income gaps between urban and rural residents

paper also selects stability indicators from social, economic, and environmental aspects. Among them, social elements mainly provide convenient living conditions and comfortable living environments for citizens, including medical care, transportation, education, public services, and other basic aspects. Economic factors are reflected in whether the economic base can support the operation of urban superstructure, including per capita GDP and GDP growth rates. The environment is to ensure that urban activities can be carried out in a good ecological environment, including vegetation growth and the interference degree of human activities to the environment. Generally, the more sound the social, economic, and environmental factors, the stronger the city's ability to withstand the interference of emergencies.

Self-organization is the dynamic mechanism of urban development. With the acceleration of globalization and urbanization, cities are more closely connected and more and more elements such as population, resources, capital, technology, and information flow in space, thus forming the self-organizing ability of cities and influencing the spatial development mode of cities [47, 48]. Therefore, the evaluation index is selected from the material, energy, and information of the urban system, including the change of population, the allocation of resources, the amount of capital invested, and information mastery.

Learning adaptability is the embodiment of urban development potential, which focuses on the adaptability of urban recovery and the rapid response ability to actively cope with external shocks, which are the fundamental and key to urban recovery [44]. Building a learning society and an urban system with adaptive capacity is a national innovation system with Chinese characteristics in line with the law of scientific and technological development [49]. Therefore, this paper uses the ability of learning and innovation to represent the ability of a city to adapt to change at a macrolevel and selects indexes from three aspects: knowledge innovation, technological innovation, and the basic environment for innovation.

Transformability refers to the ability of a city to optimize its structure and create a "new system" when making adaptation adjustments. Two crucial characteristics of conversion capability are the ability to actively disrupt and dismantle existing systems and create and build viable alternatives [50]. Moderate city size and excellent urban structure are effective means to solve the acute impact and chronic pressure of cities [51]. Therefore, this paper respectively uses regional connectivity, urban shape, investment and financing level, industrial structure and social structure to comprehensively calculate transformability. The more convenient the connection between the city and the outside world, the larger the scale of economic development, the more reasonable the industrial and social structure, and the stronger the city's transformation ability.

3.2.2. Mathematical Analysis Model. Scholars have carried out relevant studies on the stability, self-organization, learning adaptability, and transformability of the city,

respectively. Therefore, this paper adopts four common calculation methods for different features to achieve the rationality and pertinence of the final results.

(1) *Stability.* As a city's most direct response to disturbances, stability helps maintain the system function and structure, which is crucial for improving urban resilience. In this paper, the TOPSIS method is used to calculate stability, which is a common decision technology for multiobjective decision analysis of finite schemes in system engineering, and can analyze the gap between the system stability and ideal state [52].

(2) *Self-Organization.* In this paper, the entropy flow method [53] was used to measure the dissipative structure characteristics of the system to characterize the self-organization of the city. The larger the absolute value of entropy flow, the faster the city exchanges energy, material, and information with the outside world and the stronger its self-organization ability. The calculation equation is as follows:

$$S = \sum_{j=1}^m \left[(-1)^n \left(\frac{|r_j - r_1|}{r_1} \right) \cdot \omega_j \right], \quad (1)$$

where S is the sum of the entropy flow generated by the system, ω_j is the weight of the index j , and $(-1)^n$ is a symbolic function. When the index exceeds the initial state, n is 1, indicating the input of a negative entropy flow, and otherwise, n is 2. Moreover, r_j is the j th index, and r_1 is the initial value.

(3) *Learning Adaptability.* Learning adaptability is the ability of a city to adapt to environmental changes, which helps maintain urban health and safety. The stronger the learning and adaptation capacity of a city, the stronger its resilience [1]. The calculation equation is as follows:

$$L = \sum_{j=1}^n r_j \omega_j, \quad (2)$$

where L is the learning and adaptability index, r_j is the j th index, and ω_j is the weight of the index j .

(4) *Transformability.* Transformability is a necessary condition to promote the high-quality development of a city, and the urban system can adjust its structure and realize the transformation of its social and economic status through its transformability [54]. The calculation equation is as follows:

$$T = \sum_{j=1}^n r_j \omega_j, \quad (3)$$

where T is the transformability index, r_j is the j th index, and ω_j is the weight of the index j .

(5) *Urban Resilience.* Comprehensive urban resilience is calculated by stability, self-organization, learning adaptability, and transformability. The calculation equation is as follows:

$$R = \omega_1 c + \omega_2 s + \omega_3 l + \omega_4 t, \quad (4)$$

where R refers to toughness, c , s , l , and t are the stability, self-organization, learning adaptability, and transformability after standardization, respectively, and ω_1 , ω_2 , ω_3 , and ω_4 are the weights of four dimensions, respectively.

4. Result Analysis

4.1. Temporal and Spatial Pattern of Urban Resilience

4.1.1. Stability. From 2010 to 2018, the level of urban stability in the five provinces of northwest China showed an overall upward trend, but there were differences among different cities (Figure 3). From the coefficient of variation (Figure 4), the regional difference in urban stability levels showed a narrowing trend, decreasing from 0.2791 to 0.2513, with a decrease in 9.96%. From the perspective of spatial distribution, the overall level of urban stability showed an evolution trend of “expanding from northwest to southeast” from 2010 to 2018. Among them, high-level areas were mainly concentrated in Lanzhou city and Xi’an city, and the number showed an increasing trend, while low-level areas formed a flake concentrated distribution centered on Urumqi city. On the whole, the level of urban stability in the five provinces is shifting from low levels to high levels. The reason is that Xi’an, Lanzhou, and other surrounding urban areas have obvious regional advantages. Since the implementation of the Western Development Strategy in 2000, the level of social and economic development has increased significantly; especially, per capita GDP is about twice that of Aksu region and other low-stability cities.

4.1.2. Self-Organization. From 2010 to 2018, the level of urban self-organization in the five northwest provinces showed a general trend of shifting from low levels to high levels (Figure 5), and the index increases from 1.4 to 5.45, with an increase of 289.29%. From the coefficient of variation (Figure 4), regional differences in the level of urban self-organization tend to narrow, and the coefficient of variation drops from 0.4196 to 0.4069, a decrease of 3.03%. From the perspective of spatial distribution, the level of urban self-organization from 2010 to 2018 showed the distribution characteristics of “low in the middle and high around.” Among them, high-level areas are mainly distributed in Xi’an, Lanzhou, Xining, and other urban areas and gradually gather at the southern edge, while low-level areas are mainly distributed in Bayingolin, Haixi, and other cities. The reason is that the central cities in the eastern region are clustered and have convenient transportation, and it is also the core area of urban development. The rapid exchange of population, resources, capital, and information has promoted the level of urban self-organization significantly. However, due to the restriction of natural conditions and resource endowment, the level of urban self-organization in some cities of Xinjiang always lags behind.

4.1.3. Learning Adaptability. From 2010 to 2018, the level of urban learning adaptability in the five northwestern provinces showed an obvious “Matthew effect” (Figure 6). From the coefficient of variation (Figure 4), the regional difference in urban learning adaptability shows a decreasing trend, decreasing from 1.4742 in 2010 to 1.3038 in 2018, with an overall decrease of 11.53%, indicating that all cities are making efforts to improve the level of learning adaptability, but there is still a large gap. From the perspective of spatial distribution, the learning adaptability shows regional polarization. Among them, Xi’an has the highest learning adaptability, which is 0.923, 0.8773, and 0.8508 in 2010, 2015, and 2018 respectively, leading five northwest provinces. Lanzhou, Urumqi, Karamay, Yinchuan, Xining, Baoji, and Shihezi are in the second tier. The remaining cities in the region are in the third tier, and their learning adaptability index did not exceed 0.15 in 2018. The reasons are as follows: First, provincial capital cities concentrate the higher education resources of the whole province, and high-tech industries and high-tech personnel with innovative ability will spontaneously converge to provincial capital cities. Second, individual cities have the support of national policies and the help of government agencies, so they can attract a large number of enterprises and talents to settle in. Coupled with a better urban economic foundation, learning adaptability will be improved.

4.1.4. Transformability. From 2010 to 2018, the level of urban transformability in the five northwest provinces showed obvious hierarchy (Figure 7). From the coefficient of variation (Figure 4), the regional difference in urban transformability levels shows a slow increase trend, with an overall increase of 5.23%, indicating that the gap of transformability among cities is constantly widening. From the spatial distribution, the transformability from 2010 to 2018 presents multiple “center-edge” distribution characteristics. Among them, these characteristics are more obvious in Xi’an, Yinchuan, Lanzhou, Urumqi, Shihezi as the center of the region. The reason is that the economic conditions of the central area formed around the provincial capital city are superior and that labor force and enterprises from the surrounding cities flow into the central area, which promotes the optimization of the industrial and social structure of the central city. In addition, the convenient transportation and abundant employment opportunities of the central city further aggravate the polarization effect.

4.1.5. Urban Resilience. From 2010 to 2018, the level of urban resilience in the five northwest provinces was different and fluctuated (Figure 8). From the coefficient of variation (Figure 4), the regional difference in urban resilience showed a downward trend, with an overall decrease of 10.73%, indicating that the resilience level of each city was gradually improving and the gap was gradually narrowing. In terms of spatial distribution, the resilience of each city shows the

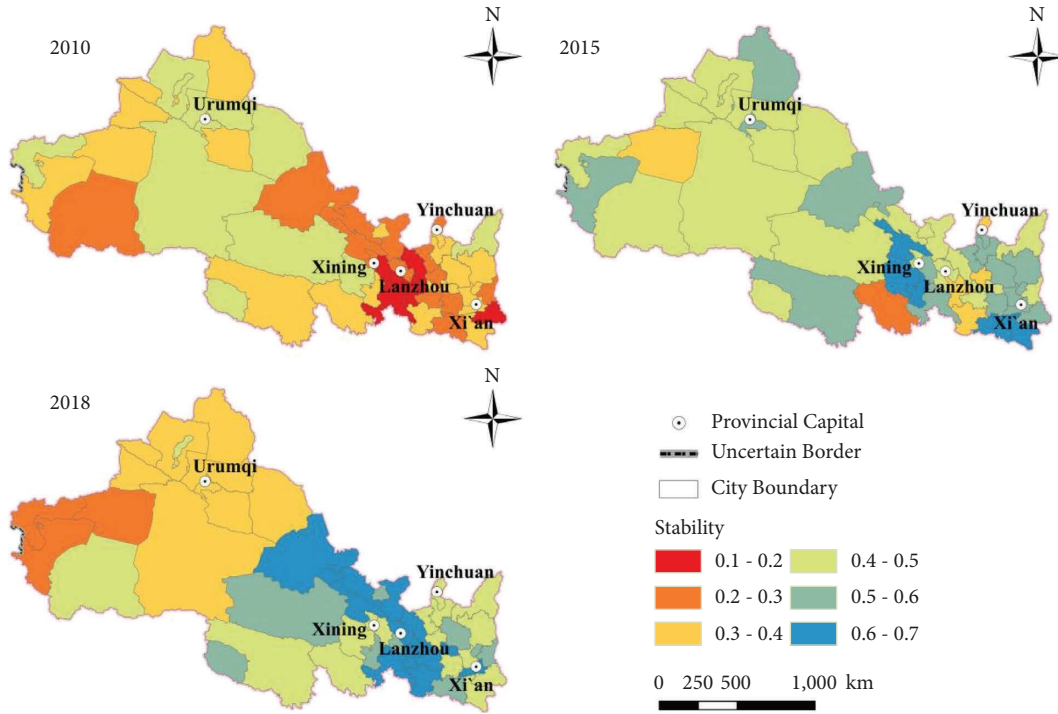


FIGURE 3: Spatial distribution pattern of urban stability.

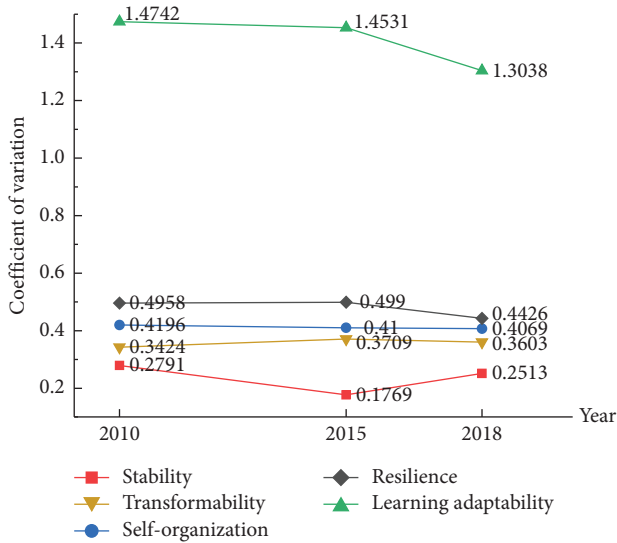


FIGURE 4: Variation coefficient of four attributes.

characteristics of “one super and many strong, high in the east, and low in the west.” Among them, “one super” means that Xi’an’s urban resilience is ahead of the whole region and plays a leading role in the whole region. “Many strong” means that Lanzhou, Yinchuan, Xining, Haidong, Urumqi, Karamay, Shihezi, and Kashgar have high resilience and can drive the development of the surrounding areas.

4.2. Variation Characteristics of Urban Agglomeration Resilience

4.2.1. Stability. From 2010 to 2018, the stability level of urban agglomerations showed two trends of a low value increase and a high value decrease (Figure 9). Among them, the stability of Guanzhong Plain urban agglomeration and the northern slope of Tianshan Mountain urban agglomeration continued to decrease, with a decrease of 27.92% and 46.36%, respectively, belonging to the high value decrease type, and the stability of Lanzhou-Xining urban agglomeration and Ningxia along Yellow River urban agglomeration kept increasing, with an increase of 69.73% and 104.16%, respectively, belonging to the low value increase type. The reasons are as follows: First, the development mode of Guanzhong Plain urban agglomeration is gradually solidified. In particular, the GDP growth rate has decreased by 57.44%, while the ratio of good air quality and public service expenditure has decreased. Second, complex natural environment and social factors limit the stable development of the northern slope of Tianshan Mountain urban agglomeration, and it is in urgent need of new development impetus to adjust the development structure. Third, while maintaining rapid economic growth, Lanzhou-Xining urban agglomeration and Ningxia along the Yellow River urban agglomeration pay attention to infrastructure construction and social security, which have great development potential and significantly improved stability.

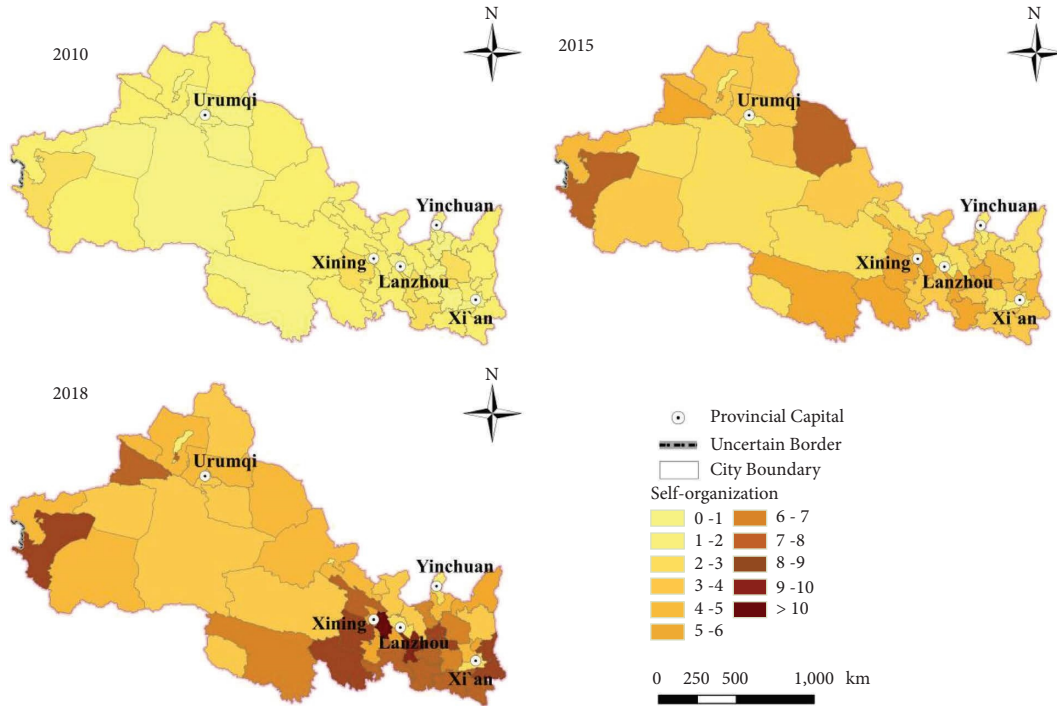


FIGURE 5: Spatial distribution pattern of urban self-organization.

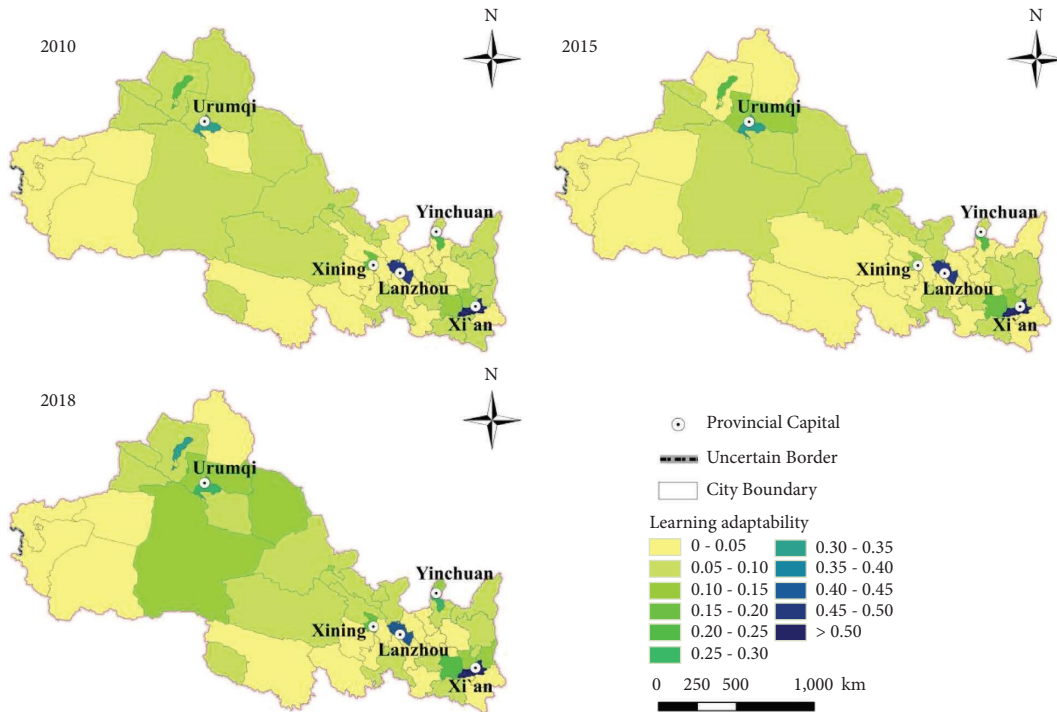


FIGURE 6: Spatial distribution pattern of urban learning adaptability.

4.2.2. Self-Organization. From 2010 to 2018, the level of self-organization of urban agglomerations showed an increasing trend. From the perspective of spatial distribution, the self-organization level generally shows a distribution characteristic of “high in the south and low in the north” (Figure 10). Among them, Guanzhong Plain urban

agglomeration and Lanzhou-Xining urban agglomeration have a higher self-organization level (4.5785 and 4.3982, respectively) and Ningxia along Yellow River urban agglomeration and the northern slope of Tianshan Mountain urban agglomeration have a lower self-organization level (3.4533 and 3.2464, respectively). This is related to the

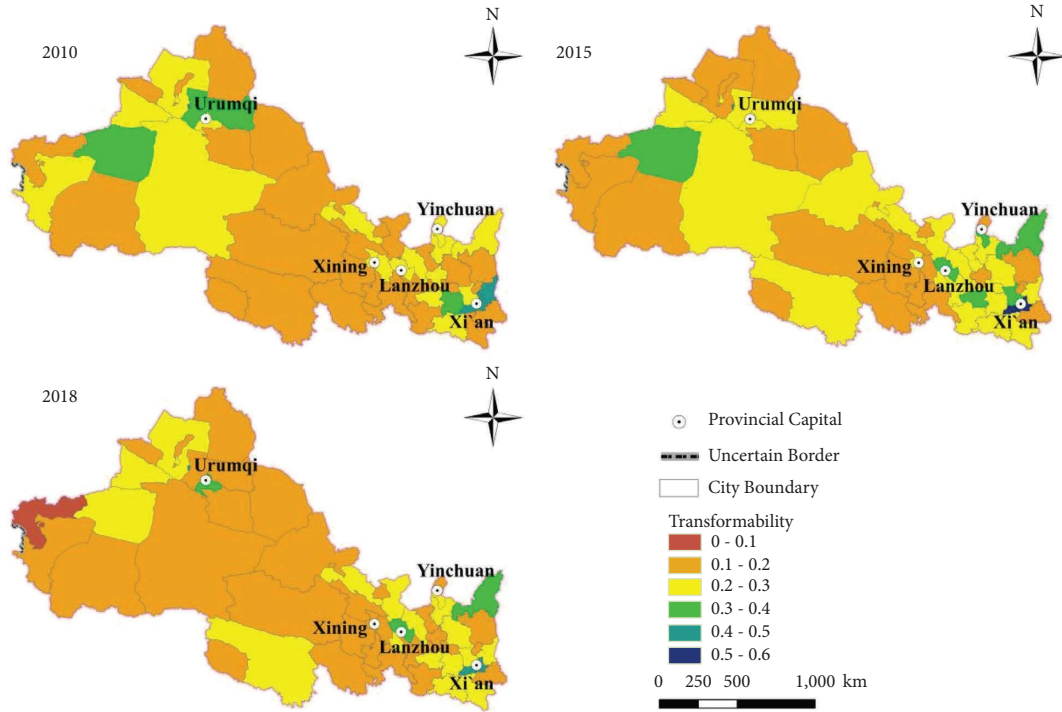


FIGURE 7: Spatial distribution pattern of urban transformability.

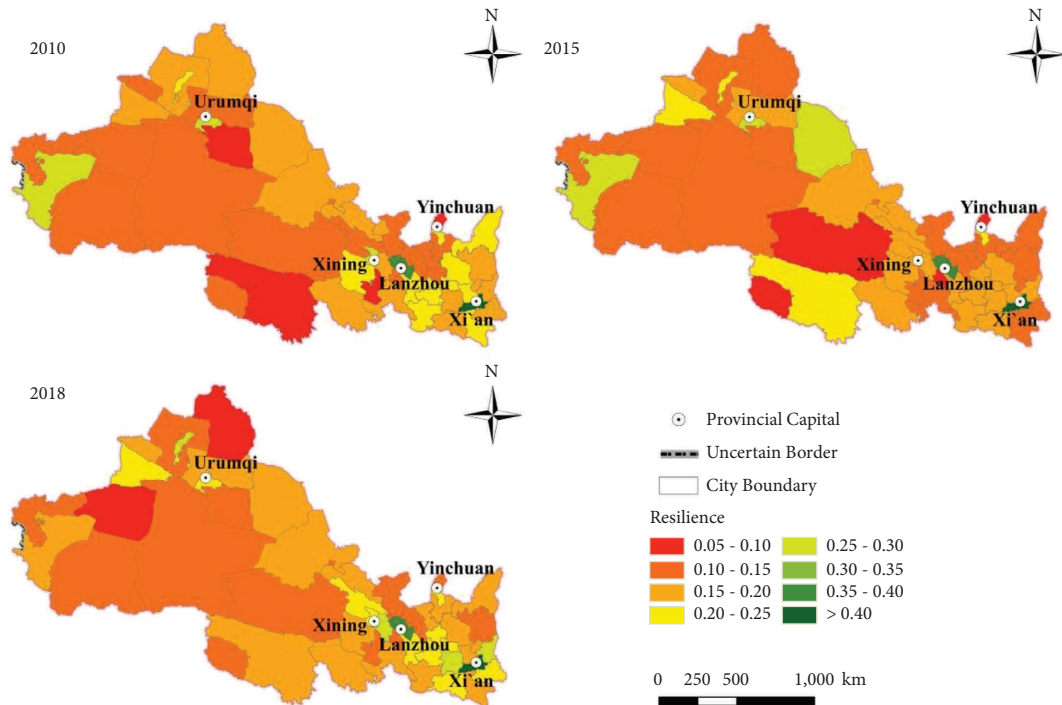


FIGURE 8: Spatial distribution pattern of urban resilience.

development orientation, geographical position, and national strategy of urban agglomeration. Guanzhong Plain urban agglomeration is a regional urban agglomeration in national planning and construction, which is close to the central and eastern developed areas, so it has great attraction

ability. Lanzhou-Xining urban agglomeration and Ningxia along Yellow River urban agglomeration are local urban agglomerations in national planning and construction, the level of urban development is not high, but they are located in the junction of the central and northwest regions, North

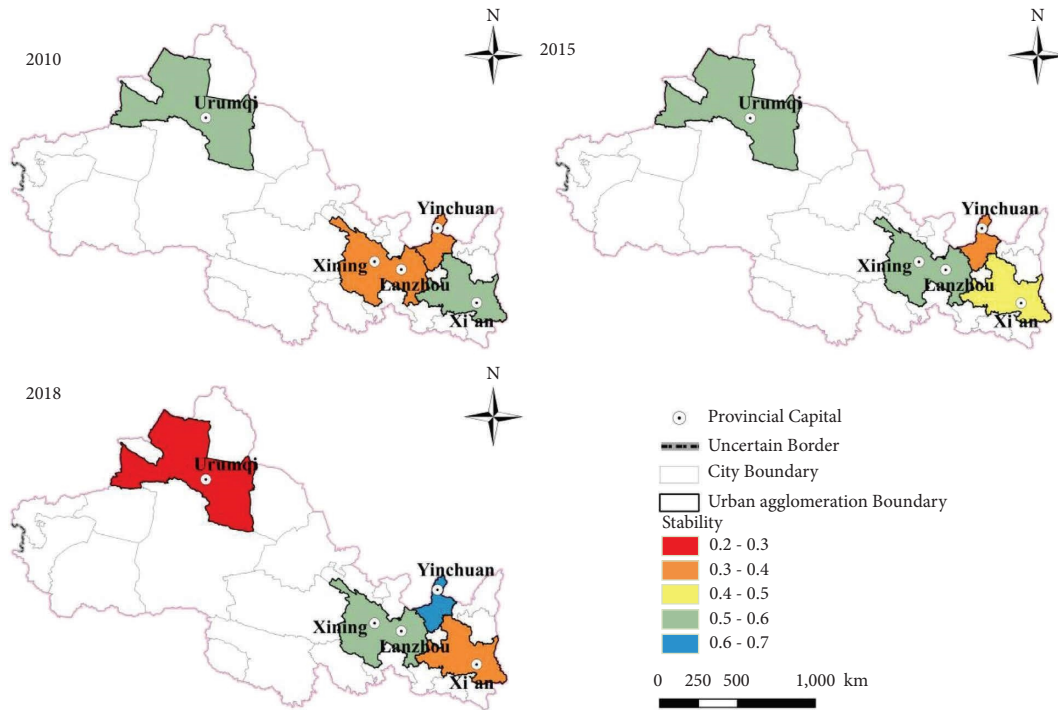


FIGURE 9: Spatial distribution pattern of urban agglomeration stability.

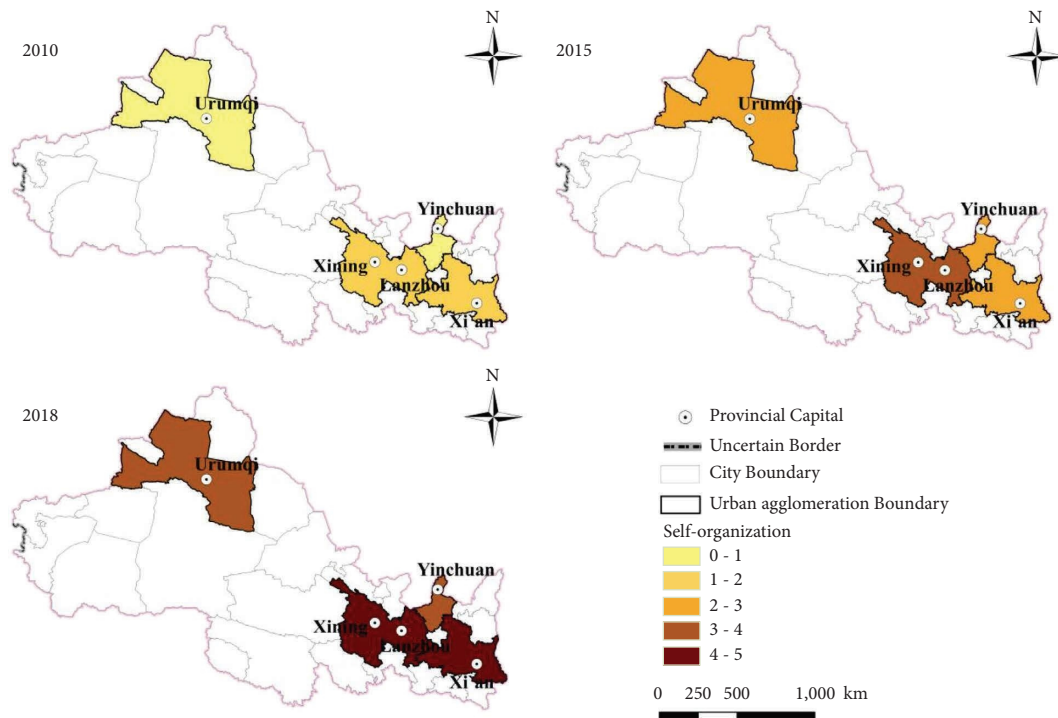


FIGURE 10: Spatial distribution pattern of urban agglomeration self-organization.

China, and northwest regions, and the hub has significant effects. In particular, Lanzhou-Xining urban agglomeration has accumulated more material and resources relying on the “Belt and Road” strategy. Although the northern slope of Tianshan Mountain urban agglomeration is also a regional

urban agglomeration in national planning and construction, with certain attracting and gathering capacity, it is too far away from the central and eastern regions and not strongly connected with other urban agglomerations in China, so its self-organizing ability is relatively low.

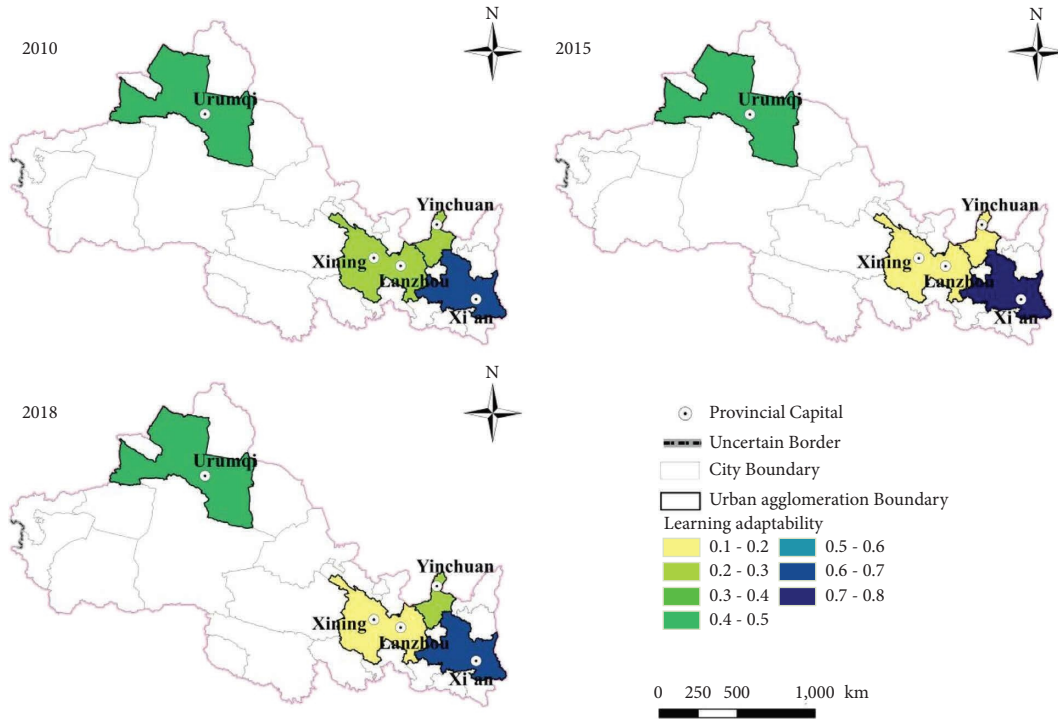


FIGURE 11: Spatial distribution pattern of urban agglomeration learning adaptability.

4.2.3. Learning Adaptability. From 2010 to 2018, the level of learning adaptability of the four urban agglomerations showed obvious hierarchical characteristics (Figure 11). In Guanzhong Plain urban agglomeration, universities and enterprises are densely distributed and science and technology input is large, so learning adaptability has always been in a leading position. The northern slope of Tianshan Mountain urban agglomeration is a medium area for the country to communicate with the outside world. The living standard of residents and the importance of science and technology are relatively high, so learning adaptability is in the middle level. Lanzhou-Xining urban agglomeration and Ningxia along Yellow River urban agglomeration are the lowest, but because of the loss of high-tech talents and high-tech enterprises in Lanzhou-Xining urban agglomeration, while the science and technology investment in Ningxia along Yellow River urban agglomeration increases significantly, the number of talents and enterprises is stable, so the learning adaptability of the latter exceeds that of the former.

4.2.4. Transformability. From 2010 to 2018, the transformability level of the four urban agglomerations showed two trends of increase and decrease (Figure 12). Among them, Ningxia along Yellow River urban agglomeration and the northern slope of Tianshan Mountain urban agglomeration show an increasing trend, while Guanzhong Plain urban agglomeration and Lanzhou-Xining urban agglomeration show a decreasing trend. This is related to the social structure and industrial structure of urban agglomeration. In 2018, the aging index of Guanzhong Plain urban agglomeration was 9.61%, the income gap between urban and rural residents was 20129 yuan (the highest in the whole study

area), the social structure was unbalanced, and urban transformability was impaired. Lanzhou-Xining urban agglomeration is dominated by agriculture and industry. The high proportion of traditional industries for a long time has reduced the rationalization of industrial structure (by 56.52%), and the speed of industrial transformation is slow, affecting the urban transformation ability.

4.2.5. Urban Agglomeration Resilience. After comprehensive processing and calculation of the data of the four urban agglomerations, the trend chart of the resilience index was obtained (Figure 13).

From the perspective of spatial distribution, the comprehensive resilience of four urban agglomerations in the five provinces of northwest China showed a distribution characteristic of “high in the southeast and low in the northwest” from 2010 to 2018 (Figure 14). The resilience index of Guanzhong Plain urban agglomeration shows a high value and steady-state characteristic. The overall resilience has decreased by 0.03 in the past 9 years, indicating that the overall development structure of urban agglomeration is stable, but the development model is gradually fixed, which is prone to path locking, resulting in insufficient development vitality. The resilience index of Lanzhou-Xining urban agglomeration is at a medium level with a slight increase. The overall resilience has increased by 0.14 in the past 9 years, indicating that the development of urban agglomeration is in an upward phase, the stability of regional structure is being established, and population, resources, capital, and information are also flowing to this region. The resilience index of Ningxia along Yellow River urban agglomeration is the lowest, but growth is stable, with an increase of 54.01%, indicating that the development of urban

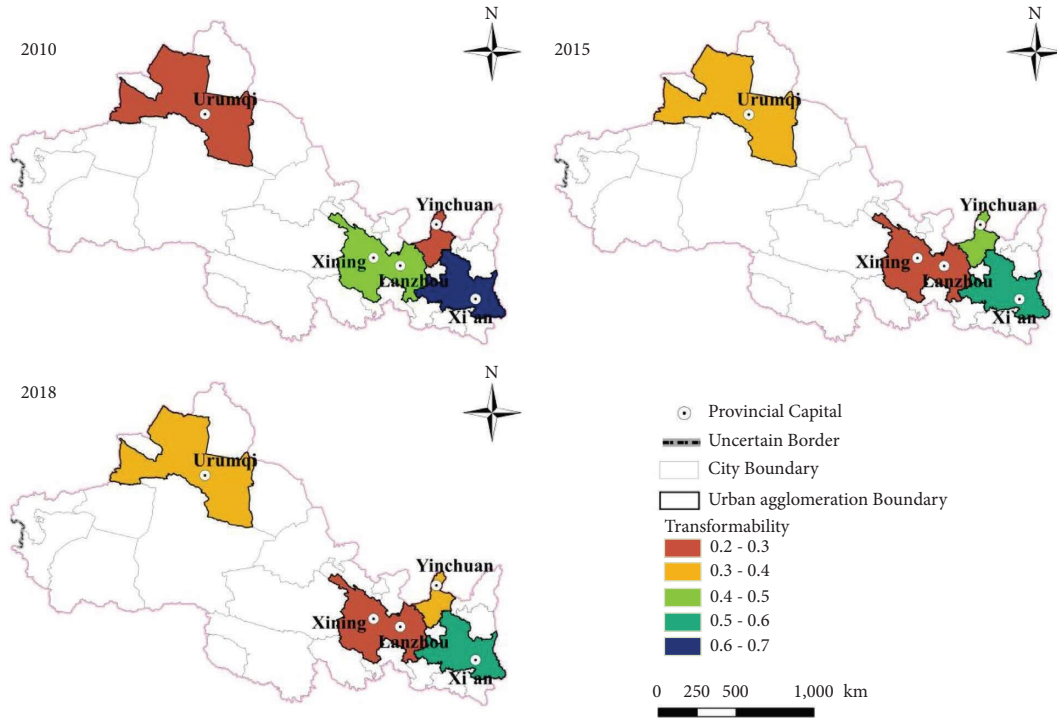


FIGURE 12: Spatial distribution pattern of urban agglomeration transformability.

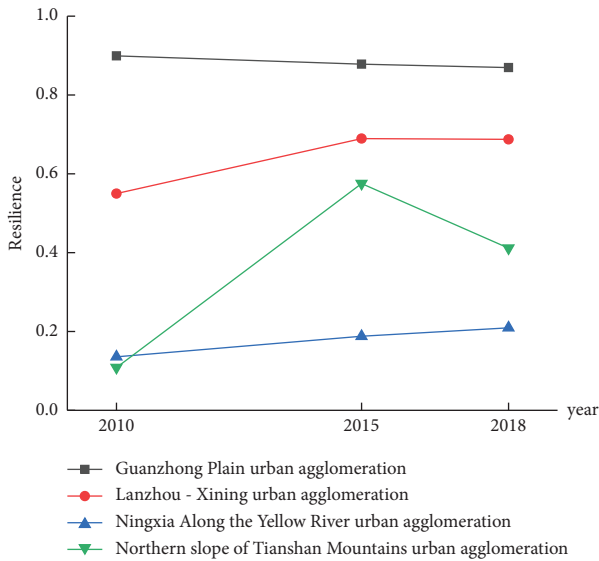


FIGURE 13: Variation trend chart of resilience in four urban agglomerations.

agglomeration is also on the rise at present, but the ability to attract external development factors is insufficient. The resilience index of the northern slope of Tianshan Mountain urban agglomeration increased first and then decreased, with the largest variation, indicating that the development path of urban agglomerations is uncertain and that system structure changes are complex, which is because the development of urban agglomerations is limited by the harsh ecological environment, and economic ties are not strong due to its distance from the central and eastern developed regions.

4.3. Variation Characteristics of Provincial Resilience

4.3.1. Stability. From 2010 to 2018, both stability level mutation and steady state were present in 5 provinces (Figure 15). The stability of Gansu Province increased by nearly two times, the stability of Shaanxi Province and Qinghai Province increased slowly, and the stability of Ningxia Autonomous Region and Xinjiang Autonomous Region continued to decline, with a decrease of 24.86% and 44.19%, respectively. This is related to the different development status and goals of each province. Gansu contains many national key ecological protection areas, so development is mainly coordinated and stability is growing rapidly. Shaanxi has a high level of development and has fixed development mode and certain development advantages, so the urban structure will not change basically. Qinghai mainly focuses on animal husbandry and resource development, and the ecological environment is fragile, so it is difficult to make big changes in the development mode of the whole province. At present, Ningxia develops the spatial pattern with the main traffic passage as the axis, the original development mode is broken, and stability shows a downward trend. The development of Xinjiang is mainly to maintain social stability. The development level of various cities is uneven, transportation is inconvenient, and the environment is harsh in the whole region. Therefore, the development mode of Xinjiang cannot be fixed, and uncertainty is high, so it cannot form a stable development path.

4.3.2. Self-Organization. From 2010 to 2018, the self-organization level of five provinces showed an increasing trend, especially Qinghai Province, which increased rapidly

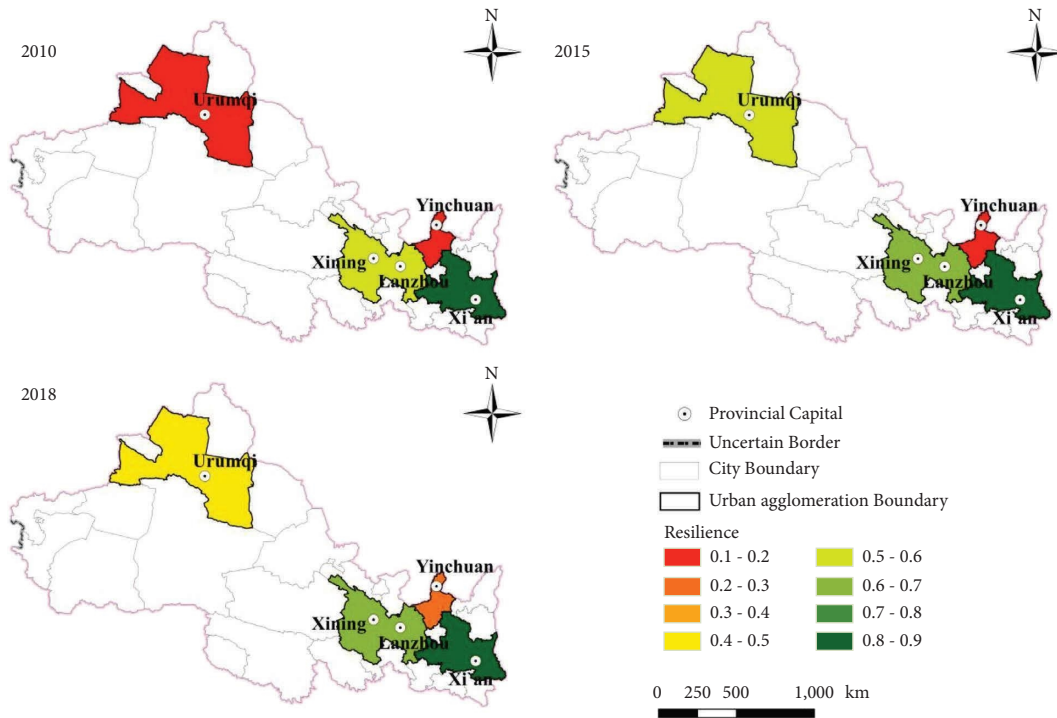


FIGURE 14: Spatial distribution pattern of urban agglomeration resilience.

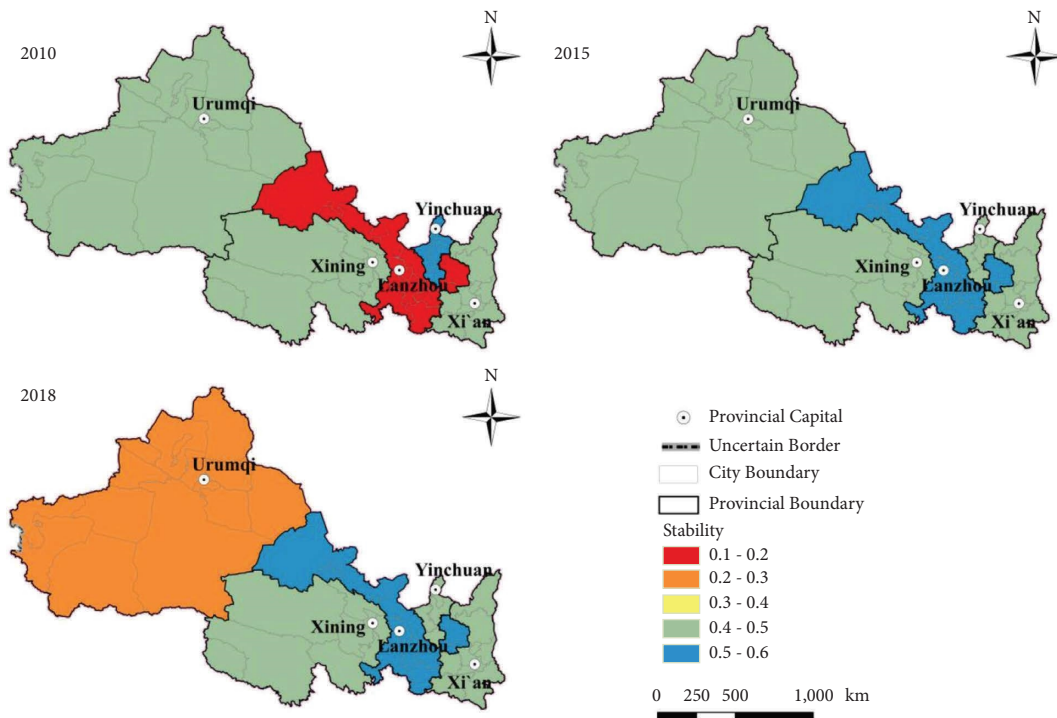


FIGURE 15: Spatial distribution pattern of provincial stability.

after 2015 (Figure 16). The reason for this change is that the implementation of national projects has added new development impetus to the region. The economy of Qinghai Province is mainly based on the development of animal husbandry and energy enterprises. The development mode is

fixed, and the development speed is slow. Until the Lanzhou-Xinjiang high-speed railway was completed and opened to traffic in 2014, the development of cities along the line has been given an opportunity, a large number of population, resources, funds, and information have flowed in, the

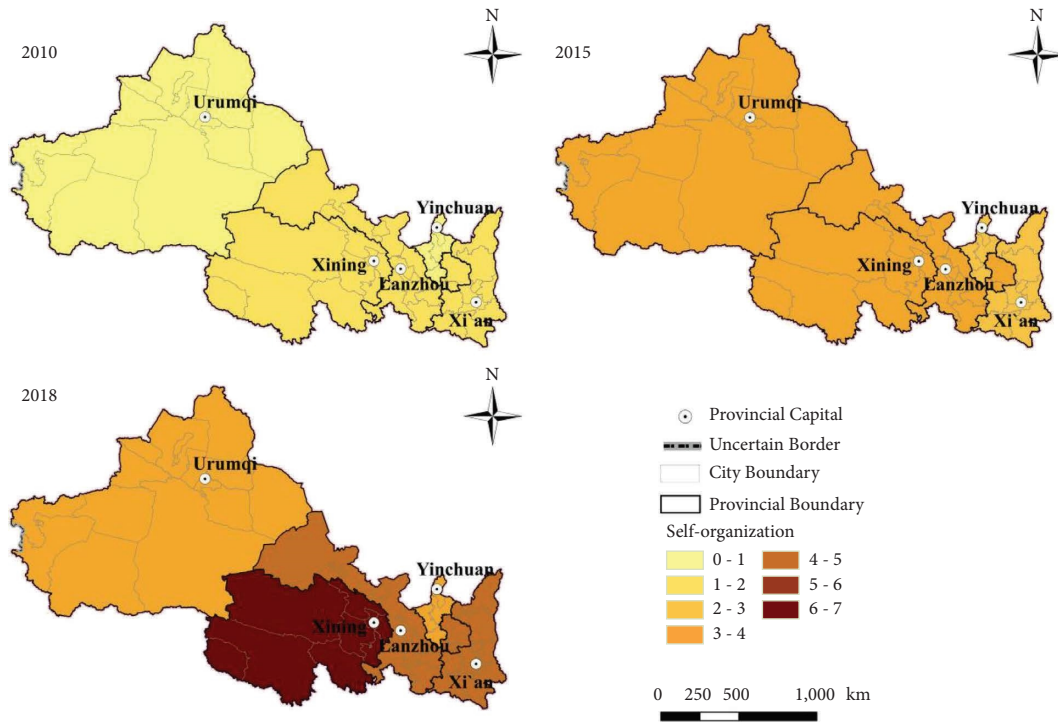


FIGURE 16: Spatial distribution pattern of provincial self-organization.

development of other cities in the province has been supplemented accordingly, and the development of the whole province has been activated.

4.3.3. Learning Adaptability. From 2010 to 2018, the level of learning adaptability in five provinces showed the “Matthew effect.” From the perspective of spatial distribution, learning adaptation presents a distribution characteristic of “low in the middle and high in both sides” (Figure 17). Among them, Shaanxi Province is far ahead (0.717 in 2018), and the learning adaptability of Gansu Province and Qinghai Province shows a downward trend, with a decline of 11.84% and 32.06%, respectively. The reason is that the number of universities, high-tech enterprises, and high-tech talents in Shaanxi Province is the largest and steadily increasing among the five provinces in northwest China. At the same time, it has invested a lot in science, technology, and education. It has also made great efforts to narrow the gap between urban and rural areas and coordinate and unify urban and rural development so as to enhance the regional ability to adapt to interference. The scientific research environment in Gansu Province and Qinghai Province generally leads to the loss of talents and enterprises. Meanwhile, there are significant differences between urban and rural areas in the province, and disturbances and challenges cannot be transformed into “activation points” for development, resulting in problems in regional development.

4.3.4. Transformability. From 2010 to 2018, the transformability level in five provinces showed two trends of increase and decrease (Figure 18). Among them, Qinghai

Province continued to decline, with a decrease of 40.98%, while other provinces showed an increase trend. This is closely related to vigorously developing regional traffic in Qinghai Province. With the improvement of transportation facilities, the tertiary industry has been fully developed, the previously solidified development model has been broken, and the industrial structure has begun to transform. At the same time, the connection between Qinghai Province and other provinces has been strengthened, and there is a phenomenon of “leaving home” population flow in the region. People either flow from second-tier cities in the province to provincial capital cities or from Qinghai Province to other provinces. This directly leads to the decrease in employment increments, the increase in aging levels, and the decrease in regional transformability.

4.3.5. Provincial Resilience. After comprehensive processing and calculation of the data of the five provinces, the trend diagram of the resilience index (Figure 19) and the spatial distribution diagram (Figure 20) were obtained.

The resilience index of Shaanxi Province shows a trend of a “high value decline,” with an overall decrease of 0.2 in the past 9 years, indicating that the development model of Shaanxi Province has begun to be fixed and the development vitality of the region needs to be activated. The resilience index of Ningxia Autonomous Region shows a trend of a “low value rising,” and the overall change range of the resilience index is not large in the past nine years, indicating that the province has stable development at the present stage and a clear development goal. The resilience index of Gansu Province shows a trend of a “middle value decline,” with an overall decrease of 46.16% in the past 9 years, indicating that

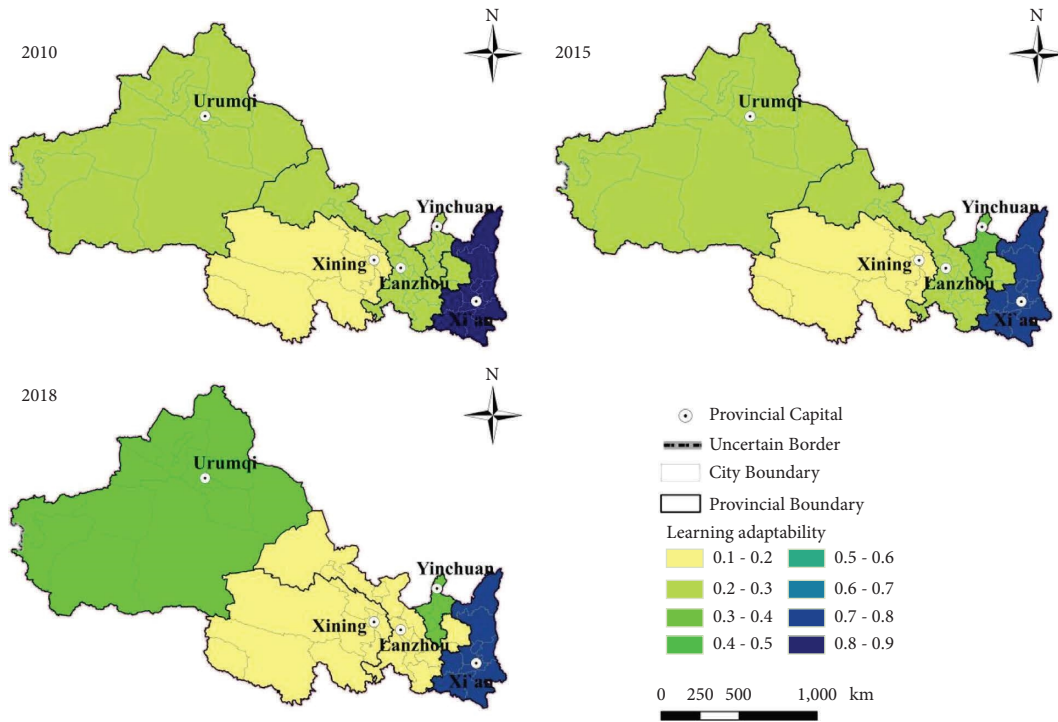


FIGURE 17: Spatial distribution pattern of provincial learning adaptability.

the province's development has reached a bottleneck stage and that the fixed development model can no longer meet the development requirements of the present stage, and urban problems become prominent. The resilience index of Qinghai province shows a trend of a "high value rising." The overall change of the resilience index in the past nine years is significant, indicating that the province is in an upward phase with vigorous development and good development prospects. The resilience index of Xinjiang Autonomous Region shows a trend of "low value fluctuation," which fluctuates significantly in the past nine years, indicating that the province's development structure is complex, its development model is not unified, and its overall adaptability is not strong in dealing with disturbance changes.

4.4. Multiscale Analysis of the Adaptive Cycle

4.4.1. The Adaptive Cycle of Cities. Based on the value and change rate of urban resilience and its attribute characteristics, combined with the evolutionary urban resilience model, this paper classifies the adaptive cycle of cities (Table 2). The number of cities in the stable conservation stage (K) is the largest in the region, the urban structure is highly stable, and the development path is locked. The second is the exploitation-conservation stage (r-K) and the conservation-release stage (K-Ω). The former city belongs to the rising stage of development, while the latter city cannot meet the needs of new changes due to the emergence of urban problems. The cities in the development reorganization stage (α) are the least, the resilience index of these cities has recovered, and the future direction and development content of cities are being determined.

4.4.2. The Adaptive Cycle of Urban Agglomerations. There are differences in the adaptive cycle of urban agglomerations in the five provinces of northwest China. From 2010 to 2018, Guanzhong Plain urban agglomeration has a high resilience index, decreasing stability, high self-organization, and little change in learning adaptability and transformability, indicating that it is in the stable conservation stage (K). Among them, Xi'an is the central city of the entire urban agglomeration, which together with Xianyang City and Xi'an-Xianyang New District constitutes the core development circle of the entire urban agglomeration. Baoji city and Tianshui city are located on the main axis of urban agglomeration development, with high-tech industrial parks, which are the driving force of urban agglomeration development. The resilience index of Lanzhou-Xining urban agglomeration increased slightly, stability showed an increasing trend, self-organization was high, and learning adaptability and transformability decreased slightly, indicating that the urban agglomeration structure tended to be stable and that it was in the exploitation-conservation stage (r-K). Among them, Lanzhou city and Xining city are located in the center of the urban agglomeration. Haidong City has frequent input and output of population, resources, capital, and information and has great potential for urban development, which provides an opportunity for development. Other cities have a low overall development level and need the trickle-down effect of the central city to drive development. The resilience index of Ningxia along Yellow River urban agglomeration is low, but the growth rate is fast, and stability continues to rise, the growth rate is large, self-organization shows an increasing trend, learning adaptability is stable, and conversion increases slowly, indicating

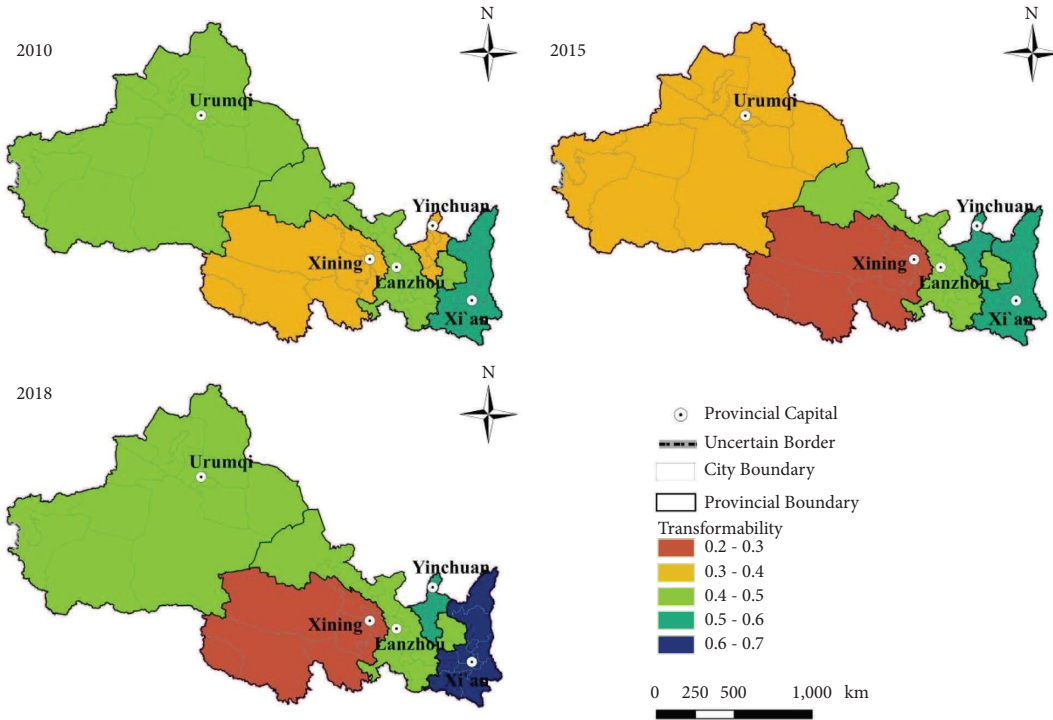


FIGURE 18: Spatial distribution pattern of provincial transformability.

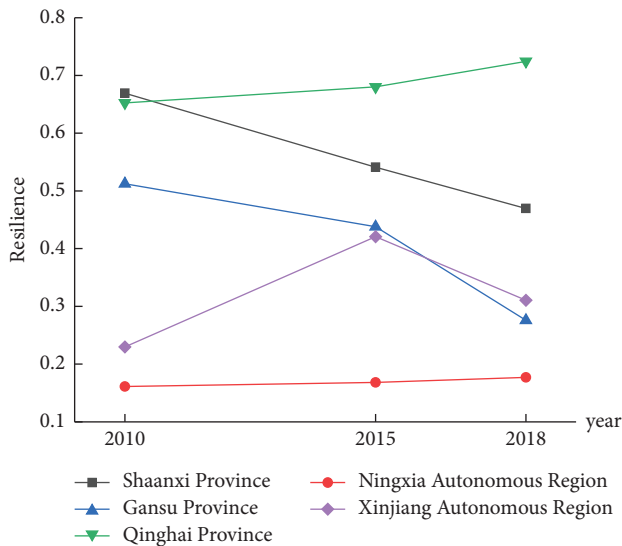


FIGURE 19: Variation trend chart of resilience in five provinces.

that it is in rapid exploitation (r). Among them, the urban circle jointly constructed by Yinchuan city and Wuzhong city is the core development area of the entire urban agglomeration. Shizuishan city and Zhongwei city are the two subcentral cities of urban agglomerations, which are closely connected with the central area to jointly support the development of urban agglomerations. The resilience index of the northern slope of Tianshan Mountain urban agglomeration first increases and then decreases, with a large range of change and a continuous decrease in stability, but the self-organization growth rate is fast, learning adaptability is high,

and transformability shows an increasing trend. The unstable development structure of urban agglomerations shows that it is in the stage of development reorganization (α). Among them, Urumqi and Changji city formed the urban circle which is the development core of the entire urban agglomeration, and other cities along the “Silk Road” economic belt constitute the development axis of urban agglomerations, but the agglomeration effect is low, and the phenomenon of industrial similarity is serious, resulting in the overall development of urban agglomeration being unstable. It can be seen that the central city or central region of urban agglomerations plays a leading role and that the adaptive cycle stage of urban agglomerations is consistent with the central city or central region.

4.4.3. The Adaptive Cycle of Provinces. There are differences in the adaptive cycle of five provinces in northwest China. From 2010 to 2018, Shaanxi Province’s resilience index was high, stability grew slowly, and self-organization was high, but its growth rate was slow, and learning adaptability and transformability tended to be stable, indicating that it was in the stable conservation stage (K). Most of the cities under the jurisdiction of Shaanxi Province are also in the stable conservation stage, with agriculture or energy industry as the main industry, have slow industrial transformation, and have lack of new driving force for development. However, there are some cities that realize rapid industrial structure transformation by a high-tech industry, such as Xi’an, Xianyang, and Baoji, which play a driving role in the development of Shaanxi Province. The resilience index of Ningxia Autonomous Region was small but showed an upward trend, stability continued to decline, self-

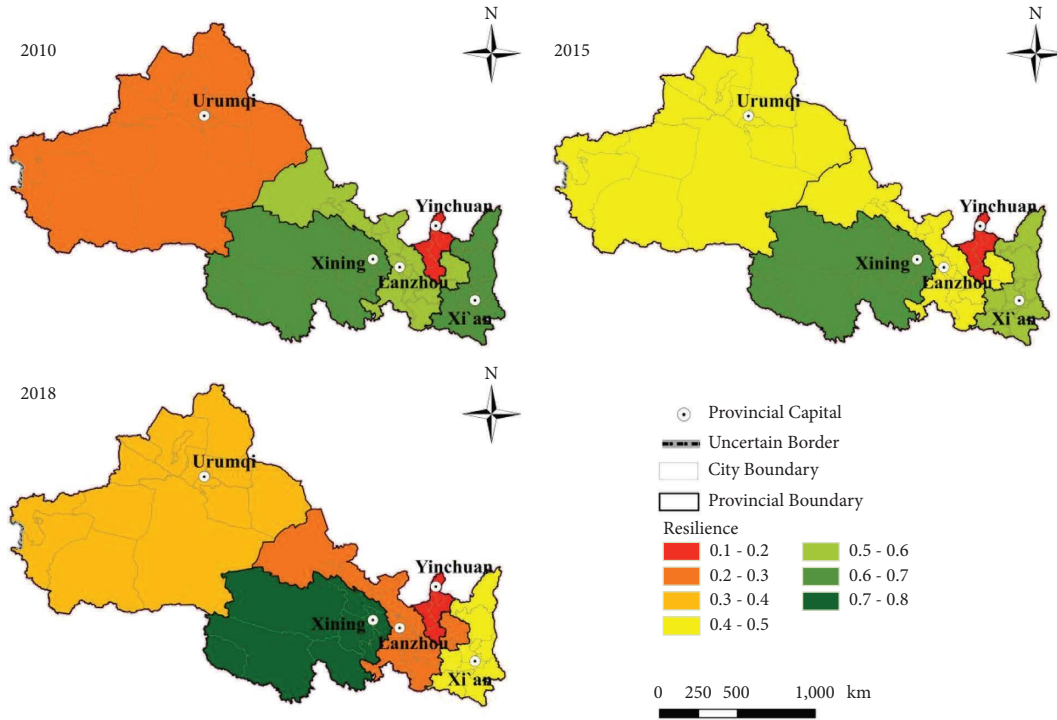


FIGURE 20: Spatial distribution pattern of provincial resilience.

organization increased greatly, and learning adaptability and transformability showed an upward trend, indicating that it was in the reorganization-exploitation stage (α -r). Yinchuan city, the capital of the province, has a high urbanization rate and a small gap between urban and rural areas. As the central city of the urban agglomeration along the Yellow River, it has received a good development opportunity and also drives the high-quality development of the whole autonomous region. The resilience index of Gansu Province continues to decline, the decline is large, stability first increases and then decreases, the self-organization change is small, and learning adaptability and transformability decrease slightly, indicating that it is in the conservation-release stage (K - Ω). The development of Gansu Province has entered a bottleneck period, the solidification of resources is obvious, and urban development is restricted. The cities under its jurisdiction are based on industry and agriculture, and the industrial structure is stable, so urban transformation is slow. At the same time, the level of urban economic development in the province is low, but the population is highly concentrated, resulting in unbalanced resource distribution, serious loss of high-tech talents and industries, low learning and adaptation ability and transformation ability of the region, and lack of potential development power. The resilience index of Qinghai Province is high and rising slowly, stability is basically unchanged, self-organization is high and increases significantly, and learning adaptability and transformation are slightly reduced, indicating that it is in the exploitation-conservation stage (r - K). The development of the province is on the rise, with good resource endowment, and the industrial structure has begun to transform. However, due to the low level of industrial

sophistication after transformation, the economic growth effect of industrial development has not been fully shown, and the income gap between urban and rural residents is widening, resulting in the imbalance between urban and rural development. The resilience index of Xinjiang Autonomous Region increased first and then decreased and fluctuated greatly, stability continued to decline, self-organization was low, and learning adaptability and transformability increased to varying degrees, indicating that it was in the stage of development reorganization (α). The development model of the province is complex, the agglomeration effect is weak, and urban development faces many disturbances due to the unreasonable economic development layout, lagging infrastructure construction and environmental conditions. It can be seen that when the development power is abundant, the adaptive cycle stage of the province is the same as the average level of all cities in the region and that when the power is insufficient and urban problems are obvious, the province will move backward the average level of all cities in the region as the adaptive cycle stage.

5. Discussion

5.1. Scale Heterogeneity of Urban and Regional Resilience.

Due to the differences in the social economic environment, the leading forces promoting regional development, and the operating mechanism, regions of different scales often have differences in their ability to resist and recover when facing external shocks. In this paper, through the comparison of resilience between cities and regions, it is found that the resilience index is significantly different at different scales,

TABLE 2: Adaptive cycle classification of cities in five provinces of northwest China.

Stages	City	Characteristic
Rapid exploitation (r)	Weinan, Hanzhong, Shangluo, Guyuan, Haidong, and Haibei	The urban resilience index increased rapidly, the stability of system structure improved, and materials, energy, and information poured in rapidly
Exploitation-conservation (r-K)	Lanzhou, Baiyin, Wuwei, Zhangye, Tianshui, Jiuquan, Xining, Huangnan, Guolu, Hama, and Turpan	The increasing speed of the urban resilience index decreases, development tends to solidify, and the changes of various attributes are gentle
Stable conservation (K)	Xi'an, Tongchuan, Xianyang, Yan'an, Yulin, Yinchuan, Jiayuguan, Jinchang, Qingyang, Linxia, Haixi, Karamay, Changji, Boltala, and Hetian	The urban resilience index is basically stable or even shows a downward trend, the self-organization ability is small, the stability of the system structure is not easy to break, and it is urgent to improve the capacity of urban transformation and upgrading
Conservation-release (K-Ω)	Hainan, Urumqi, Shihezi, Tacheng, Altay, Yili, Bayinguoleng, Aksu, Kizilsu, and Kashgar	The urban resilience index continues to decline, stability is insufficient, urban development is disturbed, and urban problems appear. At this time, self-organization, learning adaptability, and transformability begin to improve and come into play, trying to solve problems and get rid of weakness
Development reorganization (α)	Pingliang, Dingxi, and Longnan	The urban resilience index rises, one or several characteristic attribute values change significantly, and the city begins to replan the development route and prepare to enter a higher level of the adaptive cycle
Reorganization -exploitation (α-r)	Baoji, Ankang, Gannan, Yushu, Wuzhong, Zhongwei, and Shizuishan	The urban resilience index rebounded greatly, the system stability gradually improved, the accepted entropy began to increase rapidly, and the city has transitioned to a higher-level adaptive cycle

which is consistent with the widely held views of scholars [55, 56].

At the same time, this study points out that, at the city scale, the resilience of the five provincial capitals is in the leading position among the 52 cities, at the urban agglomeration scale, the resilience index of Guanzhong Plain urban agglomeration is higher than that of other urban agglomerations in the study area, and at the provincial scale, Qinghai Province is the region with the highest resilience among the five provinces in northwest China. These research results can be verified by similar studies of other scholars. Such as Lu et al. [57] conducted an empirical study on resilience of 31 provincial capital cities in China. They found that provincial capital cities have agglomeration effects and are significantly affected by their own geographical locations, development conditions, and national policies. Therefore, they have strong adaptability when facing external shocks and can quickly recover in a short period. Fang [58] found that the development orientation of each urban agglomeration in the Yellow River basin of China is different. Among them, Guanzhong Plain urban agglomeration is the strategic pivot of the country's opening to the west and an important growth pole leading the development of the northwest region. Therefore, improving the resilience of urban agglomeration, resisting shocks and achieving adaptive development are effective measures for the sustainable development of the region. Yang [59] pointed out in the comparison of the economic development status of 31 provinces in China that, in the great opportunity of the Western Development Strategy, Qinghai Province, relying on its superior resource conditions, is likely to surpass some traditional development stages and achieve local leapfrog development.

5.2. Scale Heterogeneity of Urban and Regional Adaptive Cycles. Due to different socioeconomic status and development potential, different cities and regions are in different adaptive cycle stages. The research results of this paper show that all cities or regions in the study area have great differences in their system characteristics and resilience levels, resulting in inconsistent stages of their adaptive cycles and development levels, which is consistent with the views of previous scholars [16, 60]. Some of them have stable urban development structure and coordinated development of various elements of the system, while others have rigid urban development models, and urban problems are gradually emerging. The polarization phenomenon shown in the research results is similar to that of Li et al. [61], who also pointed out that there are two half cycles of growth and weakness in the regional economic system. The reason is that the higher the urban resilience, the stronger the system's ability to absorb and transform shocks, and the adaptive cycle will be in a benign state; otherwise, it will be in a vicious circle.

The results also show that the adaptive cycle stage of urban agglomerations is consistent with its core region when the scale changes. The research by Fang et al. [62] and Ye et al. [63] can confirm this result from the side. They pointed

out that core cities play a leading role in economic development, social structure, strategic policies, and other aspects and are important growth poles leading the development of urban agglomeration. In assessing the high-quality development of urban agglomerations in the Yellow River basin of China, Ma and Xu [64] also pointed out that urban agglomerations should strengthen the radiating and driving effect of core cities on the overall urban agglomeration so as to promote the high-quality development of the entire Yellow River basin through the impact of the overall high-quality development of urban agglomerations.

In addition, when this study transforms from an urban scale to a provincial scale, it is found that the development stage of the provincial adaptive cycle is related to the average level of all cities in the region. Li [65] also conducted a similar study for the five provinces in northwest China. He found in the analysis of multifactor urban network structure that the development levels of cities in the region were significantly different and that the provinces with multiple high-level cities within their jurisdiction had a higher development level of comprehensive quality than other provinces, and vice versa. For example, when Lei [66] studied the coordinated development of cities and environment in central China at different scales, he found that when the spatial agglomeration phenomenon of well-coordinated regions at the urban scale is displayed at the provincial scale, provinces where the agglomeration phenomenon occurs also have the characteristics of good coordination between cities and environment. Therefore, regions at different scales need to pay attention to their own development and the construction of adaptive capacity.

6. Conclusion

As the direct subject of dealing with uncertain risks, it is of great importance to build resilient cities with the ability of resisting, dispelling, and adapting to uncertain risks to mitigate risk impacts and promote urban security and sustainable development. Based on the adaptive cycle model, this paper analyzed the spatial and temporal characteristics and adaptive cycle of the resilience of cities, urban agglomerations, and provinces in northwest China from 2010 to 2018. The results show that the resilience level of cities in the five provinces of northwest China is on the rise, and the differences between cities are gradually narrowing. At the same time, the spatial distribution characteristics of urban resilience are "one super and many strong, high in the east, and low in the west." The number of cities in the stable conservation stage is the largest, followed by the number of cities in the exploitation-conservation stage and conservation-release stage, and the number of cities in the development reorganization stage is the least. Second, the resilience of urban agglomerations varies greatly, showing a spatial distribution characteristic of "high in the southeast and low in the northwest." It is worth noting that the development stage of the adaptive cycle of each urban agglomeration is different, but it is consistent with its central urban area. Finally, the level of resilience varies greatly among provinces, and the development stage of the adaptive

cycle is similar to the average level of all cities in the region and is closely related to their respective development forces and urban problems.

Based on the above research results, the five provinces in northwest China should strengthen the awareness of the challenges and disturbances faced by cities and regions and pay attention to the building of resilience. Second, we should always accurately locate the development stage of the adaptive cycle and carry out targeted economic and social adjustment and transformation development. It is worth noting that, for cities in the rising period or gradually locked in the development path, when there are many interferences such as national policies, traffic construction, population aging, too fast population agglomeration, and environmental restrictions, we should give full play to urban transformation ability, accurately foresee problems, avoid the negative impact of interference to the largest extent through advanced structural reform, and seize the opportunity to achieve a higher level of development. For cities with urban problems, the main goal is to promote urban transformation and eliminate urban problems by improving the learning and innovation ability of the government, enterprises, and individuals and using innovative thinking to put forward new development ideas that can adapt to changes while improving infrastructure construction. Finally, for cities in other stages, the focus should be on strengthening the unity and coordination of the social system, economic system, and environmental system. While improving basic social services and increasing investment in production and construction, we should pay attention to protecting the environment and consolidating the stability of the system structure so as to improve urban resilience and achieve sustainable development.

Data Availability

The social and economic statistics are from the China provincial statistical yearbook, China urban statistical yearbook, and the statistical bulletin of national economic and social development of some cities. Land use-type data and vegetation index data are from the data center of resources and environment science, Chinese Academy of Sciences (<https://www.resdc.cn>). DEM data come from geospatial data cloud (<https://www.gscloud.cn/>) with a resolution of 1 km.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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Research Article

Connection Characteristics and Hierarchical Structure of China's Urban Network-Based on the Communications Technology Service Industry

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Considering the importance of China's digital economy, industrial Internet, and high-quality development, this study analyzed China's urban network from the perspective of the communications technology service industry. Three sub-networks (R & D, sales, and investment) and a comprehensive network were constructed. The density, centrality, and cohesive subgroups of the above network were identified. The results show that: (1) cohesion of urban networks in China is weak and resource sharing is low. (2) From west to east, the urban network forms a multilevel diamond structure in the periphery, a parallelogram structure in the semiperiphery, and a triangle structure in the center. (3) The spatial distribution of cohesive subgroups is scattered, disobeying the first law of geography. By constructing sub-networks and a comprehensive network, the subnetworks that dominate China's urban networks were identified and their typical characteristics described. This study clarifies the technical support pattern behind China's digital economy development and industrial internet construction and provides a basis for policy-makers to optimize the country's high-quality development in the future.

1. Introduction

Since the 1980s, in the context of the third wave of economic globalization, factors of production and product markets worldwide have been integrated, and capital flow around the world has accelerated, shifting the regional and spatial organization of the global economy from the static hierarchical model to the dynamic network model [1]. Cities serve as the primary places and important carriers of economic activities. The flow of factors and enterprise cooperation between cities results in the formation of urban networks. The correlation characteristics and spatial patterns of urban networks can reflect the organizational structure and topographic layout of economic activities, which is important in guiding a rational layout of economic activities. Urban network research has become a hot issue and attracted the attention of many academics.

Among several theoretical constructs, the space of flows [2] and world city network theories [3] still play an

important role in urban network research. In particular, the application of the world city network theory, which stems from the space of flow theory, involves a transformation in theoretical research paradigms whereby relationships are analyzed instead of conventional structures. Urban network research has been greatly enriched and supported by this theory. In terms of methodological approaches, researchers are still seeking to improve the models and methods to allow the identification of urban networks. Luthi et al. [4] conducted an empirical analysis of the applicable scale of the chain network model. They found that the top-down method from the perspective of large-scale advanced production and service industry firms is more suitable to identify the world city network, while the bottom-up method that focuses on important enterprise companies in a specific region is a more suitable model to study regional urban networks. Neal et al. [5] proposed a bipartite projection to identify enterprise or city contacts more accurately, given that “strong connection

does not necessarily mean great power.” Regarding the research content, network hierarchy, and node centrality, studying the factors that influence network formation and the impact of network embedding on other networks remains part of the basic research material of urban networks [6–8]. As urban network research is intensifying, the existing paradigms are no longer limited to measuring network structure characteristics and improving models and methods. More researchers have guided their efforts to determine the causal and developmental mechanisms of urban network formation, as well as the diversity and heterogeneity of networks [9].

At present, urban network research in China focuses on three perspectives: first, to depict the urban network through traffic flows, such as highway [10], railway flow [11], and airflow [12]; second, to determine the relationship between cities through studies on information flow, including information flow carried out on social platforms, such as Sina Weibo [13], QQ group [14], Douban [15], and the network migration information flow reflected in the Baidu migration index [16]; third, to analyze the enterprise network, using multienterprise paradigms, such as the Chinese enterprise firms listed in Fortune Global 500 [17] that list the top 500 companies [18, 19], and single enterprise approaches, such as automobile [20, 21], financial [22], and logistics enterprises [23]. Enterprise organization is the key actor in the urban network [3], making it a priority in urban network research and providing a new theoretical growth point for urban spatial interactions [24]. With the innovations in global information technology and the deepening of informatization, the communications technology service industry has become an important medium of economic and societal ties between cities. This industry includes a chain of raw material suppliers, equipment manufacturers, technical service providers, telecom operators, and end customers. Research and development of fifth-generation (5G) communication, cloud computing, big data, the Internet of Things, blockchain, artificial intelligence, and other fields are key drivers in China’s scientific and technological innovation. Concurrently, the industry is an important power source for China’s future urban economic development, supplying technological support and facilities for developing the digital economy and the construction of the industrial Internet. The “14th five-year plan” features innovation as a key strategy to accelerate the digital economy, leading to new advantages and high-quality development. The communications technology service network, as a novel perspective of urban network research, clarifies the spatial pattern of China’s digital economy and industrial Internet, technology R & D, and facilities layout. Additionally, this industry sector reflects the organizational structure and connection characteristics of China’s urban network. The layout of the communications technology service industry and the effective utilization of communications technology play an important role in improving the urban economy and promoting structural optimization.

An influential model of urban network construction is the chain network model. The model uses a complete network to simulate the organizational structure of the

enterprise, based on the assumption that connections generally exist between any two branches; thus, it does not make specific judgments on effective and invalid connections within the enterprise [25]. For example, in a communications technology service enterprise, close exchanges between R & D centers are effective contacts; the relative lack of contact between R & D centers and sales outlets is characterized as invalid. The headquarters-branch model is another common model for building urban networks. The model uses a three-level tree structure to simulate an enterprise organization, reflecting the control relationship of headquarters over branches at all levels. However, the model does not consider the cooperative relationships between various sectors within the enterprise [26]. For example, the R & D center must cooperate closely with other technology branches. The zoning core algorithm determines the connection between enterprises according to the key role of central cities in the network, considering the geographical characteristics of enterprise connection, but failing to fully consider whether there is actual business cooperation between enterprises [27]. Zhao et al. [17] put forward the “compromise network model.” The model proposes a standardized classification of functions and strict screening of organizational relations, effectively avoiding the redundant connections of the chain network model and the oversimplifications of the headquarters branch model. The study uses the “compromise network model” as a reference and introduces a simplified version based on the characteristic connections of the division of labor and cooperation among the headquarters, R & D institutions, sales institutions, and invested enterprises in the communications technology service industry. The study integrates and optimizes the chain network and headquarters-branch models, constructs subnetworks and comprehensive networks, and offers a more detailed representation of China’s current urban network.

This study identified the relationships between the communications technology service headquarters and all branches and between branches, and constructed three subnetworks: R & D city network (R & D network), sales city network (sales network), investment city network (investment network), and an integrated city network (comprehensive network). Adjusting our focus on cities at the level of the prefecture and above (Chinese mainland cities, including Hong Kong), the model describes the overall characteristics of China’s urban network, including node centrality, correlation patterns, and cohesive subgroups, and discusses the matching relationships between centrality and power and the development stage of cohesive subgroups. Research outcomes are expected to enrich research on China’s urban network and help identify the technical support pattern behind the development of the digital economy and construction of the industrial Internet. Further, outcomes can provide a basis for policy-makers to optimize China’s future urbanization and the construction of urban agglomeration areas. This study aims to build a comprehensive network through sub-networks and identify the development stage to explore the mechanisms that drive the construction and evolution of the network. Exploring the entirety,

equilibrium, centrality, power, cohesive subgroups, and other characteristics of comprehensive networks using the same data standards helps identify the heterogeneity of networks. The paper is divided into three main sections. Section 2 describes the process of network construction, research methods, and data sources. Section 3 presents the overall and central characteristics, spatial correlation patterns, and cohesive subgroup characteristics of China's urban networks. Section 4 discusses the matching relationship between centrality and power and the stages of development of cohesive subgroups.

2. Network Construction, Research Methods, and Data Sources

2.1. Construction of Urban Network. Defever's classification scheme of multinational corporations distinguishes six branches based on the separation of functions: headquarters, R & D, production, sales, business, and office [28]. In building the model, the emphasis of the communications technology service industry on R & D, the market-driving business strategy, and the supporting role of capital flow in technology R & D activities have been considered. Based on the relationships between headquarters and R & D centers and each R & D center, headquarters and sales organizations, and headquarters and invested enterprises, the R & D, sales, and investment networks were constructed. A comprehensive network was generated by superimposing the three networks. The city network is then projected through the association between different functional institutions in the communications technology service industry. The organizational structure of Huawei, ZTE, and other enterprises suggests close information and technology exchanges between the R & D centers of the same enterprise in different cities. Therefore, this study assumes that multiple R & D centers of the same enterprise are interconnected, in addition to their connection with the headquarters. Thus, the R & D network is constructed based on the chain network model (Figure 1(a)). The key consideration in building the city network is the connection between different cities. Through investigation and interviews, we found that the connection between the sales departments of the same enterprise in different cities is weaker than that in the same city, whereas connections are evident primarily between the headquarters and each sales department. Therefore, the sales network is built based on the headquarters branch model (Figure 1(b)). The construction of the investment network follows the same principle as that of the sales network (Figure 1(c)). In the final step, the above networks are superimposed to form a comprehensive network (Figure 1(d)).

Obtaining data on branch size to construct the city network has been challenging. Hence, the number of branches was estimated from the service values of an enterprise in a city using the method of simplifying the data matrix by Yao et al. [29]. According to the proportional relationship between the annual capital investment in technology R & D, investment behavior, and total annual sales, the weights of the R & D institutions, invested

enterprises, and sales institutions were calculated to be 20, 7, and 1, respectively. (The capital investment in technology R & D, investment behavior, and total sales data of 30 enterprises were obtained from the 2019 annual reports of the 30 enterprises. By calculating the average value, the proportion of the three activities for the 30 enterprises was approximately 20:7:1). In contrast, the flow of capital, technology, personnel, and other elements between different branches are usually bidirectional, and the flow of elements in different directions is difficult to scale [20]. Therefore, the connection matrices of the subnetwork and comprehensive network are a (0, 1) Boolean matrix and a weighted undirected matrix. Based on the above correlation model and combined with the relational projection idea, a 39×39 R & D network, 111×111 sales network, 109×109 investment network, and 175×175 comprehensive networks are built.

2.2. Research Method. An urban network is composed of multiple nodes and their connections. Its construction usually follows the node subgroup network process. Nodes are the supporting elements of the network, and subgroups are important bridges between nodes and the network [18]. In urban network research, attention is directed not only to the integrity and consistency of the networks but also to the connectivity, control, and indispensability of nodes and subgroups [30].

2.2.1. Network Density. Network density is obtained by dividing the number of actual connections in the network by the number of theoretical connections to measure the integrity of an urban network [31]. With higher density, the urban network assumes a higher degree of integration, stronger cohesion, and closer communication between the nodes. The calculation formula is as follows:

$$D = \frac{\sum_{i=1}^n \sum_{j=1}^n d(i, j)}{n(n-1)}, \quad (1)$$

where D is network density; N is the number of nodes; and $d(i, j)$ means the link size between nodes i and j .

2.2.2. Centrality. Regarding centrality measures, social network analysis does not consider the strength of the links between nodes and only measures "bridging" ability, including the indirect links between the three nodes. Neal's transformation centrality and control model considers the number of element flows between nodes and global indirect links [32]. The former focuses on analyzing the centrality and influence of nodes and individual networks from a local perspective, while the latter emphasizes the control and dominance of nodes over the entire network, reflecting the power of nodes in the network [33]. This study discusses the matching relationship between urban centrality and power by calculating and analyzing the centrality of the global urban network and individual nodes.

(1) Centrality Measures in Social Network Analysis. The concept of centrality applies to both nodes and networks. Node centrality is indicated by degree centrality, which

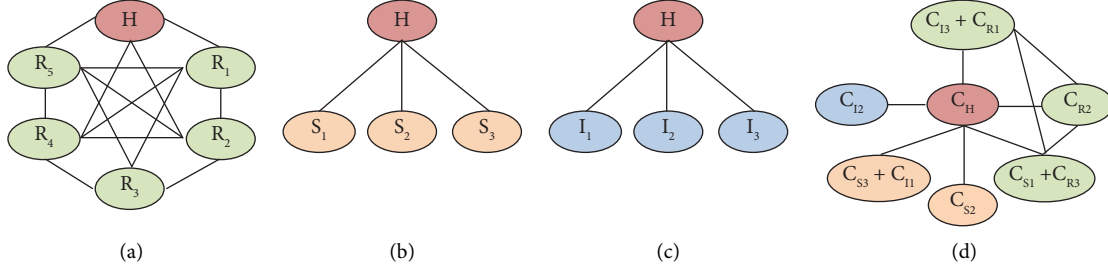


FIGURE 1: Network association model. networks: C, comprehensive; H, headquarters; I, investment; R, R & D; S, sales. (a) R & D network. (b) Sales network. (c) Investment network. (d) Comprehensive network.

measures how central the location of a node is in the network. The centrality of the network is described by centralization, which estimates the degree of difference between individual nodes in the network. Three measures of centrality are commonly used: degree centrality, betweenness centrality, and closeness centrality, which reflect indispensability, control, and the spatial accessibility of nodes or networks, respectively [31].

Centrality measures are calculated as follows:

$$\begin{aligned}
 C_{AD}(i) &= \sum_{i \neq j} X_{ij}, \\
 C_{AB}(i) &= \sum_{j=1; k=1; j \neq k \neq i}^N \frac{N_{jk}(i)}{N_{jk}}, \\
 C_c(i) &= \frac{n-1}{\sum_{j=1; j \neq i}^n d_{ij}},
 \end{aligned} \quad (2)$$

where $C_{AD}(i)$ is the degree centrality of node i , X_{ij} the correlation degree between nodes i and j ; $C_{AB}(i)$ is the betweenness centrality; $N_{jk}(i)$ the number of shortest paths between nodes j and k through node i and N_{jk} represents the number of shortest paths between nodes j and k ; $C_c(i)$ is the closeness centrality; and d_{ij} the shortest path distance between nodes i and j .

Centralization is calculated as follows:

$$\begin{aligned}
 C_{AD} &= \frac{\sum_{i=1}^n (C_{AD_{\max}} - C_{AD}(i))}{(n-1)(n-2)}, \\
 C_{AB} &= 2 \times \frac{\sum_{i=1}^n (C_{AB_{\max}} - C_{AB}(i))}{(n-1)^2(n-2)}, \\
 C_c &= \frac{\sum_{i=1}^n (C'_{AP_{\max}} - C'_{AP}(i))}{(n-2)(n-1)} \times (2n-3),
 \end{aligned} \quad (3)$$

where C_{AD} is the degree of centralization $C_{AD_{\max}}$ the maximum value of degree centrality; C_{AB} is the betweenness centrality and $C_{AB_{\max}}$ the maximum value of betweenness centrality; C_c is the closeness centralization; $C'_{AP_{\max}}$ the maximum value of closeness centrality; and C'_{AP_i} the closeness centrality of node i .

(2) *Centrality Measures of Transformation Centrality and Control.* Neal proposed the transformation of the centrality

and control models to measure the status and capture the ability of the city network structure to promote resource agglomeration or diffusion [32]. The method comprises “the scale of the connection network that can be effectively mobilized” and indirect links to account for centrality [20] and to determine the relationship structure of the network more accurately. The transformation control is calculated as follows:

$$AP_i = \sum_j^n \frac{r_{ij}}{C_j}, \quad (4)$$

where AP_i is the transformation control of city i , C_j the degree centrality of city j , and r_{ij} the strength of the link between city i and j .

2.2.3. Cohesive Subgroup. In social network analysis, the secondary groups formed by closely related actors in the network are called cohesive subgroups [31]. In this study, we performed a cohesive subgroup analysis to examine the relationship between the nodes in the network and to decipher the importance of connectivity between subgroups. To this end, the convergence of iterated correlations (CONCOR) was used to divide China’s urban network into cohesive subgroups. In this procedure, the correlation coefficients of each row or column in the network matrix are calculated repeatedly. After multiple iterative calculations, the number of cohesive subgroups and the city nodes in each subgroup are expressed in the tree view. Finally, the relationship between subgroup density was obtained to analyze the relationships and contacts between the subgroups [31].

2.3. Data Sources. The top 100 communications technology service enterprises in China in 2019, published by the Communication Industry Network (<https://www.ccidcom.com>), have been selected, and the data on their headquarters, R & D centers, and sales organizations has been collected. Data on the location of investment companies and corporate relationships required for this study were compiled from the National Enterprise Credit Information Publicity System, Tianyancha, and other corporate credit investigation systems. The data on urban economic and social development are obtained from the Statistical Yearbook of China and the Statistical Yearbook of China’s Cities in 2020. Based on the collected data, the number of cities and their links vary across networks. The R & D, sales, investment, and

comprehensive networks comprise 39 cities with 1130 links, 111 cities with 3840 links, 109 cities with 1368 links, and 175 cities with 30,450 links, respectively. Administrative boundaries have been obtained from 1:400 map data published by the basic geographic information center of the State Bureau of Surveying and Mapping (<https://ngcc.sbsm.gov.cn/>). The drawing number is GS (2016) 2556, and the base drawing was not modified.

3. Characteristics of China's Urban Network

3.1. Overall Characteristics. The comparison of network densities (Table 1) shows that the R & D network has the largest density score (0.2362), and the actual correlation between cities accounts for 23.62% of the theoretical correlation. The ratio for the remaining networks does not exceed 10%, showing that R & D network cities are closely linked and share resources. The cohesion among other network cities is weak, and the degree of resource sharing is low. As the core sites in the competitiveness of the communications technology service industry, R & D centers have strict location requirements and are primarily distributed in large cities with concentrated scientific research institutions (40.14% of the R & D centers of the top 100 enterprises are located in Beijing, Shenzhen, and Shanghai), which impacts the network scale. Network density is limited by the network scale to some extent, and small-scale networks often have a high density [31]. The R & D network scale (39) is significantly smaller than that of the sales (111), investment (109), and comprehensive networks (175); thus, its density and degree of connection between cities are high.

Differences in network centralization indicate that the R & D network is the most balanced of the examined networks. Accessibility between the investment network nodes was slightly poor. The sales and comprehensive networks' "intermediary" center polarization is evident. The data in Table 1, show that the centralization degree of the R & D (0.4723) and the investment networks (0.4441) is low, indicating small differences in the centrality degree of each node; therefore, network polarization due to many links between nodes appears rare. The scores for the betweenness centrality of the sales (0.5345) and comprehensive networks (0.5465) are relatively high, indicating that these rely on individual nodes for transmission, resulting in network imbalance. Across all networks, the closeness centrality score of the investment network was the highest (0.4827), indicating that the accessibility between the investment network nodes was slightly poor.

3.2. Feature of Cities' Centrality. Based on the relationships between the different functional branches of the communications technology service industry, a contact matrix for the R & D, sales, investment, and comprehensive networks was built. Ucinet software was used to measure the degree of centrality, betweenness centrality, and closeness centrality of the network nodes. The natural fracture method in ArcGIS10.2 was used to divide the centrality degree of each node

into five categories to estimate the central position and spatial differentiation characteristics of the urban nodes in the network [34].

Figure 2(a) shows the overall spatial pattern of the constructed R & D network and its core cities. Shenzhen, Shanghai, Beijing, and Chengdu recorded the top four centrality scores (Table 2), indicating strong connections, a strong "intermediary" function, and a high possibility of spatial interaction with other cities. The four cities represent the scientific and technological innovation core of the eastern Guangdong-Hong Kong-Macao Greater Bay Area, the Yangtze River Delta Urban Agglomeration, Beijing-Tianjin Hebei Urban Agglomeration, and western Chengdu-Chongqing urban agglomeration, respectively; the cities are also fast becoming core nodes of the R & D network of China's communications technology service industry. Hangzhou, Xi'an, Nanjing, Wuhan, Hong Kong, Guangzhou, and Dongguan also ranked highly. Of these, Wuhan and Xi'an, as core cities of the urban agglomerations in the middle reaches of the Yangtze River and the Guanzhong Plain, respectively, are major nodes of the R & D network in the central and western regions based on their high degree and betweenness centrality scores. Overall, the R & D network core cities capture the actual layout of eastern, middle, and western China.

The sales network is characterized by clusters of cities with high centrality scores along the Beijing-Shenzhen axis and the east; the network is further supported by provincial capital cities, forming a multicore distribution pattern (Figure 2(b)). Of the cities with the top 10 scores (Figure 2(a), Table 2), Shenzhen, Hangzhou, and Beijing belong to the first level (degree centrality scores of 47–69), while Jinan, Nanjing, Wuhan, Guangzhou, Shanghai, Suzhou, and Wuxi belong to the second level (degree centrality scores of 14–46). The distribution of these cities along the Beijing-Shenzhen line and in the east reflects the spatial layout of the economic sector: the eastern region features high economic development and consumption levels, and the sales network overlaps with this layout. Most provincial capital cities comprise the third-level core cities (with degree centrality scores of 8–13). As important nodes of the sales network, these cities are distributed across all provinces, forming a multicore spatial pattern that is further supported by the provincial administrative centers.

The investment network features cities with high-centrality scores in the east and low-centrality scores in the west. Hefei and Shenyang are typical cities in this network with a high centrality score. The core cities of the investment network are primarily distributed in the eastern and central regions, and the centrality of the western cities is low (Figure 2(c)). These characteristics are consistent with the pattern of the spatial organization of China's economy [35], indicating that the investment behavior of the communications technology service industry reflects the characteristic behavior of the "economic man." Hefei occupies a more prominent central position in the investment network compared to that in the R & D and sales networks (Table 2), which reflects the city's active role in scientific research,

TABLE 1: Overview of network characteristics.

Index	R & D network	Sales network	Investment network	Comprehensive network
Network density	0.2362	0.0711	0.0455	0.0474
Mean degree centrality	8.974	7.82	4.917	7.669
Mean betweenness centrality	13.641	65.865	82.679	114.869
Mean closeness centrality	19.603	46.486	40.486	43.93
Degree of centralization	0.4723	0.5664	0.4441	0.56
Betweenness centrality	0.1489	0.5345	0.349	0.5465
Closeness centrality	/	0.3908	0.4827	0.3597

Note. / indicates that the closeness centrality of the R & D network approaches 0 and is not displayed.

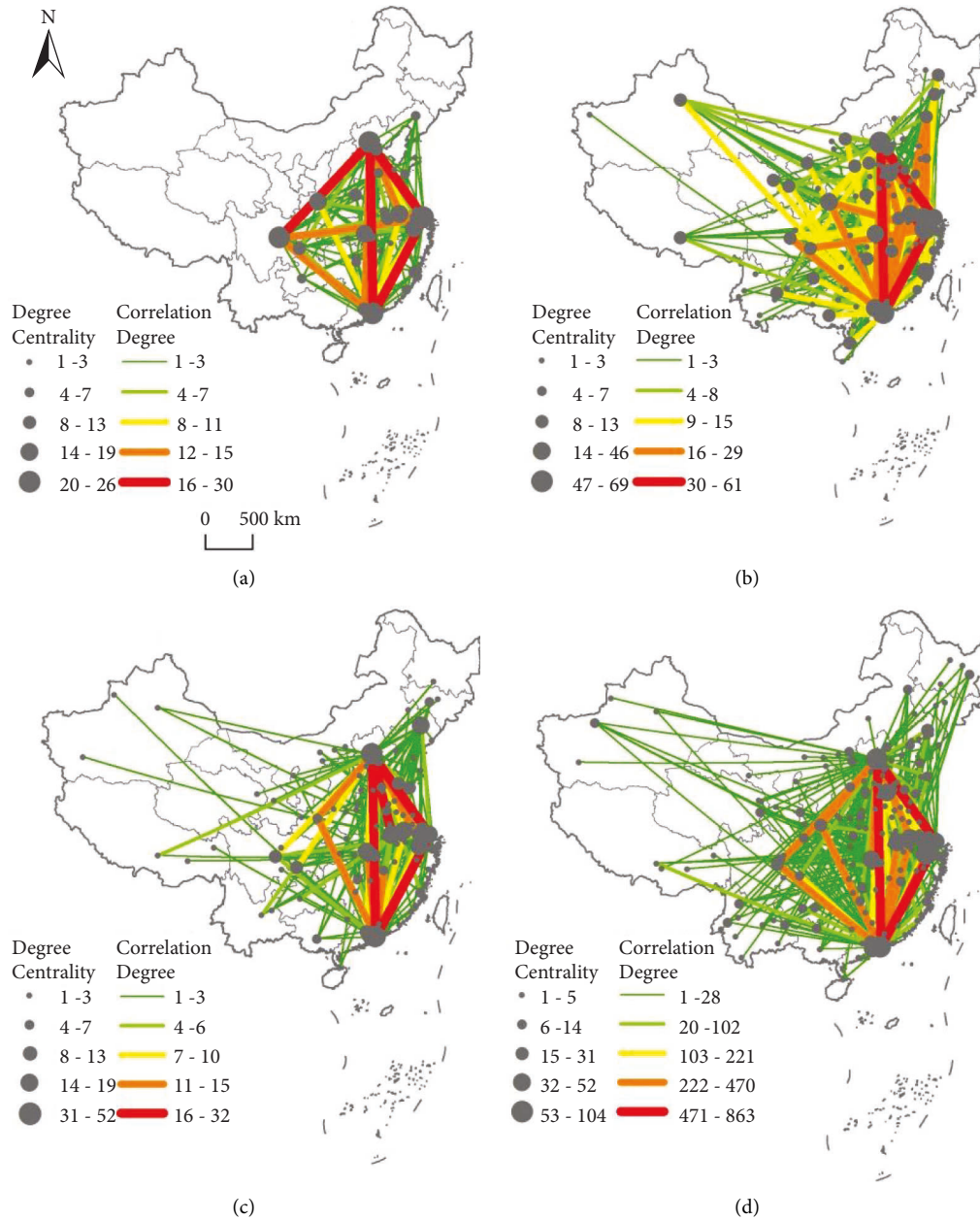


FIGURE 2: Hierarchical divisions and spatial distribution of degree centrality and relevance of the cities for each network. (a) R & D network. (b) Sales network. (c) Investment network. (d) Comprehensive network.

education, and modern manufacturing industry as a sub-central city of the Yangtze River Delta urban agglomeration. Shenyang shows a strong “bridging” capacity, as it is directly

related to many cities in terms of investment activities and as an overall important, high-centrality city in northeast China. These data highlight the transformation of Shenyang from a

TABLE 2: Centrality measures for each network in the top 10 cities.

Rank	R & D network				Sales network						
	City	Degree centrality	City	Betweenness centrality	City	Closeness centrality	Degree centrality	City	Betweenness centrality	Closeness centrality	
1	Shenzhen	26	Shenzhen	115.62	Shenzhen	23.602	69	Shenzhen	2387.329	Shenzhen	72.848
2	Shanghai	26	Shanghai	111.851	Shanghai	23.457	64	Hangzhou	1956.144	Hangzhou	70.513
3	Beijing	25	Beijing	72.703	Beijing	23.457	57	Beijing	1033.813	Beijing	67.485
4	Chengdu	22	Chengdu	41.355	Chengdu	23.03	46	Jinan	947.147	Jinan	63.218
5	Hangzhou	19	Dongguan	37.081	Hangzhou	22.619	38	Shanghai	415.255	Nanjing	60.44
6	Xi'an	18	Xi'an	31.168	Nanjing	22.353	36	Wuhan	252.494	Wuhan	59.783
7	Nanjing	17	Hangzhou	28.659	Xi'an	22.353	36	Nanjing	97.596	Guangzhou	59.783
8	Wuhan	16	Hong Kong	23.192	Wuhan	22.093	33	Guangzhou	71.977	Shanghai	58.824
9	Hong Kong	13	Nanjing	23.179	Hong Kong	21.714	33	Wuxi	48.964	Suzhou	58.824
10	Guangzhou	12	Wuhan	16.154	Guangzhou	21.591	33	Suzhou	35.32	Wuxi	58.824
Rank	Investment network				Comprehensive network						
1	Shenzhen	52	Shenzhen	2080.654	Shenzhen	64.286	104	Shenzhen	5497.934	Shenzhen	71.02
2	Beijing	49	Beijing	1747.953	Beijing	63.529	92	Beijing	3731.205	Beijing	67.969
3	Shenyang	30	Hefei	1009.418	Shanghai	55.959	74	Hangzhou	2736.438	Hangzhou	63.273
4	Hefei	29	Shenyang	720.376	Shenyang	55.102	52	Jinan	1351.758	Shanghai	58.784
5	Shanghai	24	Wuhan	439.505	Hefei	55.102	52	Shanghai	1202.622	Nanjing	58.586
6	Suzhou	19	Shanghai	410.369	Suzhou	51.923	49	Hefei	1065.531	Wuhan	58
7	Wuhan	19	Nanjing	405.179	Wuhan	51.675	48	Wuhan	789.385	Suzhou	57.616
8	Hangzhou	18	Suzhou	382.275	Nanjing	51.675	48	Suzhou	677.083	Jinan	57.237
9	Nanjing	17	Hangzhou	273.256	Hangzhou	50.467	38	Nanjing	624.68	Zhongshan	55.414
10	Huangshi	12	Huangshi	266.736	Guangzhou	48.869	36	Shenyang	495.266	Wuxi	55.414

heavy industry to a high-end equipment manufacturing center [36].

The centrality scores of the cities that comprise a comprehensive network reflect a distinct hierarchy. Bound by the Hu Line, the southeast region is a dense area of high-level cities, whereas the northwest shows the opposite trend (Figure 2(d), Table 3). Shenzhen, Beijing, and Hangzhou are classified as first-level core cities; Hangzhou plays an important role in the communications technology service industry. Shanghai, Nanjing, Suzhou, Wuxi, Hefei, Wuhan, Zhongshan, and Jinan are second-level central cities. They are the leading cities in the communications technology service industry in the Yangtze River Delta urban agglomeration, the urban agglomeration in the middle reaches of the Yangtze River, the Guangdong-Hong Kong-Macao Greater Bay Area, and the Shandong Peninsula Urban Agglomeration, respectively. The third-level core cities include Shenyang, Chengdu, Xi'an, Hong Kong, and Guangzhou. Chengdu and Xi'an are important cities in western China and play an innovative and exemplary role in advancing the communications technology service industry in their respective regions; the investment centrality and sales centrality scores for Shenyang are relatively high, but the R & D centrality is low (Table 2). The lack of innovation platforms is likely the reason behind the low development of its communications technology service industry, a problem encountered in many cities in northeast China [36]. Dongguan, Huangshi, Chongqing, and 38 other cities are fourth-level core cities. The degree centrality value is generally higher than the average value of 7.669, and the closeness centrality and betweenness centrality values are lower than the average values (Table 1); these findings indicate that the fourth-level cities have more direct links to the outside world. However, the communication costs with other cities are high, and "bridging" is discouraged. Jiaxing, Nanchang, Huainan, and 121 other cities belong to the fifth level, with centrality values lower than the average level. These cities comprise the budding nodes of the urban network.

3.3. Connection Patterns of the Urban Network. The natural fracture method in ArcGIS10.2 was used to divide the degree of correlation of the city of each network into five categories to identify the backbone structure and correlation patterns of the urban network [34]. The R & D network assumes a diamond structure that largely contains all related nodes (Figure 2(a)). Shenzhen, Shanghai, Beijing, and Chengdu are not only the top 4 cities regarding centrality but also the top 4 connected cities. The sum of their connectivity scores accounts for 49.38% of the total score in the R & D network. As the apexes of the diamond structure, the above cities are interconnected and radiate outward to form the frame of the R & D network.

The sales network in the east forms a characteristic triangle, with a "funnel" effect (Figure 2(b)). The connectivity scores for Shenzhen, Hangzhou, Beijing, Shanghai, and Suzhou bring them into the top 5 cities, accounting for 51.02% of the total connectivity score. The combined

connectivity score of 27 provincial capitals accounts for 50.94% of the total score, resulting in many interconnected provincial capital cities in the sales network. The connection direction of the western core provincial capital results in a "funnel" effect upon the main structure formed by the cities in the east. Few low-centrality nodes or small networks are developed in the western provinces or regions, reflecting the uneven correlation across the east and west of the sales network.

The investment network forms a parallelogram structure that shrinks eastward (Figure 2(c)). This configuration is particularly evident compared with the diamond structure of the R & D network. The structure reflects the strong connections between Beijing and Shenzhen, Hefei, Shanghai, Xi'an, and other eastern and northwestern cities; connections with Chengdu, Chongqing, and other southwestern cities are relatively weak. Shenzhen is mainly connected to Beijing, Shanghai, Hangzhou, Xi'an, and other cities in the east and northwest. The apexes of the parallelogram are occupied by Beijing, Shanghai, Shenzhen, and Xi'an.

The strong correlation pattern in the comprehensive network (the correlation degree is greater than 103) results in a mostly vertical topography, and the network structure combines elements from the R & D, investment, and sales orientations (Figure 2(d)). From west to east, strong correlations are mainly noted along a south-north axis, such as Beijing-Chengdu-Shenzhen, Beijing-Xi'an-Shenzhen, Beijing-Wuhan-Shenzhen, Beijing-Suzhou-Shenzhen, Beijing-Hangzhou-Shenzhen, and Beijing-Shanghai-Shenzhen. The correlation intensity along the east-west direction is comparatively weak; this finding is related to the lack of cities with high-centrality scores in the west, reflecting the east-west imbalance in the spatial organization of the comprehensive network. In summary, the combined effect of R & D, investment, and sales networks, with Shanghai, Hangzhou, Suzhou, Shenzhen, Chengdu, Xi'an, and Beijing as apex cities, results in multi-level network structures (peripheral diamond, semi-peripheral parallelogram, and central triangle) from west to east.

3.4. Characteristics of the Cohesive Subgroup. China's urban network is divided into eight cohesive subgroups [37] using the convergence of iterated correlations procedure (CONCOR) (Figure 3, Table 4). The constructed map has two distinctive features. First, the subgroups are interrelated and combined through some mechanism, and the spatial distribution is scattered, in contrast to the first law of geography. Subgroup 1 is the largest and includes cities with high-centrality scores, such as Shenzhen, Beijing, and Shanghai, as well as medium- and low-centrality cities, such as Lijiang, Baoshan, and Hechi. These cities are distributed in the eastern, central, and western regions of China. The number of high-centrality cities in the other subgroups is lower than that in subgroup 1; however, the urban spatial distribution characteristics are similar to those of subgroup 1, consistent with the results of Sheng et al. [18] on the cohesive subgroups of China's urban network. The communications technology service industry is mainly based on

TABLE 3: Centrality hierarchy of the cities of the comprehensive network.

Level	City examples	Centrality	Number
1st	Shenzhen, Beijing, Hangzhou	104–53	3
2nd	Shanghai, Nanjing, Wuhan, Jinan, Suzhou, Zhongshan, Wuxi, Hefei	52–32	8
3rd	Shenyang, Chengdu, Xi'an, Hong Kong, Guangzhou	31–15	5
4th	Dongguan, Huangshi, Chongqing, Hengyang, Weifang, Tianjin, Qingdao, Nanyang, Deyang, Hanzhong, Huizhou, Lijaing, Zhuhai, Jinzhong, Fuzhou	14–6	38
5th	Jiaxing, Nanchang, Huainan, Foshan, Wenzhou, Shijiazhuang, Changchun, Xiamen, Changzhou, Ningde, Wuhu, Baoding, Jinzhou, Langfang, Shanwei	5–1	121

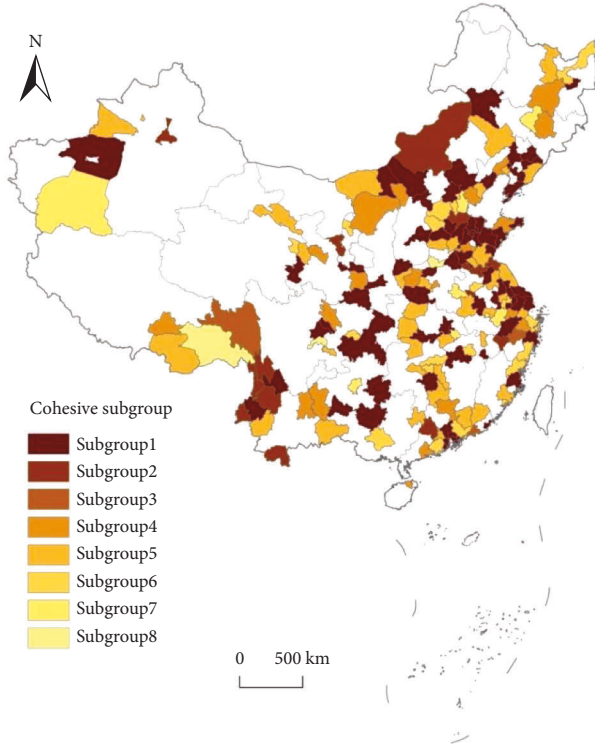


FIGURE 3: Cohesive subgroups of China's urban network.

the Internet and is hardly subject to distance constraints and spatial friction; thus, characteristics of geographical agglomeration are not prominent. Second, the tendency is for cities in the various subgroups to cluster with high-centrality cities: the high-centrality cities clustered in subgroup 1 attract other cities, producing the large-scale subgroup 1. This trend and attraction pattern only occur at the quantitative level, and the low-centrality cities that form subgroups with high-centrality cities show a heterogeneous spatial distribution and resource richness.

4. Discussion

4.1. Relationship between Centrality and Power Matching and the Characteristics of Cities with Different Matching Types. Based on published research [20], degree of centrality, and transformation control force have been selected as statistical measures to explore the relationship between centrality and power in the urban networks. The correction coefficients R^2

TABLE 4: Analysis results of cohesive subgroups.

Subgroups	City examples	Scale
1	Shenzhen, Beijing, Dongguan, Zhuhai, Hefei, Shanghai, Wuhan, Heze, Ezhou, Jingzhou, Hengyang, Suzhou, Fuzhou, Yangzhou, Taizhou, Suqian, Wuxi, Xi'an, Nanjing, Zhengzhou, Nantong, Hangzhou	68
2	Quzhou, Zhongwei, Dali, Huainan, Zhoushan, Cangzhou, Xuzhou, Zhaoqing, Jinghong, Lianyungang	14
3	Jinhua, Changdu, Shanwei	3
4	Hohhot, Baoji, Huzhou, Yantai, Jinzhou, Urumqi, Luohe, Erdos, Kunming, Haikou	22
5	Linyi, Yinchuan, Heyuan, Handan, Xianning, Jiaxing, Yichang, Changde, Pingdingshan, Yancheng	38
6	Jiangmen, Wenzhou, Ningde, Changzhou, Jiamusi, Huizhou, Guang'an, Ningbo, Bengbu, Yinchuan	19
7	Huangshi, Tongling, Tianjin, Fuyang, Changchun, Hotan, Guiyang, Xuancheng	8
8	Meishan, Xinxiang, Linzhi	3

between the degree of centrality of each network and the transformation control force are as follows: 0.771, 0.660, 0.847, and 0.818 for the R & D, sales, investment, and comprehensive networks, respectively. These high values indicate an overall positive relationship between centrality and power. The transformation control power of the city is divided into five levels using the natural fracture method [34]. According to the hierarchical matching relationship between degree centrality and transformation control force, five types of cities are identified (Table 5): a city with the highest network centrality and power (HT-CP city) (indicated as levels 11 and 12; i.e., the city's transformation control force and degree centrality are both allocated to the first level or one parameter to the first and the other to the second level); a city with relatively high centrality and power (HR-CP city; levels 22 and 23); a city with medium centrality and power (M-CP city; levels 33 and 34); a city with low centrality and power (L-CP city; levels 44, 45, and 55); and a city with high power and low centrality or high centrality and low power (H-L city; levels 13, 14, 15, 24, 25, and 35).

Cities show the following characteristics: Shenzhen and Beijing are classified as HT-CP cities in any network. As a gathering place for China's universities and scientific research institutes, the center of China's economic development, and

TABLE 5: City types according to the relationship between centrality and power matching.

Type	Comprehensive network	R & D network	Sales network	Investment network
HT-CP city	Beijing, Shenzhen, Shanghai (3)	Beijing, Shenzhen, Shanghai, Chengdu (4)	Beijing, Shenzhen, Hangzhou (3)	Beijing, Shenzhen, Hefei (3)
HR-CP city	Hangzhou, Nanjing, Chengdu, Wuhan, Xi'an, Guangzhou (6)	Hangzhou, Nanjing, Wuhan, Xi'an (4)	Shanghai, Jinan, Wuhan, Suzhou, Nanjing, Guangzhou (6)	Shanghai, Wuhan, Suzhou, Hangzhou, Nanjing, Shenyang (6)
M-CP city	Hong Kong, Suzhou, Jinan, Chongqing, Fuzhou, Dongguan, Zhongshan (7)	Hong Kong, Guangzhou, Suzhou, Dongguan, Fuzhou, Hefei, Chongqing, Huizhou, Tianjin, Zhengzhou (10)	Hong Kong, Changsha, Hefei, Shenyang, Chengdu, Chongqing, Tianjin (7)	Huangshi, Nantong, Dongguan, Wuxi, Weifang, Guangzhou, Chengdu, Qingdao, Chongqing (9)
L-CP city	Huizhou, Tianjin, Zhuhai, Zhengzhou, Huangshi (159)	Nantong, Zhuhai, Jinan, Changsha, Huangshi. (20)	Weifang, Xianning, Ezhou, Yichang, Nantong (76)	Changsha, Zhongshan, Zhuhai, Jinan, Fuzhou (89)
H-L city	Shenyang (1) (HC-LP city)	Zhongshan (1) (HP-LC city)	Wuxi, Fuzhou, Xi'an, Guiyang, Zhengzhou (19) (HC-LP cities)	None

Note. Figures in brackets represent the number of cities.

the country's largest transportation hub, Beijing is in an absolutely advantageous position regarding technology R & D, market expansion, and attracting investment; thus, the conditions for establishing an R & D center, sales organizations, and production sites for communications technology can be easily satisfied in Beijing. The strategic location and convenient transportation network of Beijing contribute to the development of many links with other cities, reflecting its high centrality. The strong control over the accumulation and allocation of resources to other cities fully reflects Beijing's "capital" effect. Unsurprisingly, well-known communications technology service enterprises, such as Huawei and ZTE, were initially established in Beijing, where they continue to grow. Shenzhen hosts the headquarters of many communications technology service enterprises (the headquarters of the top 100 firms are concentrated in 33 cities, with 17 firms having their head offices in Shenzhen). The Guangdong-Hong Kong-Macao Greater Bay Area, with Shenzhen as one of the central cities, is a densely populated and economically developed area. The "headquarters economy" effect, combined with sufficient labor supply and strong consumerism trends, makes Shenzhen one of the leading cities in China's communications technology service industry; thus, it shows high network centrality and strong dominance and control over other cities. Importantly, Shenzhen and Beijing have supported the balanced development of the communications technology service industry between north and south China.

Each subnetwork comprises typical HT-CP cities. Shanghai and Chengdu are typical examples of HT-CP cities in the R & D network. Shanghai has adjusted its industrial structure since the financial crisis of 2008, supports scientific and technological innovation and R & D development and retains close exchanges with foreign high-tech enterprises; for these reasons, Shanghai is the first choice location for establishing many R & D centers a finding supported in the 2019 report on the Construction of the Shanghai scientific and technological innovation center. The "eastward" strategy implemented by authorities in Chengdu as a means to stabilize its status as a national central city aims to promote a shift of the advanced manufacturing and production services

eastward. These initiatives have stimulated the strong growth momentum of Chengdu's communications technology service industry, making Chengdu the only HT-CP city in western China.

Hangzhou is a typical HT-CP city in the sales network. At present, Hangzhou has joined the list of China's new first-tier cities that are characterized by high economic development and consumption levels (Hangzhou ranked 9th in GDP and 5th in per capita consumption level in 2019). Thus, the city can fully meet the demand threshold of products and technologies in the communications technology service industry. Additionally, the logistics industry in Hangzhou has developed rapidly [23], offering excellent channels for product transport and assuming firm control over the accumulation and allocation of resources to other cities. Hefei is a typical HT-HP city in the investment network. It is not only the key investment hub of the communications technology service enterprises but also has the infrastructure to control and allocate resources across the investment behavior chain, acting as a leading city in the investment network.

The emergence of H-L cities, such as Shenyang, Zhongshan, and Wuxi (Table 5), shows that the positive relationship between centrality and power is not absolute. Shenyang emerges as an HC-LP city in the comprehensive network and an HR-CP city in the investment network. Although, this result indicates the city's direct links with many cities in the high-end equipment manufacturing sector, most of the linked cities have limited resources, and thus the index does not grasp the real power of adjusting resources in the network. For example, Zhongshan is an HP-LC city in the R & D network, directly linked with only a few cities. However, most of these cities have large amounts of resources, and the scale of indirect links is sufficiently large to exert great power in the network. Furthermore, a large number of H-L cities in the sales network have been detected; they are all HC-LP cities, indicating that, although many high-centrality nodes in the sales network have been identified, most of them have no real power. Wuxi, Fuzhou, Xi'an, Guiyang, Zhengzhou, and other provincial capitals are

TABLE 6: Index identifying subgroup development stage.

Index	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	Subgroup 5	Subgroup 6	Subgroup 7	Subgroup 8
Number of HT-CP cities	3	0	0	0	0	0	0	0
Number of HR-CP cities	7	0	0	0	0	0	0	0
Number of M-CP cities	7	0	0	0	0	0	0	0
Number of L-CP cities	0	14	3	22	38	19	8	3
Number of HL-CP cities	1	0	0	0	0	0	0	0
Scale of subgroup	70	14	3	22	38	19	8	3
Density of subgroup	0.194	0	0	0	0	0.005	0	0

TABLE 7: Density of subgroups.

	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	Subgroup 5	Subgroup 6	Subgroup 7	Subgroup 8
Subgroup 1	0.194	0.022	0.024	0.025	0.024	0.056	0.057	0.01
Subgroup 2	0.022	0	0	0	0	0	0.009	0
Subgroup 3	0.024	0	0	0	0	0.017	0	0
Subgroup 4	0.025	0	0	0	0	0.005	0.011	0
Subgroup 5	0.024	0	0	0	0	0	0.01	0
Subgroup 6	0.056	0	0.017	0.005	0	0.005	0.019	0
Subgroup 7	0.057	0.009	0	0.011	0.01	0.019	0	0.042
Subgroup 8	0.01	0	0	0	0	0	0.042	0

H-L cities in the sales network (Table 5). Although these cities feature high centrality, they cannot mobilize network resources.

4.2. Identification of the Development Stages of Cohesive Subgroups. The development stages of the various subgroups were qualitatively and quantitatively identified by considering the numbers of HT-CP, HR-CP, M-CP, L-CP, and H-L cities, subgroup density, and the scale of subgroup membership (Table 6). The process of subgroup development within the comprehensive networks in China is currently divided into three stages. The first stage is termed the decentralized node stage; that is, each subgroup comprises a decentralized node, node centrality is low, and there are no connections between the nodes. Subgroups 2, 3, 4, 5, and 8 are typical subgroups in the first stage. These subgroups are composed of L-CP cities, and the subgroup density is 0, indicating a lack of links with other cities; in other words, subgroup 1 cities are relatively isolated. The second stage is the pre-network stage. Here, despite the overall low node centrality, weak connections between the nodes are detected, with a tendency to form a network. Subgroups 6 and 7 are typical subgroups in the second stage and are composed of L-CP cities. The network density of subgroup 6 is 0.005, indicating that the cities in this subgroup begin to connect and tend to form a network. In contrast, the network density of subgroup 7 is 0. Considering that the connection density between subgroups 1 and 7 is 0.057 and that between subgroups 1 and 6 is 0.056 (Table 7), it is highly probable that subgroup 7 will connect with subgroup 6 through subgroup 1 [37] and form a network. The third stage is the initial network stage, which is characterized by a distinct hierarchy of node levels, relatively close connections between nodes, and the formation of a network structure. Subgroup 1 is at this stage. It comprises cities with distinct hierarchies and various characteristics, including HT-CP, HR-CP, M-CP,

and H-L cities. The network density of subgroup 1 is 0.194 (Table 7), indicating that the cities in this subgroup are closely connected. The connection density between subgroup 1 and other subgroups is >0 , reflecting the importance of subgroup 1 as the necessary channel through which other subgroups connect. Thus, subgroups can interconnect through subgroup 1 to complete the urban network structure.

5. Conclusions

The communications technology service industry represents the technical support and infrastructure network of the digital economy and is one of the leading industries contributing to China's high-quality development. This study examined the communications technology service industry in the context of China's emerging urban network research, drew lessons from it, and simplified the "compromise network model." Additionally, subnetworks and comprehensive networks based on the same enterprises have been constructed, and the connection characteristics and hierarchical structure of China's urban networks have been analyzed.

The results of the study show that the urban network cohesion in China is weak, and the degree of resource sharing is low. Beijing, Shenzhen, and Shanghai show high centrality and power. The R & D network assumes a symmetrical global distribution pattern, with Wuhan as the central symmetry node, and Beijing, Shenzhen, Shanghai, and Chengdu as apexes. The sales network forms a multicore distribution structure supported by several provincial capital cities. The centrality of the investment network cities is generally high in the east and low in the west. Hefei and Shenyang show high investment centrality, and these cities can serve as a reference constructing China's industrial Internet. Based on the top national node system of China's industrial internet, Shenzhen, Chengdu, Hefei, and

Shenyang emerge as the national secondary vertex systems of China's industrial internet.

China's urban network is constructed along Beijing-Chengdu-Shenzhen, Beijing-Xi'an-Shenzhen, Beijing-Wuhan-Shenzhen, Beijing-Suzhou-Shenzhen, Beijing-Hangzhou-Shenzhen, Beijing-Shanghai-Shenzhen, and other south-north linkages that form multilevel networks of peripheral diamond, semi-peripheral parallelogram, and central triangle structures from west to east. The south-north backbone line and multilevel structure represent the core axes of China's digital economic development and industrial Internet that radiate across central and western regions to coordinate China's high-quality development plan. According to the relationship between centrality and power matching, Chinese cities can be divided into five categories: HT-CP, HR-CP, M-CP, L-CP, and H-L. Shenzhen and Beijing are HT-CP cities in each network; Shanghai and Chengdu are typical HT-CP cities in the R & D network; Hangzhou in the sales network; and Hefei in the investment network; these findings indicate that cities such as Shenzhen, Chengdu, Hefei, Shenyang, and Hangzhou have the potential to form a national secondary apex system of China's industrial Internet.

The cohesive subgroups of China's urban network are characterized by a scattered spatial distribution, in contrast to the first law of geography. The cities in the cohesive subgroups have a tendency to form groups with high-centrality cities. However, this trend is evident only at the quantitative level, and the low-centrality cities that form subgroups with high-centrality cities show a heterogeneous spatial distribution and resource richness. Thus, it is reasonable to expect a coordinated and balanced development among regions in the context of China's digital economic evolution and to avoid transfer processes from high-centrality to low-centrality cities.

This study refines some of the typical characteristics of China's urban networks into specific networks through the construction of subnetworks. For example, the diamond structure of China's urban networks can be largely attributed to the R & D network orientation. The administrative center orientation is apparent primarily in the sales network, and typical core cities, such as Chengdu, Hangzhou, and Hefei, participate in the R & D, sales, and investment subnetworks. China's urban network, examined from the perspective of traffic flow, has weak spatial dependence, a finding with important theoretical ramifications for the overall layout of China's industrial Internet.

Based on the analysis of the characteristics of the communications technology service industry, this study not only offers a new perspective on the construction of China's urban network in the context of China's digital economy, industrial Internet, and high-quality development. To further explore the mechanisms responsible for the formation of the network structure of the urban communications technology service industry and provides more practical suggestions for developing China's digital economy. The optimization of future urbanization patterns and the construction of urban agglomerations and metropolitan areas are the focus of the authors' follow-up research.

Data Availability

The data of the communication equipment technology service industry can be obtained from <https://www.ccidcom.com>. The socioeconomic data of cities can be collected from the Statistical Yearbook of China's Cities and the Statistical Yearbook of China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Digital Economy's Spatial Implications on Urban Innovation and Its Threshold: Evidence from China

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The digital economy has great potential to sustain China's high-quality economic growth and substantially strengthen urban innovation capacity. This paper developed a digital economy index using city-level data from China and measured the level of urban innovation with patents per capita. We used a spatial econometric model to explore the spatial implications of the digital economy on urban innovation, probed into the mechanism by which the digital economy affects urban innovation, and further measured the spatial spillover distance and threshold of the digital economy on urban innovation. The findings suggest that China's digital economy and urban innovation are characterized by spatial aggregation, and the spatial distribution varies from region to region. The digital economy, with strong spatial spillover effects on the innovation capacity of cities in China, may not only enhance the innovation capacity of one city but also drive a simultaneous growth of the innovation capacity in peripheral cities. The analysis of mechanisms indicates that the digital economy enhances local innovation capacity directly through promoting human resources and increasing science and technology spending and drives the improvement of the innovation capacity in peripheral cities through the spatial spillover of human resources and science and technology spending. The effects of the latter one outweigh those of the former one. The analysis of heterogeneity shows that the central, western, and northern regions, where the digital economy is relatively less developed, have the latecomer advantage, and the digital economy has more prominent effects on innovation capacity. Calculating the spillover distance and threshold demonstrates that the digital economy influences urban innovation within a spatial spillover range and threshold of approximately 500 kilometers. Within 500 kilometers, the positive spatial spillover effects prevail, while beyond 500 kilometers, the negative siphon effect prevails. Therefore, it is necessary to consider the differences in the impact and role of the digital economy on urban innovation from a spatial perspective.

1. Introduction

It is a critical time for China's economy, which is undergoing structural change and transforming from high-speed growth to high-quality development. New economic engines represented by the digital economy are gathering strength and will experience explosive growth, producing inestimable energy to further develop China's economy. During a structural transformation of an economy, innovation is essential. Innovation is also necessary to transition from the old drivers to the new engines of China's economic growth

and the nation's shift from an economic powerhouse to a superpower in innovation. As the spatial units of economic growth, cities are where innovation activities and outcomes congregate and urban innovation activities are promoted; strengthening urban innovation capacity has formed the foundation of the nation's innovation strategy. The ongoing development of the digital economy has presented tremendous strategic opportunities for enhancing urban innovation capacity. According to the White Paper on the Global Digital Economy published by the China Academy of Information and Communications Technology (CAICT), in

2020, the global digital economy reached 32.6 trillion US dollars, accounting for 43.7% of the global GDP. China's digital economy was worth 5.4 trillion US dollars, ranking second in the world, rising from 14.2% in 2005 to 38.6% in 2020. Meanwhile, China's aggregate innovation capacity has improved substantially. It ranked 14th in the Global Innovation Index (GII) 2020, making progress by 15 spots compared to its ranking in 2015. The development of the digital economy and the enhancement of innovation capacity in China has aroused extensive attention and provoked thought in academic circles. Can the growing digital economy drive China's urban innovation capacity? How can the digital economy enhance urban innovation capacity? What are the mechanisms? In addition, along with the spatial differentiation of economic growth, the growing digital economy and urban innovation development have also gradually shown the feature of spatial differentiation. As for regions, the digital economy and urban innovation in the eastern coastal regions are ahead of those of China's central and western regions. At a provincial level, the digital economy and urban innovation in capital cities outpace those of other cities. Then, how to account for the impact of the digital economy on urban innovation from the spatial perspective? Can the digital economy cause spatial spillover effects on urban innovation, synergistically enhancing the level of innovation across cities and even regions? Exploring this issue could not only help us consider the role of developing the digital economy rationally and comprehensively, creating appropriate ideas for developing the digital economy and encouraging urban innovation in China but also provide authorities with the basis and valuable references for making decisions on developing the digital economy and strengthening urban innovation.

The rest of this paper comprises several sections. Section 2 reviews and summarizes the relevant research literature. Section 3 sets out the empirical design of this research, including how to create a spatial econometric model, the method for constructing the spatial weight matrix, the decomposition of the spatial effects, the calculation of the spatial spillover distance, the method for mechanism analysis, and the description of variables as well as the sources of data. Section 4 illustrates the results of the empirical analysis in this research, including the results of the estimation of the spatial econometric models, the results of the decomposition of the spatial effects, how to address the endogeneity problem, and the results of robustness testing. Section 5 further explores the spatial implications of the digital economy on urban innovation, including the results of the mechanism analysis, the results of the analysis of heterogeneity, and the results of the calculation of the spatial spillover distance and threshold. Section 6 summarizes and discusses the conclusions and policy recommendations.

2. Literature Review

In recent years, the digital economy's theoretical research and application have become hot topics in academic circles, and scholars have explored relevant issues from various aspects. The first key area of research is the concept and

definition of the digital economy. This term was coined for the first time by Tapscott in his book, in which he explains multiple aspects of the digital economy, such as the next-generation digital economy and its fundamentals, industrial governance against the context of the Internet [1]. In 1998, the US Department of Commerce released a report, the *Emerging Digital Economy*, which focuses on analyzing the decisive role of information as a core resource in the economy at the macro and microlevels. Thus, the term "digital economy" was officially defined [2]. The widely used definition of the digital economy was proposed in the G20 Digital Economy Development and Cooperation Initiative passed at the 2016 G20 Hangzhou Summit. In this initiative, the digital economy refers to a broad range of economic activities that include using digitized information and knowledge as the key factor of production, modern information networks as an important activity space, and the effective use of information and communication technology as an important driver of productivity growth and economic structural optimization [3]. The China Academy of Information and Communications Technology (CAICT) provided further supplementation and clarification for the definition, arguing that the digital economy shall include not only the emerging digital industries—such as the Internet, cloud computing, big data, the Internet of Things, and e-commerce—but also the digital transformation of traditional industries. As there has been no universally agreed variable for measuring the digital economy, many institutions and scholars have adopted different indicator systems to measure the digital economy. The United Nations World Bank, International Monetary Fund, and OECD defined relevant matters concerning the digital economy and provided an overall approach for measuring the digital economy in the System of National Accounts 2008. Scholars and institutions, such as the US Department of Commerce, International Telecommunication Union, and CAICT, also evaluated and measured the digital economy by using multiple evaluation models, such as the TOPSIS method, entropy weight method, principal component analysis (PCA) approach, and expert scoring method [4–7]. The second key area of research is the digital economy by country. Scholars performed calculations and studies on the degree of digital economy development in major economies, such as the measures of the digital economy in China [8, 9]; the patterns of spatial distribution, and regional differences of the digital economy in China [10, 11]; the measurement approaches and development trend of the digital economy in the USA [12, 13]; the development and drivers of the EU digital economy [14–16]. The last key area of research is the impact of the digital economy on different aspects of economic growth. Scholars discussed the impact of the digital economy on economic growth [17, 18]; industrial structural upgrading [19, 20]; Ecology and Environment [21, 22]; and total factor productivity [23, 24]. Their findings proved that the digital economy could prominently play a positive role and indicated that the digital economy could have a positive impact on every aspect of economic growth.

The impact of the digital economy on innovation and entrepreneurial activities has been one of the most active

fields of research in recent years. With the growing digital economy, innovation and entrepreneurial activities are increasingly influenced by the digital economy, and the digital economy has become an essential factor influencing entrepreneurial activities and innovation capacity. Many papers on the digital economy and innovation activities were published. Most scholars explored the impact of the digital economy on corporate innovation activities mainly at a microlevel, such as the influence of the digital economy on business model innovation [25, 26]; the role of digital transformation in innovation activities [27, 28]; the application of the digital technologies and corporate innovations [29, 30]; the influence of artificial intelligence on corporate innovation activities [31, 32]. These studies found that digital economy development can play a significant role in the process of corporate innovation and serves as an essential factor for enterprises that conduct innovation activities. Many microlevel studies have explored the impact of the digital economy on corporate innovation activities; however, not so many papers discussed the outreach and impact of the growing digital economy on urban innovation capacity at a macrolevel. Since the digital economy is the main direction of future economic development, cities, as the main body of the regional economy, will inevitably increase their investment in the digital economy to continuously improve their capacity and level of innovation to gain a sufficient leading edge in economic competition. Some papers mainly focused on the effects of the digital economy on urban innovation. For example, Caragliu and Del Bo [33] used building a smart city as a quasinelastic experiment to measure the level of the digital economy and reached the conclusion that European cities, with a higher level of smart cities, may tend to apply for more patents and therefore improve urban innovation capacity and levels. J. Li and B. Li [34] used the digital financial inclusion index to measure the level of the digital economy and adopted the difference-in-difference (DID) model to explore the effects of digital financial inclusion on innovation in China's cities. Li found that promoting digital financial inclusion could increase the number of patents in cities by 5.3%, and digital financial inclusion could play a positive role in urban innovation. Wang et al. [35] discussed the effects of the digital economy on green innovation at a city level and confirmed the positive effects of the digital economy on urban green innovation. Lu et al. [36] studied the relationship between the digital economy and urban innovation capabilities from a macro perspective, with a focus on the role of the innovation environment, concluded that the digital economy can significantly strengthen a city's innovation capabilities and explored the mechanisms of the digital economy to influence urban innovation.

The above studies showed that much microlevel research on the effects of the digital economy on innovation activities has been carried out. However, the macrodiscussion on the impact of the digital economy on the innovation capability at the city level is insufficient. Available literature has, to a certain extent, explored how the digital economy can affect a city's capacity and level of innovation, but it is still far from being sufficient. The following flaws and weaknesses can also be found in those papers. First, most research on the digital

economy and urban innovation does not take into account the spatial effects and spatial implications. Some latest research believes that the digital economy, as a knowledge-intensive economy, can push the geographical boundaries and have an impact on the economic activities in other regions, resulting in strong spatial spillover effects. Ding et al. [37] found that the digital economy displays pronounced spatial spillover effects when promoting high-quality economic development. The digital economy can not only directly promote the high-quality development of the local economy but also play a positive role in the high-quality economic growth in other surrounding areas. Ma and Zhu [38] also identified that the digital economy in a region can play a role in the high-quality green development in surrounding areas through spatial spillover effects. Therefore, ignoring the spatial implications and spillover effects may produce biased coefficient estimates for the impact of the digital economy on urban innovation, which could hinder us from understanding the impact of the digital economy on urban innovation. Second, some research on the impact of the digital economy on urban innovation analyzed the mechanisms, i.e., how and through what channels the digital economy affects urban innovation, but those mechanisms have not undergone sufficient research. Particularly, if the spatial implications and spillover effects are taken into account, it needs to further discuss the mechanisms of the digital economy to influence urban innovation. Last, currently published research verified the trend and size of the impact of the digital economy on urban innovation, and almost all of them turned out to be positive. However, will this conclusion be somehow different from a spatial perspective? How long is the meaningful spatial spillover distance of the digital economy for urban innovation, and how extensive is the range that it takes effect? In other words, within what distance can the growing digital economy in a city influence and drive the enhancement of innovation capacity in other cities? Is there any threshold for such impetus and enhancement? They are seldom mentioned in currently published papers.

This paper's novel features and marginal contributions are to improve the weaknesses of the above-given research. First, we examined the impact of the digital economy on urban innovation from a spatial perspective and found that both the digital economy and urban innovation are characterized by spatial aggregation. The digital economy can drive innovation in local cities to a higher level and boost peripheral cities' innovation. Therefore, while developing the digital economy and improving the innovation capacity, the local areas need to attach importance to the synergy across regions. This is of great significance for developing the intercity digital economy and enhancing innovation capacity. Second, this paper sought to enrich and improve the mechanisms of the digital economy to influence urban innovation and identified how the digital economy had improved urban innovation capacity in the context of spatial spillover effects. We not only focused on the direct mechanisms of the digital economy to influence urban innovation but also analyzed how the spatial spillover effects of the digital economy may work on urban innovation. Last, we

explored the spillover distance, range, and threshold of the digital economy to influence the spaces of urban innovation. Different from most studies, we found that the digital economy can only strengthen the innovation capacity of other cities within a distance of 500 kilometers that roughly reaches the provincial boundaries; beyond this range, the digital economy often has a negative siphon effect on urban innovation, indicating that the digital economy could force regions to scramble for urban innovation. This finding is this paper's most significant marginal contribution and a novel feature. We hope it will provide meaningful references for theorists and policy-makers who seek to appropriately understand the impact of the digital economy on urban innovation and improve the strategies for developing the digital economy and urban innovation.

3. Design of Empirical Research on the Impact of the Digital Economy on Urban Innovation

3.1. Building the Spatial Econometric Models for Empirical Research. Spatial econometrics is a branch of econometrics that originated in the 1970s and 1980s. It refers to multiple methods for estimating and testing spatial effect models by adding factors into an empirical model to measure the spatial implications of variables. Over the last decades, academic circles have been increasingly actively engaged in spatial econometric theories and empirical applications, which have become a widely used modeling approach in the field of economics now. For research on spatial implications and spatial spillover, spatial econometric models have often been a preferred option for empirical modeling. The spatial econometric models mainly include the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM) [39]. These models are presented in equations (1)–(3):

(1) the Spatial Lag Model:

$$y_{it} = \alpha + \rho \sum_{j=1}^n w_{ij} y_{jt} + \beta x_{it} + u_i + v_t + \varepsilon_{it}, \quad (1)$$

(2) the Spatial Error Model:

$$y_{it} = \alpha + \beta x_{it} + \mu_{it}, \mu_{it} = \rho \sum_{j=1}^n \mu_{jt} + \varepsilon_{it}, \quad (2)$$

(3) the Spatial Durbin Model:

$$y_{it} = \alpha + \rho \sum_{j=1}^n w_{ij} y_{jt} + \beta x_{it} + \theta \sum_{j=1}^n w_{ij} x_{jt} + u_i + v_t + \varepsilon_{it}, \quad (3)$$

where y_{it} is the dependent variable and refers to the level of urban innovation we study herein; x_{it} is the explanatory variable and includes the level of the digital economy as the core explanatory variable and a variety of control variables that affect the level of urban innovation. w_{ij} is the spatial weights matrix; $w_{ij}x_{jt}$ represents the spatial lag term of the dependent variable; ρ represents the spatial autocorrelation

coefficient. $w_{ij}x_{jt}$ represents the spatial lag term of the explanatory variable; μ_{it} is the error term; μ_{jt} is the spatial lag term of the error term; u_i and v_t represent individual and time fixed effects, respectively; ε_{it} is a disturbance term. Among these three spatial econometric models, the spatial Durbin model (SDM) is the most common one, and LeSage [40] compared and discussed these three spatial econometric models in his paper. In his opinion, the SDM is a spatial econometric model that can produce unbiased estimates even if there are modeling mistakes. This paper selected the optimal one from the SLM, SEM, and SDM through the model selection tests and used it in the following empirical analysis.

3.2. Method for Constructing the Spatial Weights Matrix.

The spatial weight matrix is essential when a spatial econometric model is used for empirical analysis. In this paper, we chose the spatial distance weight matrix, which is presented in the following equation:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, & (i \neq j), \\ 0, & (i = j), \end{cases} \quad (4)$$

where d_{ij} is the straight-line distance between two cities. If the straight-line distance between two locations is longer, then the value of the matrix element $1/d_{ij}^2$ is smaller, and the degree of interaction is lower. We observed the spatial implications of each observation by assigning different weights to the observation value, thereby avoiding the homogenized defects and weaknesses of observation values in conventional econometrics.

3.3. Spatial Autocorrelation Test. A spatial correlation test was performed on the dependent and core explanatory variables before the spatial econometric analysis. In spatial econometrics, the variables at close geographic locations or adjacent areas are characterized by a tendency to approach each other. Generally, Moran's I is used to perform the spatial autocorrelation test. Values of Moran's I range from -1 to 1 . Values of Moran's I between 0 and 1 indicate positive spatial autocorrelation, which means locations with high values cluster together. Values of Moran's I between -1 and 0 indicate negative spatial autocorrelation, which means locations with high values and low values are spatially mixed. The way to calculate Moran's I is presented in the following equation:

$$\text{Moran's } I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}. \quad (5)$$

Apart from the global spatial autocorrelation test in equation (5), we performed a local spatial autocorrelation test. The Moran scatterplot was used to classify the cluster patterns of all locations. The four quadrants in the Moran scatterplot represent the clusters that fall into the High-High (H-H), Low-High (L-H), Low-Low (L-L), and high-

low (H-L) categories. We determined which cluster the digital economy and urban innovation at the level of Chinese cities belongs to by classifying the clusters.

3.4. Decomposition of the Spatial Effects. As we explored the spatial implications of the digital economy on urban innovation in this paper, it was necessary to study further the spatial spillover effects of the digital economy on urban innovation. However, as the spatial Durbin model includes spatial lag terms of both the independent variable and dependent variable due to modeling, the coefficient estimates of the independent variable relative to the dependent variable cannot directly reflect the impact of the independent variable on the dependent variable. In other words, it is impossible to calculate the spatial spillover effects of the digital economy on urban innovation through model estimation. In response, we adopted the method used by LeSage and Pace: divide the total effects of the digital economy on urban innovation into direct effects and indirect effects by decomposing the partial differential equation [41]. The direct effects represent the direct impact of the local digital economy on local urban innovation. In contrast, the indirect effects refer to the impact of the local digital economy on urban innovation in peripheral areas, which means the spatial spillover effects [42]. We changed the spatial Durbin model in equation (3) into the following equation:

$$\begin{aligned} y &= \sum_{r=1}^m \beta_r (I - \lambda w)^{-1} x_r + (I - \lambda w)^{-1} \varepsilon, \\ \varepsilon &= \sum_{r=1}^m S_r(w) x_r + (I - \lambda w)^{-1} \varepsilon, \end{aligned} \quad (6)$$

where $s_r(w) = \beta_r (I - \lambda w)^{-1}$ is a matrix of order m . We further transformed equation (6) into a matrix, as shown in the following equation:

$$\begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_m \end{pmatrix} = \begin{pmatrix} s_r(w)_{11} & s_r(w)_{12} & \dots & s_r(w)_{1m} \\ s_r(w)_{21} & s_r(w)_{22} & \dots & s_r(w)_{2m} \\ \dots & \dots & \dots & \dots \\ s_r(w)_{m1} & s_r(w)_{m2} & \dots & s_r(w)_{mm} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \dots \\ x_{mr} \end{pmatrix} + (I - \lambda w)^{-1} \varepsilon. \quad (7)$$

where the total effects of the digital economy on urban innovation is the average value obtained by summing up in the matrix, as shown in equation (8). It represents the overall effect of the digital economy on urban innovation across all regions.

$$\text{Total effects} = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n s_r(w)_{ij} = \frac{1}{n} i'_n s_r(w) i_n. \quad (8)$$

The impact of the local digital economy on local urban innovation is called the direct effects, such as the effects of Beijing's digital economy on Beijing's urban innovation and those of Tianjin's digital economy on Tianjin's urban

innovation. In equation (7), it is the element that lies on the main diagonal of the matrix $s_r(w)$. The computing method is shown in the following equation:

$$\text{Direct effects} = \frac{1}{n} \text{trace}[s_r(w)]. \quad (9)$$

The impact of the local digital economy on urban innovation in peripheral areas is called the indirect effects, such as the effect of Shanghai's digital economy on urban innovation in peripheral cities, Hangzhou, Suzhou, and Nanjing. In equation (7), it is the element that lies outside the main diagonal of the matrix $s_r(w)$ and the total effects minus the direct effects, as shown in the following equation:

$$\text{Indirect effects} = \frac{1}{n} \{i'_n s_r(w) i_n - \text{trace}[s_r(w)]\}. \quad (10)$$

3.5. Calculation of the Spillover Distance and Range. With the decomposition of the spatial effects, we obtained the spatial implications and spillover effects of the digital economy on the level of urban innovation. We further explored the distance such spatial implications cover and the range within which the spillover effects occur. In other words, we attempted to explore the distance within which the digital economy can influence urban innovation. Therefore, we adopted the method Yu et al. used to calculate the threshold for the spillover effects of the digital economy on urban innovation by setting different thresholds and estimating with spatial weights matrices [43]. The thresholds are set in the following equation:

$$w_{ij}(T) = \begin{cases} \frac{1}{d_{ij}^2}, & d_{ij} \geq T, \\ 0, & d_{ij} < T, \end{cases} \quad (11)$$

where d_{ij} represents the straight-line distance between two cities, and T represents the threshold. 50 kilometers was set as the initial distance, and every 50 kilometers as a threshold (such as 50, 100, 150, and 200 kilometers) to create different spatial weights matrices. The range of spatial effects and the threshold of the spillover effects were obtained by analyzing the changes in the values of the direct and indirect effects of the digital economy on urban innovation at various distances.

3.6. Mechanism of the Empirical Research. We applied the mediation effect for mechanism analysis to identify how the digital economy acts on urban innovation. First, we performed the regression of the digital economy as the core explanatory variable relative to the mediator variable and then the regression of the mediator variable relative to urban innovation, and finally added the mediator variable to the benchmark regression model [44], as shown in the following equations:

$$Z_{it} = \alpha + \rho_z \sum_{i=1}^n w_{ij} Z_{jt} + \beta x_{it} + \theta \sum_{i=1}^n w_{ij} x_{jt} + u_i + v_t + \varepsilon_{it}, \quad (12)$$

$$y_{it} = \alpha + \rho \sum_{i=1}^n w_{ij} y_{jt} + \beta_z Z_{it} + \theta_z \sum_{i=1}^n w_{ij} Z_{jt} + u_i + v_t + \varepsilon_{it}, \quad (13)$$

$$y_{it} = \alpha + \rho' \sum_{i=1}^n w_{ij} y_{jt} + \beta' x_{it} + \theta' \sum_{i=1}^n w_{ij} x_{jt} + \beta'_z Z_{it} + \theta'_z \sum_{i=1}^n w_{ij} Z_{jt} + u_i + v_t + \varepsilon_{it}, \quad (14)$$

where for the sake of brevity, y_{it} represents urban innovation; x_{it} represents the digital economy solely; Z_{it} represents the mediator variable. Only the following conditions are met could we prove that the digital economy does influence urban innovation through the mediator variable Z_{it} . First, the coefficient estimates of the digital economy relative to the mediator variable shall be significant. Second, the coefficient estimates of the mediator variable relative to urban innovation shall be significant. Lastly, when the mediator variable is added to the benchmark model, the coefficient estimate of the impact of the digital economy on urban innovation decreases or is no more significant. While in the spatial Durbin model, the total effects of the digital economy on urban innovation are decomposed into direct effects and indirect effects. Therefore, the analysis of the mechanisms of mediation effect testing should also be divided into two sections: direct effects and indirect effects. In this way, we can understand the mechanisms of how the digital economy acts on and influences urban innovation from the perspectives of spatial implications and spillover effects.

Then, how to identify the mediator variables for the impact of the digital economy on urban innovation? Generally, it is impossible to achieve scientific and technological innovations in cities without human engagement. All innovation activities involve human participants. When the high-caliber talent pool in a city expands, the city will have greater potential for innovation, which could be translated into more innovative output, taking urban innovation to a higher level. Therefore, human resources may be a vital mechanism of the digital economy to influence urban innovation. In addition, strong government support is necessary for urban scientific and technological innovations. Governments generally support local scientific and technological innovation activities via financial expenditure. The more they spend on science and technology, the more robust protection and support for innovation activities they will provide, and thus the more likely to boost urban innovation in local areas. For this reason, science and technology spending may also be a vital mechanism of the digital economy to influence urban innovation. The mechanism analysis further explored whether the digital economy acts on urban innovation through human resources and scientific and technological innovations.

3.7. Variable Explanation and Date Sources. The variables used in this paper are set out as follows: the first one is the explained variable, Urban Innovation. This paper measured urban innovation with city-level patents per capita. The more patents per capita, the higher the level of urban innovation is. The city-level data for patents granted include the number of invention patents, utility model patents, and design patents granted. In this paper, the sum of those three was used to compute the patents per capita in a city. The core explanatory variable is the Digital Economy. The approach from Zhao et al. [45] was applied herein for measuring the city-level digital economy index. The composite digital economy index was calculated as the average of five standardized indicators, including the number of Internet and broadband users per 10,000 people, the number of practitioners in the computer service and software industries per 10,000 people, the total telecommunication business per capita, the number of mobile users per 10,000 people, and the digital financial inclusion index. Other control variables are set out as follows: (1) Economic Development. The level of the local economy could influence innovation activities, so the control variable Economic Development was incorporated and measured by local GDP per capita. (2) Population Size. The larger and denser population in a local area indicates the growing market size, which can provide a broader market space for innovative activities and innovative products. The Population Size was measured by the total local population. (3) Fixed Investment. Increasing investment in local fixed assets and improving infrastructure can provide innovation activities with more infrastructure support. This indicator was measured by the local investment in fixed assets per capita. (4) Industrial Level. A higher local industrial level can offer more industrial support and initial incubation for local innovation activities and provide innovation activities with more technological support. The industrial level was measured by local gross output by industry per capita. (5) Wages level. The higher wage level indicates that the overall local benefits are favorable, which can offer better benefit support and create a better environment for entrepreneurs and innovation activities. This indicator was measured by local wage per capita. (6) Road Condition. If road conditions improve, they can facilitate accessibility inside and outside cities, benefit people's mobility and communication and accelerate the dissemination of knowledge and information. This indicator was expressed as the local road density. (7) Urbanization Level. With a higher local urbanization level and improved urban function, it is more likely to provide urban innovation activities with high-quality public services. This indicator was expressed as the local urbanization level. (8) Financial Development. The better financial development and more developed financial market in the region can better provide urban innovation and entrepreneurial activities with the necessary financial support and easy access to financing and facilitate the healthy development of urban innovation. This indicator was expressed as the total local loans and deposits per capita. (9) Foreign Investment. It reflects the degree of cooperation between the local area and international markets. More state-of-the-art technology and management

experience will be introduced into places where foreign investment is more active, significantly contributing to local urban innovation activities. This indicator was expressed as the local foreign direct investment. Lastly, there are mediator variables, mainly Human Resources and Technology Spending. They were expressed as the number of local college students per 10,000 people and local government spending on science and technology per capita, respectively. In addition, several variables, such as Urban Innovation, Economic Development, Population Size, Fixed Investment, Industrial Level, Wages Level, Road Condition, Financial Development, Foreign Investment, Human Resources, and Technology Spending, were subject to the logarithmic transformation.

The data sources used in this paper include but are not limited to China City Statistical Yearbook, CEIC, and China Economic and Social Data Platform (CNKI). The digital financial inclusion index used for creating the digital economy index is based on The Digital Financial Inclusion Index of China prepared by Guo (2020) from the Institute of Digital Finance, Peking University [46]. The results for the descriptive statistics of each variable are shown in Table 1.

4. Spatial Econometric Analysis of Empirical Findings on the Impact of the Digital Economy on Urban Innovation

4.1. Results of the Spatial Autocorrelation Test of Urban Innovation and Digital Economy. When exploring the impact and role of the digital economy on urban innovation through spatial econometric analysis, the first step was to test the spatial autocorrelation of urban innovation and the digital economy and explore its spatial correlation and clustering features. The spatial econometrics was not applicable until this test was passed and all conditions were satisfied. Using the Moran's I , we carried out the spatial autocorrelation test, and the test results are shown in Table 2. In Table 2, from 2011 to 2020, all test values of the Moran's I on urban innovation and the digital economy are positive and significant, above 1%. This indicates that in space, the two variables: urban innovation and digital economy demonstrate a positive and strong spatial correlation, that is, the feature of spatial clustering. From the perspective of the urban space, both the urban innovation and digital economy are characterized by high-high clusters and low-low clusters. These are in line with reality: in the city clusters in the wealthy east coastal areas in China, the level of urban innovation and the digital economy index is higher, while in most western cities, these two indicators are lower, with large spatial differences and a distinct feature of clustering. Therefore, using spatial econometrics to analyze the impact of the digital economy on urban innovation is reasonable.

4.2. Spatial Clustering Features of Urban Innovation and Digital Economy. After analyzing the spatial autocorrelation feature of urban innovation and digital economy, the second step was to explore their spatial clustering features divided by the Moran scatterplot. Cities in the upper right quadrant

are identified as the high-high ("H-H") cluster, where the level of urban innovation and the digital economy index are higher. Cities in the upper left quadrant are identified as the low-high ("L-H") cluster, where cities with a lower level of urban innovation and digital economy index are surrounded by those with higher indicators. Cities in the lower left quadrant are identified as the low-low ("L-L") cluster, where the level of urban innovation and the digital economy index are lower. Cities in the lower right quadrant are identified as the high-low ("H-L") cluster, where cities with a higher level of urban innovation and digital economy index are surrounded by those with lower indicators. The results are shown in Figures 1 and 2. The two figures suggest that, for urban innovation and digital economy indicators, most cities are in the upper right and lower left quadrants and belong to the H-H cluster and L-L cluster, respectively. This aligns with the results of the spatial autocorrelation test. We also provide a spatial distribution map of China's digital economy and urban innovation in 2020 (Note: this map is based on the map numbered GS (2016) No. 1063, downloaded from the standard map service website of the China Bureau of Surveying, Mapping and Geographic Information, and the base map has not been modified), as shown in Figures 3 and 4. It can be seen that the level of the digital economy and urban innovation is higher in eastern coastal regions and capital cities of China. In comparison, the typical cases in the central and western regions are the L-L cluster with a lower level of the digital economy and urban innovation.

After we found that both urban innovation and digital economy demonstrate a positive and strong spatial correlation and an identical spatial clustering pattern, we explored the relationship between urban innovation and urban economy. The scatterplot was used to express their relationship, and a scatterplot with a line of best fit and the linear equation were obtained, as shown in Figure 5. This figure indicates a perfect positive correlation between them. The line of best fit with a positive slope and the value of r (0.534) for the linear relationship both indicate that, irrespective of other factors, the digital economy has positive implications on urban innovation and strong explanatory power concerning urban innovation. This should be further analyzed and explored by empirical analysis.

4.3. Estimation Results of Spatial Econometric Models for Impact of the Digital Economy on Urban Innovation. Table 3 shows that the OLS model, the SLM, SEM, and SDM were used to analyze the impact of the digital economy on urban innovation. The spatial Durbin models included the random effects model, city fixed effects model, year fixed effects model, and individual-year fixed effects model. The model estimation results are presented in Rows (1)–(7) of Table 3. In the OLS model, the coefficient estimate of the digital economy relative to urban innovation is 1.691, positive and significant at the 1% level. In the spatial econometric models, the coefficient estimates of the digital economy relative to urban innovation are 0.564, 1.157, 1.102, 0.961, 1.414, and 0.961, respectively, all positive and

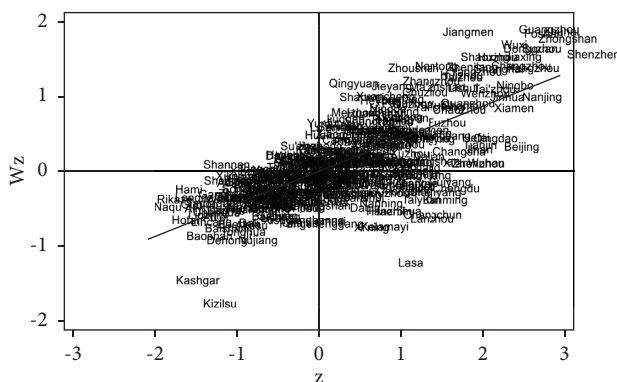
TABLE 1: Results for the descriptive statistics of variables.

Variable	Variable explanation	N	Mean	Sd	Min	Max
lnUI	Urban innovation	3370	1.609	0.988	0.000	4.927
DE	Digital economy	3370	0.178	0.080	0.017	0.679
lnED	Economic development	3370	10.653	0.590	8.707	12.324
lnPS	Population size	3370	5.336	1.425	0.277	8.885
lnFII	Fixed investment	3370	6.519	1.661	0.363	10.663
lnIL	Industrial level	3370	6.812	2.197	0.008	12.374
lnWL	Wages level	3370	10.921	0.328	9.753	12.207
lnRC	Road condition	3370	0.640	0.293	0.029	1.421
UL	Urbanization level	3370	52.313	17.205	7.370	100.000
lnFD	Financial development	3370	2.353	0.687	0.914	4.835
lnFOI	Foreign investment	3370	1.243	1.166	0.000	5.498
lnHR	Human resources	3370	1.441	1.171	0.000	5.110
lnTS	Technology spending	3370	3.875	1.922	0.000	9.011

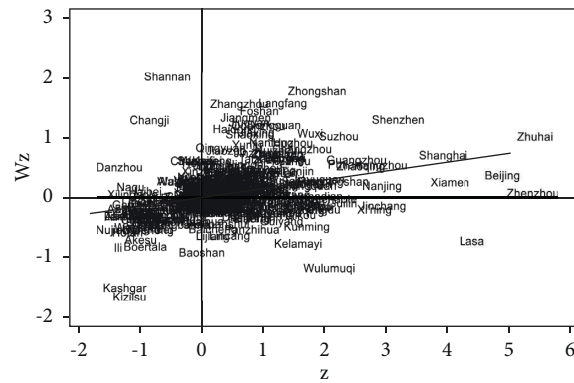
TABLE 2: Spatial autocorrelation test results of urban innovation and digital economy.

Year	lnUI (urban innovation)		DE (digital economy)	
	Moran's I	p -value	Moran's I	p -value
2011	0.471***	0.001	0.258***	0.001
2012	0.476***	0.001	0.214***	0.001
2013	0.484***	0.001	0.257***	0.001
2014	0.474***	0.001	0.251***	0.001
2015	0.472***	0.001	0.252***	0.001
2016	0.461***	0.001	0.244***	0.001
2017	0.456***	0.001	0.258***	0.001
2018	0.471***	0.001	0.231***	0.001
2019	0.464***	0.001	0.185***	0.001
2020	0.436***	0.001	0.148***	0.001

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively.

Moran scatterplot (Moran's I = 0.4356 and P -value = 0.0000) lnUI2020FIGURE 1: Moran's I in spatial clustering of urban innovation in 2020.

significant at the 1% level. Those coefficient estimates are less than that obtained from the OLS model (1.691), indicating that the OLS estimation may have a higher coefficient estimate which needs to be corrected by taking into account the spatial factors and applying the spatial econometric

Moran scatterplot (Moran's I = 0.1476 and P -value = 0.0000) DE2020FIGURE 2: Moran's I in spatial clustering of digital economy in 2020.

approach. In addition, the spatial autocorrelation coefficient estimates in Rows (1)–(7) are 0.640, 0.743, 0.748, 0.696, 0.695, and 0.696, respectively, demonstrating the obvious spatial spillover effects of urban innovation. 1% of the level of urban innovation in a region improved would drive the level of urban innovation in peripheral cities to increase by about 0.7%, playing a very significant role as impetus and enhancement.

Table 3 provides the analysis results for the SLM, SEM, and SDM with different effects. Thus, the optimal model was selected from those models for further analysis. Table 4 represents the model selection tests for the spatial econometric approach. In the first step, model selection tests were run, in which the optimal model was chosen from the SLM, SEM, and SDM. This was accomplished through the Wald and LR tests, as shown in Table 4. The corresponding chi-square test values are 202.94, 145.90, and 72.89, and the corresponding p -values are all 0.001. It indicates that the SDM model is optimal among these three models. The next step was the fixed effects tests. The results of the Hausman test show that the SDM needs to use fixed effects. In the final step, we identified which form of the fixed effects model should be applied for the SDM. The corresponding results of the LR test are 31.50 and 4351.18, and the p -values are 0.001

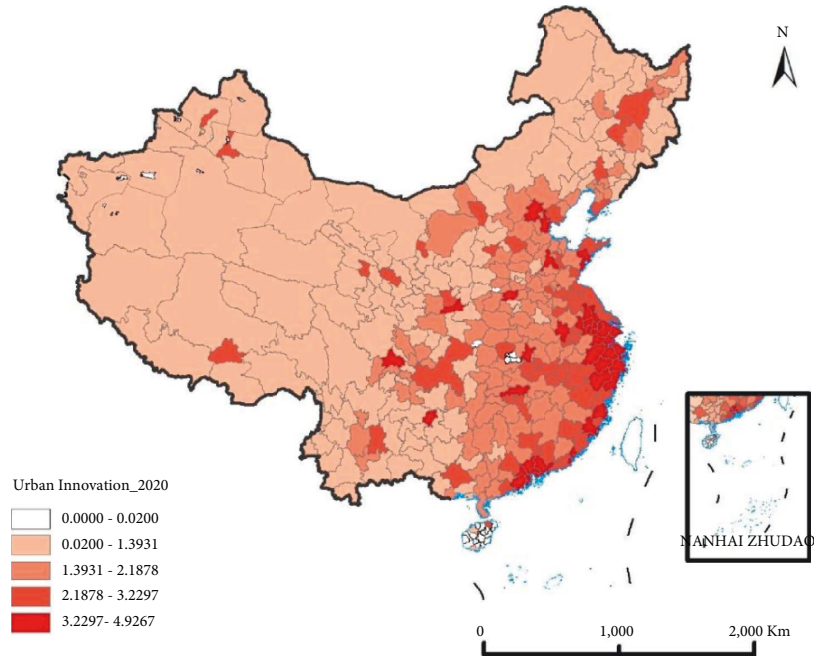


FIGURE 3: Spatial distribution map of China's urban innovation in 2020.

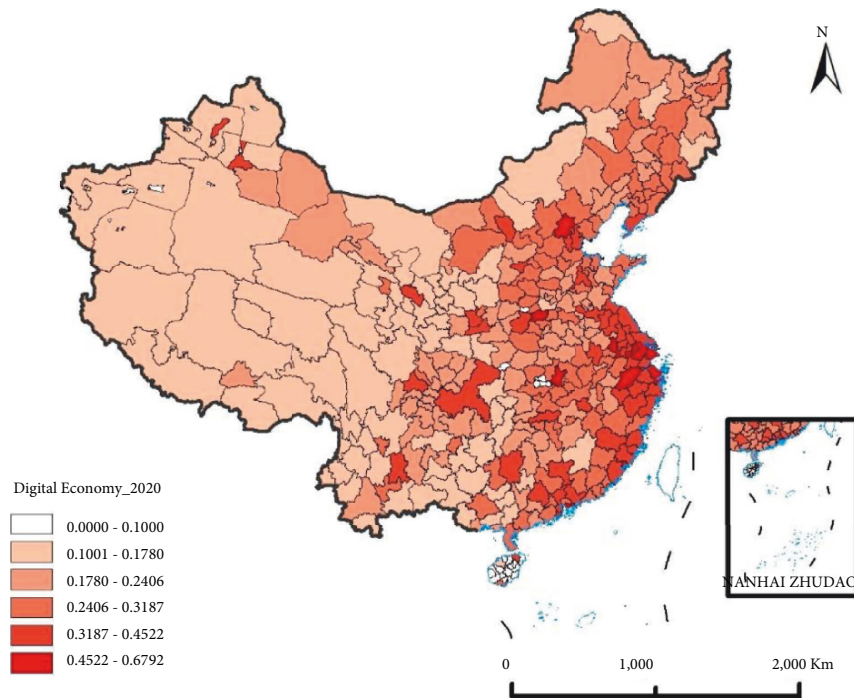


FIGURE 4: Spatial distribution map of China's digital economy in 2020.

and 0.001. It indicates that the individual-year fixed SDM should be selected with respect to the fixed effects. Therefore, the optimal model used in the following empirical analysis is the individual-year fixed SDM.

4.4. Decomposition of the Spatial Effects of the Digital Economy on Urban Innovation. In spatial econometrics, the results of the SDM are relatively special as the coefficient estimates of

its explanatory variables cannot directly reflect its impact on the explained variables. Therefore, the method of decomposing the spatial effects was applied to classify the impact of the digital economy on urban innovation into direct, indirect, and total effects. The direct effects refer to the direct effects of the local digital economy on local urban innovation, and the indirect effects refer to the spatial spillover effects of the local digital economy on urban innovation in peripheral regions. The results are shown in Table 5. In

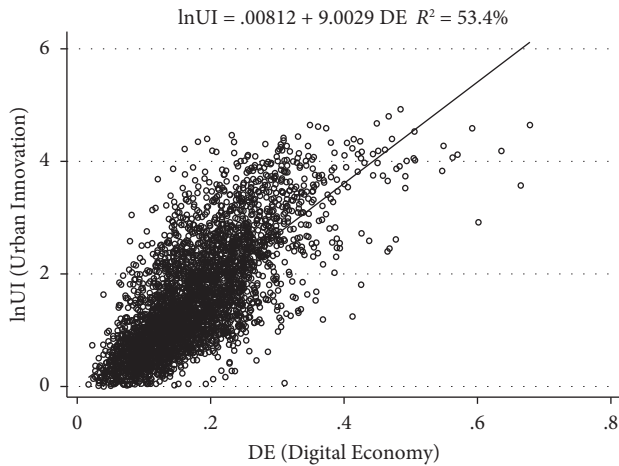


FIGURE 5: Fitted scatter plot of urban innovation and digital economy.

Table 5, the coefficient estimates of the direct effects, indirect effects, and total effects of the digital economy on urban innovation are 1.095, 4.368, and 5.463, respectively; they are all positive and significant at the 1% level, which indicates that the development of the local digital economy can not only directly promote local urban innovation but also have a positive effect on the level of urban innovation in peripheral regions as there are strong spatial spillover effects. Therefore, we must encourage regions to promote the remarkable progress of the digital economy, enhance the level of the digital economy, and, on that basis, remarkably drive the innovation in local and peripheral regions to a higher level, which helps create a countrywide environment conducive to urban innovation driven by digital economy and growth driven by innovation.

Next, we analyzed the impact of the control variables on urban innovation. In control variables, Economic Development (lnED) has positive and significant direct effects on urban innovation. In contrast, its indirect effects are negative and significant, which shows that local economic development can promote local urban innovation only but has a negative siphon effect on the urban innovation of peripheral regions. The indirect and total effects of Population Size (lnPS) and Fixed Investment (lnFII) on urban innovation are all positive and significant, while their direct effects are not significant, indicating that the population size and fixed investment have particularly strong spatial spillover effects on urban innovation. Foreign Investment (lnFOI) and Industrial Level (lnIL) have no significant direct effects or strong spatial spillover effects. Wages Level (lnWL) has positive and significant direct effects on urban innovation, indicating that higher local wages would better boost local urban innovation. However, local wages have neither significant indirect effects nor strong spatial spillover effects on urban innovation in peripheral regions. The direct, indirect, and total effects of Road Condition (lnRC) on urban innovation are all positive and significant, which indicates that the road condition can not only substantially promote local urban innovation but also enable a massive increase in the

urban innovation of peripheral regions. Urbanization Level (UL) has positive and significant direct effects on urban innovation, indicating that an increase in the local urbanization level may directly drive local urban innovation. However, its indirect effect is not significant, showing that the urbanization level has no strong spatial spillover effects on urban innovation in peripheral regions. The direct effects of Financial Development (lnFD) on urban innovation are positive and significant, indicating that a higher level of financial development tends to more effectively provide financial support for local urban innovation activities and drive urban innovation. However, the indirect effects of Financial Development on urban innovation are negative and significant, indicating that better financial development in local areas is easy to impose a siphon effect as it attracts innovation activities in peripheral regions to flow into the local areas and weakens the urban innovation capacity of peripheral regions at the expense of urban innovation improvement of peripheral regions.

4.5. Addressing the Endogeneity Problem of Impact of the Digital Economy on Urban Innovation. For the impact of the digital economy on urban innovation, the endogeneity problem arises due to the reciprocal cause-and-effect relationships between the digital economy and urban innovation; that is, the digital economy may influence urban innovation and vice versa. Therefore, instrumental variables were used to address the endogeneity problem in this section. When selecting the instrumental variables, we considered two criteria: correlation and exogeneity. For correlation, an instrumental variable must be correlated with the digital economy. For exogeneity, an instrumental variable must be uncorrelated with other factors that affect urban innovation. We adopted panel models to perform the estimation of instrumental variables. Meanwhile, instrumental variables with a spatial factor were taken into account. In this paper, the spatial lag term and spatio-temporal lag term of the digital economy were selected as the instrumental variables. The spatial lag item of the digital economy is the average value of the digital economy of other cities except for the city in the province where the city is located. The spatio-temporal lag term is the spatial lag term with a lag of one period. From the perspective of correlation, the digital economy of cities in the same province is highly correlated, even though the lag period is considered, which meets the assumption of correlation. From the perspective of exogeneity, the possibility that the spatial lag term and spatio-temporal lag term of the digital economy are correlated with other factors that affect urban innovation is limited, which generally meets the requirements of exogeneity. The results of the instrumental variables estimation are shown in Table 6.

In Table 6, with the spatial lag term and spatio-temporal lag term of the digital economy as instrumental variables, the instrumental variables estimates for the impact of the digital economy on urban innovation are 2.856 and 2.585, both positive and significant at the 1% level. The coefficient and significance level are consistent with the results of OLS estimation and spatial econometric model estimation.

TABLE 3: Results of spatial econometric analysis for impact of the digital economy on urban economy.

Variable	OLS	SAR	SEM	SDM			
	(1)	(2)	(3)	RE (4)	Individual-FE (5)	Year-FE (6)	Individual-year-FE (7)
DE	1.691*** (8.37)	0.564*** (3.46)	1.157*** (6.52)	1.102*** (6.21)	0.961*** (5.47)	1.414*** (6.75)	0.961*** (5.19)
lnED	0.118*** (3.78)	0.056** (1.99)	0.115*** (3.41)	0.157*** (4.86)	0.114*** (3.35)	0.130*** (3.92)	0.114*** (3.18)
lnPS	0.111 (1.26)	-0.191** (-2.37)	-0.177** (-2.19)	0.096*** (3.48)	-0.119 (-1.51)	0.050** (2.23)	-0.119 (-1.43)
lnFII	0.002 (0.15)	-0.013 (-1.39)	-0.016 (-1.64)	-0.018* (-1.82)	-0.008 (-0.89)	-0.046*** (-3.43)	-0.008 (-0.84)
lnIL	-0.002 (-0.12)	0.010 (0.89)	0.014 (1.15)	0.018 (1.62)	0.014 (1.28)	0.059*** (4.74)	0.014 (1.22)
lnWL	0.365*** (6.73)	0.137*** (3.43)	0.466*** (10.33)	0.355*** (7.08)	0.408*** (8.16)	0.101* (1.90)	0.408*** (7.74)
lnRC	0.251** (2.42)	0.260*** (2.75)	0.199** (2.10)	0.149* (1.86)	0.208** (2.31)	0.320*** (5.54)	0.208** (2.19)
UL	0.005*** (3.00)	0.004** (2.30)	0.007*** (4.21)	0.007*** (5.94)	0.006*** (3.61)	0.005*** (6.55)	0.006*** (3.43)
lnFD	0.150*** (3.68)	0.107*** (3.07)	0.229*** (6.15)	0.316*** (10.11)	0.205*** (5.73)	0.392*** (14.73)	0.205*** (5.44)
lnFOI	0.022* (1.78)	0.026** (2.33)	0.012 (1.03)	0.034*** (2.97)	0.015 (1.31)	0.113*** (12.17)	0.015 (1.25)
Wx_DE				-0.338 (-0.95)	0.671* (1.87)	1.928*** (3.73)	0.671* (1.78)
Wx_lnED				-0.195*** (-2.93)	-0.194*** (-2.85)	-0.075 (-0.87)	-0.194*** (-2.70)
Wx_lnPS				0.030 (0.47)	1.257*** (5.74)	-0.088 (-1.60)	1.257*** (5.45)
Wx_lnFII				0.046** (2.27)	0.045** (2.19)	-0.025 (-0.80)	0.045** (2.08)
Wx_lnIL				-0.064** (-2.13)	-0.058* (-1.88)	-0.016 (-0.46)	-0.058* (-1.78)
Wx_lnWL				-0.366*** (-4.03)	-0.303*** (-3.07)	0.676*** (5.13)	-0.303*** (-2.91)
Wx_lnRC				-0.019 (-0.10)	0.804*** (2.90)	0.281** (2.20)	0.804*** (2.75)
Wx_UL				-0.002 (-0.86)	-0.006* (-1.69)	-0.001 (-0.31)	-0.006 (-1.60)
Wx_lnFD				-0.221*** (-3.23)	-0.408*** (-4.85)	-0.382*** (-6.00)	-0.408*** (-4.60)
Wx_lnFOI				0.008 (0.33)	0.029 (1.07)	-0.096*** (-4.32)	0.029 (1.01)
Rho/lambda		0.640*** (26.87)	0.743*** (30.77)	0.748*** (34.34)	0.696*** (29.14)	0.695*** (30.07)	0.696*** (27.64)
Individual-FE	Yes	Yes	Yes	No	Yes	No	Yes
Year-FE	Yes	Yes	Yes	No	No	Yes	Yes
Adj. R-sq	0.7090	0.6858	0.6904	0.6902	0.7102	0.6837	0.7102
N	3370	3033	3033	3370	3370	3370	3033

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values t .

Moreover, in Table 6, the coefficient estimates of the results in the first stage regression are 0.828 and 0.797, both positive and significant at the 1% level. Values of the KP Wald-F statistic test performed by instrumental variables are

1055.908 and 424.375, both much higher than 10 (recognized critical value). These demonstrate that the results of modeling and estimation for the impact of the digital economy on urban innovation are reasonable and reliable,

TABLE 4: Model selection tests for the spatial econometric approach.

Model selection test	Chi2 statistic	p-value
Hausman test	31.76	0.001
Wald test	202.94	0.001
LR test (SDM vs SAR)	145.90	0.001
LR test (SDM vs SEM)	72.89	0.001
LR test (Ind-year-FE vs individual-FE)	31.50	0.001
LR test (Ind-year-FE vs year-FE)	4351.18	0.001

and the digital economy can remarkably boost urban innovation.

4.6. Robustness Tests for Impact of the Digital Economy on Urban Innovation. We performed robustness tests to ensure the robustness of the empirical results to the impact of the digital economy on urban innovation and measured the reliability and credibility of the empirical results through changes in criteria. The robustness tests were mainly conducted in the following ways. First, the explained variable, Urban Innovation, was replaced, which means other indicators were used to replace Urban Innovation and included in the model's regression. On the one hand, this paper adopted the Innovation Index of Cities in China released by Professor Kou Zonglai-led team from Fudan University to measure the level of urban innovation [47]. On the other hand, in the existing patent data, the urban patent density used to measure the innovation level of a city was obtained by calculating the regional area of the city. Second, the core explanatory variables were replaced. On the one hand, the underlying data of the digital economy were replaced by those with a lag of one period to measure the impact of the digital economy on urban innovation. On the other hand, after standardizing the five indicators for measuring the digital economy, their aggregate was incorporated into the model's regression to replace the average as an alternative indicator of the digital economy. Third, the spatial weights matrix was replaced. Different weights matrices may also affect the results of model estimation. On the one hand, the spatial distance matrix was replaced by the spatial contiguity matrix. The spatial contiguity weights matrix was constructed in the following way: all matrix elements in cities of the same province are 1, and the others are 0. On the other hand, we used the mixing spatial matrix which was obtained by mixing and summing up the spatial distance matrix and spatial contiguity matrix. Different spatial weights matrices were used to replace the original matrix for regression. Lastly, the sampling period was adjusted. Different sampling periods were adopted to measure the robustness of the estimation results. In this paper, the samples are divided into samples of even-numbered years and those of odd-numbered years, and the regressions were conducted, respectively, to verify the impact of different sampling periods on the empirical results.

The results of the robustness tests are shown in Table 7. In rows (1)–(8) of Table 7, the coefficient estimates and the spatial autocorrelation coefficients of the impact of the digital economy on urban innovation are all positive and

significant at the 1% level. Meanwhile, they are overall close to the coefficient estimates obtained in Table 7; the direct effects, indirect effects, and total effects of the digital economy on urban innovation are all statistically positive and significant. Therefore, it reflects that the results of the estimates in the model of the impact of the digital economy on urban innovation are robust, which means the digital economy can boost urban innovation. Such impetus is not only evidenced by the local digital economy as an incentive for local urban innovation but also reflected in the spatial spillover effects of the local digital economy on urban innovation in peripheral regions.

5. Further Analysis of the Spatial Implications of the Digital Economy on Urban Innovation

5.1. Analysis of Mechanisms of the Digital Economy to Influence Urban Innovation. After the robustness tests, we analyzed the mechanisms of how the digital economy influences urban innovation. The mechanisms were analyzed by considering the mediation effect of two variables: Human Resources and Technology Spending. The results are shown in Table 8, where Row (1) presents the results of the regression benchmark for the impact of the digital economy on urban innovation, which is not intended to repeat in this section. Rows (2) and (3) reflect the impact of the digital economy on the mediator variables, a.k.a., Human Resources and Technology Spending. The spatial autocorrelation coefficients are 0.348 and 0.557, both positive and significant at the 1% level. It indicates a strong positive spatial correlation between Human Resources and Technology Spending. An increase of 1% in Human Resources and Technology Spending in a region can drive a simultaneous growth of Human Resources and Technology Spending in peripheral regions by 0.348% and 0.557%. Such spatial spillover values are smaller overall than urban innovation (0.696%). The values of the direct effects show that the coefficients of the direct effects of the digital economy on Human Resources and Technology Spending are 0.486 and 2.660, respectively, both positive and significant at the 1% level. It means the growing local digital economy can boost the growth of local human resources and science and technology spending. In actual circumstances, the development of the digital economy in a region could attract workers to flow into this region; likewise, a region with a more established digital economy may invest more in scientific and technological innovations. This has been adequately reflected in the size of spending on human resources and science and technology by Chinese governments at all levels in recent years. The values of the indirect effects that represent the indirect effects of the digital economy on Human Resources and Technology Spending are 0.963 and 1.248, respectively; only the former is positive and significant at the 1% level. This result indicates that the development of the local digital economy can drive a substantial accumulation of human resources in peripheral regions, serving as a model and providing good practices, which in turn leads to positive spatial spillover effects.

TABLE 5: Results of decomposition of the spatial effects of digital economy on urban innovation.

Variable	Direct effect		Indirect effect		Total effect	
	Coefficient value	<i>t</i> -statistic	Coefficient value	<i>t</i> -statistic	Coefficient value	<i>t</i> -statistic
DE	1.095***	(5.90)	4.368***	(3.53)	5.463***	(4.30)
lnED	0.099***	(3.30)	−0.372*	(−1.78)	−0.273	(−1.28)
lnPS	−0.002	(−0.02)	3.734***	(4.91)	3.732***	(4.69)
lnFII	−0.003	(−0.28)	0.140**	(2.10)	0.137*	(1.95)
lnIL	0.007	(0.51)	−0.160	(−1.45)	−0.153	(−1.31)
lnWL	0.409***	(8.34)	−0.056	(−0.19)	0.353	(1.19)
lnRC	0.305***	(3.08)	3.145***	(3.40)	3.449***	(3.61)
UL	0.005***	(3.42)	−0.005	(−0.44)	0.001	(0.07)
lnFD	0.178***	(5.12)	−0.899***	(−3.37)	−0.721***	(−2.63)
lnFOI	0.019	(1.51)	0.129	(1.36)	0.148	(1.54)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

TABLE 6: Results of instrumental variables estimation for impact of the digital economy on urban economy.

Variable	Urban innovation					
	(1)			(2)		
2SLS two-stage regression results spatial lag term/space-time lag term	2.856*** (8.33)			2.585*** (5.36)		
Simplified result	2.365*** (5.44)			2.061*** (3.56)		
The first stage regression results	0.828*** (21.96)			0.797*** (16.17)		
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Individual-FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3370	3370	3370	3033	3033	3033
Adj. <i>R</i> -sq	0.655	0.692	0.907	0.602	0.647	0.864
KP Wald-F statistic	1055.908			424.375		

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

TABLE 7: Results of the robustness tests for impact of the digital economy on urban innovation.

Variable	Replace the explained variable		Replace the explanatory variable		Replacing the spatial weight matrix		Adjusted sample period	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DE	0.259** (2.38)	1.147*** (5.51)	1.047*** (4.39)	0.192*** (5.19)	1.029*** (5.55)	1.013*** (5.48)	0.578** (2.19)	1.392*** (4.56)
Wx_DE	0.846*** (4.15)	1.354*** (3.20)	0.577 (1.26)	0.137* (1.81)	0.563* (1.83)	0.593* (1.83)	0.923* (1.69)	0.562 (0.91)
Rho	0.772*** (26.51)	0.661*** (24.70)	0.711*** (27.49)	0.695*** (27.58)	0.577*** (30.65)	0.620*** (31.72)	0.695*** (17.83)	0.688*** (18.04)
DE-direct effect	0.390*** (3.46)	1.340*** (6.43)	1.187*** (4.90)	0.220*** (5.91)	1.169*** (6.43)	1.155*** (6.34)	0.712*** (2.69)	1.543*** (5.05)
DE-indirect effect	4.605*** (4.70)	6.164*** (4.87)	4.567*** (2.82)	0.880*** (3.57)	2.641*** (3.97)	3.130*** (3.98)	4.368** (2.36)	4.882** (2.51)
DE-total effect	4.995*** (4.92)	7.504*** (5.78)	5.754*** (3.43)	1.099*** (4.34)	3.811*** (5.57)	4.285*** (5.33)	5.081*** (2.68)	6.425*** (3.23)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. <i>R</i> -sq	0.7046	0.7674	0.6697	0.7105	0.7157	0.7157	0.7012	0.7373
<i>N</i>	1685	3033	2696	3033	3033	3033	1348	1348

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

TABLE 8: Results of analysis of mechanisms of the digital economy to influence urban innovation.

Variable	lnUI (1)	lnHR (2)	lnTS (3)	lnUI (4)	lnUI (5)	lnUI (6)	lnUI (7)
DE	0.961*** (5.19)	0.462*** (4.54)	2.619*** (7.95)			0.908*** (4.89)	0.648*** (3.51)
lnHR				0.152*** (4.60)		0.133*** (4.02)	0.148*** (4.55)
lnTS					0.089*** (8.82)		0.088*** (8.62)
W _x _DE	0.671* (1.78)	0.470** (2.29)	−0.906 (−1.35)			0.652* (1.71)	0.317 (0.83)
W _x _lnHR				−0.029 (−0.35)		−0.106 (−1.26)	−0.144* (−1.73)
W _x _lnTS					0.101*** (4.34)		0.086*** (3.63)
Rho	0.696*** (27.64)	0.348*** (10.19)	0.557*** (19.03)	0.720*** (29.90)	0.668*** (26.05)	0.697*** (27.75)	0.657*** (25.02)
DE-direct effect	1.095*** (5.90)	0.486*** (4.84)	2.660*** (8.16)			1.036*** (5.51)	0.711*** (3.83)
lnHR-direct effect				0.161*** (4.75)		0.128*** (4.31)	0.142*** (5.21)
lnTS-direct effect					0.104*** (10.34)		0.101*** (9.31)
DE-indirect effect	4.368*** (3.53)	0.963*** (2.96)	1.284 (0.85)			4.136*** (3.27)	2.013** (2.13)
lnHR-indirect effect				0.299 (0.94)		−0.067 (−0.28)	−0.101 (−0.47)
lnTS-indirect effect					0.478*** (6.57)		0.408*** (6.05)
DE-total effect	5.463*** (4.30)	1.449*** (4.50)	3.944** (2.56)			5.171*** (3.97)	2.725*** (2.78)
lnHR-total effect				0.460 (1.41)		0.060 (0.24)	0.041 (0.19)
lnTS-total effect					0.582*** (7.83)		0.509*** (7.24)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.7102	0.3798	0.4221	0.7029	0.7245	0.7112	0.7296
N	3033	3033	3033	3033	3033	3033	3033

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values t .

During the analysis of the mediation effect mechanism, we explored the impact of the digital economy on mediator variables (Human Resources and Technology Spending), followed by the analysis of the impact of these mediator variables on urban innovation. The results are shown in Rows (4) and (5) of Table 8. For the spatial autocorrelation coefficients, the coefficient estimates are 0.720 and 0.668, and both are positive and significant at the 1% level and close to 0.696 in Row (1). When the local urban innovation gets 1% better, it would simultaneously increase the urban innovation in peripheral cities by about 0.7%. For direct effects, the values of the direct effects of Human Resources and Technology Spending on urban innovation are 0.161 and 0.104, both positive and significant at the 1% level. It indicates that local human resources and science and

technology spending can directly boost local urban innovation. For indirect effects, the values of the indirect effects of Human Resources and Technology Spending on urban innovation are 0.299 and 0.478; only the latter one is positive and significant at the 1% level. It means that only increasing science and technology spending can significantly drive the improvement of urban innovation in peripheral cities, leading to robust spatial spillover effects. However, the increase of human resources cannot effectively create positive and significant spatial spillover effects on urban innovation, as human resources are mainly located in large and capital cities and flow to such cities, which provides a noticeable boost to urban innovation in large and capital cities, but its impact on urban innovation of peripheral cities is not significant.

Lastly, the mediator variables (Human Resources, followed by Technology Spending) were added to the benchmark model for regression. The results are presented in Table 8. The impact of the digital economy on urban innovation after the incorporation of the mediator variables is shown in Rows (6) and (7) of Table 8, and then whether the digital economy acts on urban innovation through two aspects, a.k.a., human resources and science and technology spending, was verified. For the spatial autocorrelation coefficients, the coefficient estimates are 0.697 and 0.657, both positive and significant at the 1% level. Upon incorporating Human Resources, the spatial autocorrelation coefficient in the benchmark model changes slightly from 0.696 to 0.697, while upon incorporating Technology Spending, the spatial autocorrelation coefficient in the benchmark model is decreased from 0.697 to 0.657. The significant decline indicates that the incorporation of Technology Spending has a greater impact on the benchmark model's regression results, which means the digital economy is more likely to act on local urban innovation via a rise in science and technology spending. For direct effects, upon incorporating the mediator variables, the coefficient estimates of the impact of the digital economy on urban innovation are 1.036 and 0.711, both positive and significant at the 1% level. In comparison with the regression result in Row (1) (1.095), the former just changes slightly while the latter sees a more considerable decline, indicating that science and technology spending is more likely to be the mechanism of the digital economy to influence urban innovation. The local digital economy prominently boosts the cities' level of innovation through more spending on science and technology. For indirect effects, upon incorporating the mediator variables, the values of the indirect effects of the digital economy on urban innovation are 4.136 and 2.103, both positive and significant. In comparison with the benchmark model, by adding Human Resources, the value of indirect effects of the digital economy on urban innovation is decreased from 4.368 to 4.136; by adding Technology Spending, the value of indirect effects sees a sharp decline, from 4.136 to 2.013. It demonstrates that from the perspectives of indirect effects and spatial spillover, both human resources and science and technology spending are the mechanisms of the digital economy to create spatial spillover effects on urban innovation; from the perspective of the coefficient estimates, the impact of science and technology spending outweighs that of human resources. The development of the digital economy in the local region puts the spatial spillover effects on urban innovation in peripheral regions via two channels, a.k.a., human resources and science and technology spending, and the effects of the latter one outweigh those of the former one.

5.2. Analysis of Heterogeneity in the Impact of the Digital Economy on Urban Innovation. After the mechanism analysis, we explored the heterogeneity in the empirical results. In this paper, samples were categorized by the

regions where the cities are located, namely, the eastern, central and western, southern, and northern regions, to compare the effects of policies in different regions. The results are presented in Table 9. First, we compared the eastern region with the central and western regions. In Rows (1) and (2), the coefficient estimates of the impact of the digital economy on urban innovation are 0.394 and 0.874, and only the latter is significant at the 1% level. For the spatial autocorrelation coefficients, the coefficients of the eastern region and the central and western regions are 0.532 and 0.650, both positive and significant at the 1% level. The results of the decomposition of the spatial effects show that only the direct effects, indirect effects, and total effects of the central and western regions' digital economy on urban innovation are positive and statistically significant, while all coefficient estimates in relation to the eastern region are not significant. This means, in comparison with the eastern region, the digital economy in the central and western counterpart is more likely to substantially improve urban innovation, primarily for the following reasons that we found in the eastern region: the innovation atmosphere and entrepreneurial activities are more favorable; the overall level of urban innovation is higher; it is challenging for the growing digital economy to create more substantial marginal effects on urban innovation. On the contrary, as the western region sees a lower level of urban innovation and a less developed digital economy, along with the greater potential for improving urban innovation, making more efforts to develop the digital economy may provide urban innovation with solid support in information infrastructure and services, which could help transform the digital economy into innovation activities and boost urban innovation.

Next, we compared the southern region and northern region. The coefficient estimates of the impact of these regions' digital economy on urban innovation are 1.162 and 1.605, both positive and significant at the 1% level. Their spatial autocorrelation coefficients are 0.641 and 0.627, both positive and significant at the 1% level. These indicate a positive spatial correlation of urban innovation in southern and northern regions. For the decomposition of the spatial effects, the direct, indirect, and total effects of the northern region's digital economy on urban innovation are positive and significant at the 1% level. In contrast, only the direct and total effects in the southern region are positive and significant, and the indirect effects are not significant. For the values of the coefficients, those coefficient estimates of the southern region are smaller than those of the northern region, which indicates that the effects of the northern region's policies on the digital economy relative to urban innovation are better than those of the southern region. Such results are closely related to the overall level of the digital economy and urban innovation in these two regions. As such, the southern region, with a higher level of the digital economy and urban innovation, is home to a large group of companies in the digital economy, such as Hangzhou-based Alibaba and Shenzhen-based Tencent. Urban innovation there is very active. However, generally speaking, the digital economy and urban innovation in the northern region lag behind those in the southern region. Therefore, the northern

TABLE 9: Results of analysis of heterogeneity in the impact of the digital economy on urban innovation.

Variable	Eastern (1)	Middle-western (2)	Southern (3)	Northern (4)
DE	0.394 (1.29)	0.874*** (3.74)	1.162*** (4.69)	1.605** (2.12)
Wx_DE	-0.497 (-0.78)	0.747* (1.73)	-0.138 (-0.27)	1.383*** (2.66)
Rho	0.512*** (11.54)	0.633*** (21.43)	0.641*** (17.49)	0.627*** (18.82)
DE-direct effect	0.375 (1.22)	1.013*** (4.32)	1.219*** (4.89)	1.812*** (2.82)
DE-indirect effect	-0.452 (-0.33)	3.478*** (3.06)	1.746 (1.18)	4.602*** (3.42)
DE-total effect	-0.077 (-0.05)	4.490*** (3.80)	2.965* (1.94)	6.414*** (3.83)
Control variable	Yes	Yes	Yes	Yes
Individual-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
Adj. R-sq	918	2115	1620	1413
N	0.7910	0.7002	0.7698	0.6661

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values t .

region has latecomer advantages, and the effects of its policies on the digital economy relative to urban innovation surpass those of the southern region.

5.3. Spatial Spillover Distance and Threshold of the Digital Economy on Urban Innovation. In the above-given analysis, we explored the spatial implications and mechanisms of the digital economy on urban innovation and discovered that the digital economy has significant direct effects and more potent spatial spillover effects on urban innovation. We further analyzed the specific forms of spatial spillover effects of the digital economy on urban innovation, including the distance within which the spatial spillover effects occur and how the spatial spillover effects change with geographic distance. Furthermore, we sought to determine the range within which the digital economy can influence urban innovation and the threshold of its impact. In this regard, we performed a regression with the spatial weights matrices of different thresholds to obtain the coefficient estimates of the direct and indirect effects of different thresholds, which were mapped to the corresponding thresholds. The results are shown in Table 10 and Figure 4. In Table 10, the coefficient estimates of direct effects within the range of 50–2,000 kilometers are all positive and significant at the 1% level, which indicates that even at different thresholds the development of the local digital economy can have a significant positive effect on local urban innovation. From the perspective of indirect effects, within the range of 500 kilometers, the digital economy has positive and strong spatial spillover effects on urban innovation, and the development of the local digital economy can substantially drive the significant improvement of urban innovation in other cities within the range of 500 kilometers. However, within the range of 600–1,600 kilometers, the coefficient estimates of the indirect effects of the local digital economy development on

urban innovation are primarily negative, which means that within this range, the digital economy fails to boost urban innovation in other regions, and instead, it considerably weakens the innovation of cities in these regions, leading to a strong siphon effect.

Why can the digital economy generate positive spatial spillover on urban innovation within 500 kilometers? In his research, Yu et al. argues that 500 kilometers generally reach the provincial boundaries [43]. We also provide new evidence for the 500 kilometers provincial boundaries, where we plot the geographic distances of cities from provincial capital cities as a histogram. Figure 6 shows that except for a few extreme values (16, less than 5%), the distance between most cities and their provincial capital cities will not exceed 500 kilometers. Such a provincial boundary imposes considerable influence and a specific limit on the spatial spillover effects; there is a particular regional threshold that is often created by local markets. On the one hand, giving preference to local companies, producers and service providers tend to do business with local companies they are familiar with. On the other hand, local protectionism could also contribute to the regional threshold for spatial spillover effects; provincial authorities often seek to maximize the benefits within the administrative region, preventing the effects of policies from spilling over outside the province. Yu's conclusion can help explain why the spatial spillover of the digital economy on urban innovation has a threshold within 500 kilometers. The main reasons are that during the development of the digital economy in regions, those that benefit most are local companies and individuals; there is a local market effect; local companies and individuals can fully benefit from the policies on the digital economy due to geographic advantages and an accurate grasp of market information and policies in their provinces. In addition, due to local protectionism, the primary purposes for each

TABLE 10: Spatial spillover distance of the digital economy on urban innovation.

Distance threshold (km)	Direct effect		Indirect effect		Distance threshold (km)	Direct effect		Indirect effect	
	Coefficient	t-statistic	Coefficient	t-statistic		Coefficient	t-statistic	Coefficient	t-statistic
50	1.236***	(6.60)	8.814***	(3.55)	1050	1.605***	(8.08)	-13.719***	(-5.12)
100	1.196***	(6.14)	23.590***	(3.11)	1100	1.732***	(8.68)	-14.941***	(-5.46)
150	1.119***	(5.62)	25.373**	(2.25)	1150	1.753***	(8.79)	-14.937***	(-5.97)
200	1.005***	(4.94)	25.018**	(2.46)	1200	1.778***	(8.86)	-15.720***	(-6.41)
250	1.075***	(5.29)	25.246***	(2.92)	1250	1.823***	(9.07)	-14.624***	(-5.55)
300	1.235***	(6.02)	30.410***	(2.87)	1300	1.884***	(9.30)	-12.793***	(-5.12)
350	1.280***	(6.24)	31.194***	(2.86)	1350	1.864***	(9.20)	-12.028***	(-5.36)
400	1.391***	(6.72)	33.692***	(2.85)	1400	1.759***	(8.66)	-10.877***	(-5.48)
450	1.460***	(7.10)	17.557**	(2.49)	1450	1.802***	(8.92)	-9.590***	(-4.66)
500	1.391***	(6.78)	9.572*	(1.75)	1500	1.739***	(8.56)	-6.770***	(-3.66)
550	1.465***	(7.15)	0.087	(0.02)	1550	1.655***	(8.13)	-3.377*	(-1.94)
600	1.453***	(7.16)	-10.970**	(-2.51)	1600	1.536***	(7.54)	-0.801	(-0.51)
650	1.525***	(7.60)	-14.189***	(-3.50)	1650	1.406***	(6.92)	1.922	(1.30)
700	1.487***	(7.46)	-14.165***	(-4.50)	1700	1.389***	(6.86)	2.196	(1.62)
750	1.509***	(7.59)	-14.920***	(-4.61)	1750	1.486***	(7.41)	2.985**	(2.29)
800	1.516***	(7.59)	-15.817***	(-4.79)	1800	1.517***	(7.66)	3.560***	(2.96)
850	1.373***	(6.88)	-14.943***	(-5.27)	1850	1.566***	(8.02)	3.392***	(3.02)
900	1.441***	(7.22)	-14.397***	(-5.36)	1900	1.603***	(8.24)	2.985***	(2.74)
950	1.509***	(7.58)	-14.771***	(-5.28)	1950	1.551***	(8.05)	3.540***	(3.50)
1000	1.536***	(7.73)	-13.766***	(-5.18)	2000	1.587***	(8.18)	1.960**	(2.02)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values t .

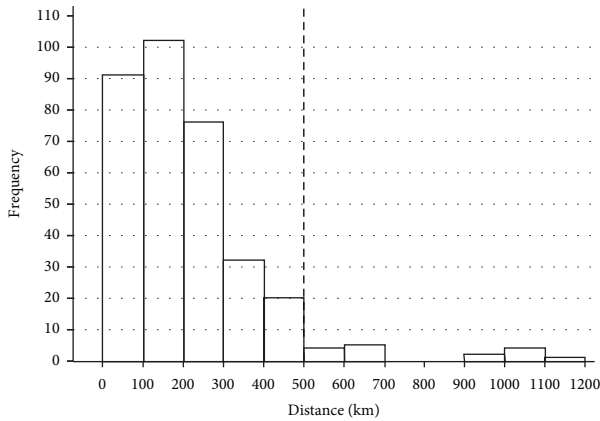


FIGURE 6: The distance distribution between cities and provincial capital cities.

province to develop the digital economy are to serve local companies and residents, boost urban innovation in the province, and maximize the effects of policies and benefits in the province.

Why does the digital economy have a considerable siphon effect on urban innovation in 600–1600 kilometers? For geographic distance, 600 kilometers are generally beyond the provincial boundaries and categorized as a cross-province, cross-region case. In this range, the development of the digital economy in a province will generate a pronounced siphon effect on other provinces, attracting various resources to aggregate in provinces with a developed digital economy. Nationwide, the imbalance is a challenge in China's digital economy and urban innovation. The digital economy and urban innovation in the wealthy east coastal

provinces are generally at a higher level. However, the central and western counterpart, especially underdeveloped provinces in the west, generally has a less developed digital economy and urban innovation. The trend is that various resources flow from the central and western regions and inland provinces to the southeastern coastal regions and accumulate there to cause a siphon effect on the central and western regions and inland provinces. Therefore, even though in empirical econometrics, we reached the conclusion that the digital economy can put prominent spatial spillover effects on urban innovation, from the spatial perspective, such spatial spillover effects could only occur within 500 kilometers, in most cases, without crossing provincial boundaries. However, in a larger space, the digital economy imposes a significant siphon effect on urban innovation, in line with the regional dualism of China's current economy. Therefore, the conclusions of this paper are also characterized by regional dualism. The digital economy can significantly boost urban innovation within the provincial boundaries, i.e., 500 kilometers. In other words, the digital economy can only contribute to substantial improvements in urban innovation of other cities in the same province, but it imposes an obvious siphon effect on the innovation of other cities outside the province.

Figure 7 describes the trends of the digital economy's direct and indirect effects on urban innovation with changes in distance. We found that the direct effects of the digital economy on urban innovation have small coefficient estimates and change little, while the coefficient estimates of indirect effects are positive in the first place and then fall into the negative territory, with a trend of "rise, fall, and rise." Therefore, the indirect effects of the digital economy on urban innovation demonstrate distinct changes and

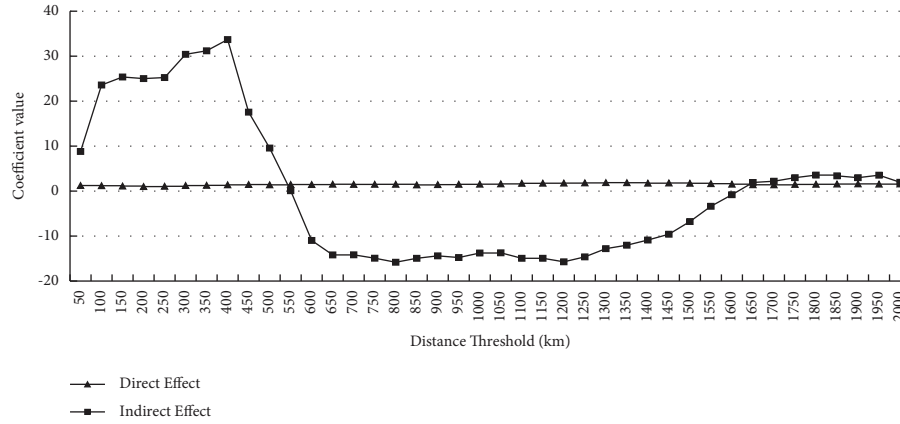


FIGURE 7: Spatial trends of the impact of the digital economy on urban innovation.

TABLE 11: Spatial spillover distance of the impact of the eastern region's digital economy on urban innovation.

Distance threshold (km)	Direct effect		Indirect effect		Distance threshold (km)	Direct effect		Indirect effect	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic		Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
50	0.370	(1.19)	-0.405	(-0.22)	1050	-0.020	(-0.06)	-1.960	(-0.83)
100	0.356	(1.15)	1.635	(0.63)	1100	0.110	(0.35)	-2.647	(-1.08)
150	0.158	(0.50)	3.986	(1.34)	1150	0.167	(0.53)	-1.146	(-0.51)
200	0.101	(0.32)	8.424***	(2.68)	1200	0.115	(0.36)	-4.274*	(-1.87)
250	0.331	(1.02)	6.548**	(2.23)	1250	0.254	(0.79)	-2.369	(-1.00)
300	0.137	(0.41)	8.500***	(2.62)	1300	0.351	(1.10)	2.498	(0.96)
350	0.140	(0.42)	1.466	(0.38)	1350	0.341	(1.07)	2.643**	(2.10)
400	0.117	(0.35)	-0.325	(-0.07)	1400	0.400	(1.25)	2.231	(0.85)
450	-0.060	(-0.18)	-3.738	(-0.82)	1450	0.528	(1.62)	2.829	(1.35)
500	-0.042	(-0.13)	-1.886	(-0.43)	1500	0.528	(1.63)	3.626*	(1.73)
550	0.070	(0.22)	0.372	(0.09)	1550	0.397	(1.23)	2.125***	(2.72)
600	0.061	(0.19)	0.366	(0.09)	1600	0.279	(0.88)	2.481*	(1.84)
650	0.051	(0.16)	-4.505	(-1.03)	1650	0.286	(0.92)	1.337	(1.35)
700	-0.042	(-0.13)	-4.059	(-0.89)	1700	0.453	(1.46)	1.166	(1.44)
750	0.108	(0.35)	-3.524	(-0.81)	1750	0.569*	(1.88)	0.998	(1.54)
800	0.058	(0.19)	-3.737	(-0.87)	1800	0.685**	(2.27)	-0.246	(-0.46)
850	0.052	(0.17)	-0.178	(-0.05)	1850	0.383	(1.27)	-0.502	(-0.89)
900	0.171	(0.54)	-1.110	(-0.36)	1900	0.226	(0.74)	-0.520	(-0.94)
950	0.142	(0.45)	-0.883	(-0.32)	1950	0.266	(0.88)	-1.169*	(-1.73)
1000	0.011	(0.04)	-2.465	(-0.96)	2000	0.321	(1.05)	-0.939	(-1.39)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

volatility, which indicates that the impact of the digital economy on urban innovation is dominated by indirect effects and mainly presented with spatial spillover effects. Therefore, in the process of developing the digital economy, bringing the digital economy of cities to the next level, and promoting urban innovation, it is necessary to focus on the intercity synergy and collaboration for developing a province's digital economy and give full play to the spatial spillover effects of the digital economy on urban innovation through coordination and cooperation to maximize the effects of policies within the province.

After a nation-level analysis of the spatial spillover effects and spatial threshold of the digital economy on urban innovation, we explored the spillover distance and threshold

from the regional perspective. First, we looked at the eastern region. As shown in Table 11 and Figure 8, for direct effects, the values of the direct effects of the eastern region's digital economy on urban innovation are small and not statistically significant, which means, for the eastern region, the local digital economy does not have a major impact on local urban innovation, in line with the results of the analysis of heterogeneity. For indirect effects, in the range of 200–300 kilometers, the values of the indirect effects of the digital economy on urban innovation are positive and significant, indicating that the digital economy can remarkably drive urban innovation in other cities within this range. In comparison with the nation-level results, the range of the spatial spillover of the eastern region's digital economy on

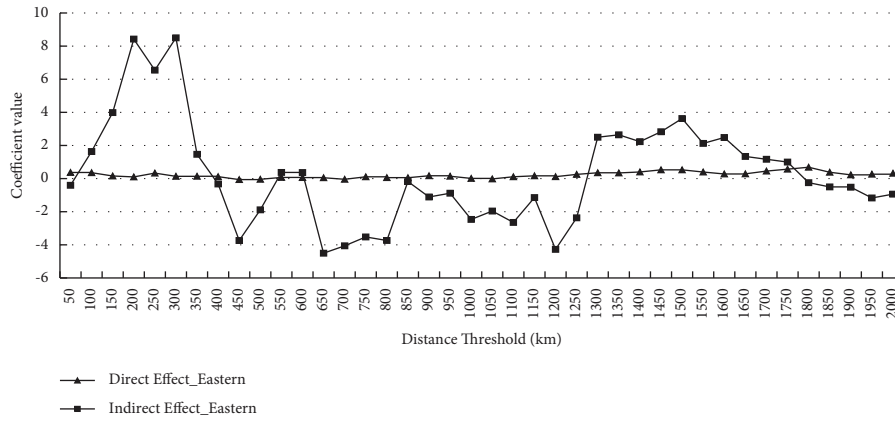


FIGURE 8: Spatial trends of the impact of the eastern region's digital economy on urban innovation.

urban innovation is smaller. For the eastern region, there are no adjacent and obvious areas with a siphon effect, which indicates the eastern region is characterized by a developed digital economy, balanced intercity digital economy and innovation, weak spatial spillover effects, and no strong intercity siphonage.

Next, we looked at the central and western regions. The digital economy and urban innovation in the central and western regions are generally at a low level, with enormous potential for growth and plenty of scope for improvement. As shown in Table 12 and Figure 9, for direct effects, the values of the direct effects of the digital economy on urban innovation are all positive and significant, which shows that the local digital economy can substantially boost local urban innovation at different thresholds. Compared with the nation-level results, the values of the direct effects of the central and western regions are generally higher, which indicates that the direct effects of the digital economy on urban innovation in the central and western regions outweigh the country's overall direct effects. For indirect effects, in a range of 50–250 kilometers, the development of the digital economy in the central and western regions can considerably drive urban innovation in other cities within this range. This range does not differ much from the eastern region, but the distance is shorter than the nation-level spatial spillover distance. In the range of 750–1,600 kilometers, the indirect effects of the digital economy on urban innovation are negative and significant, which indicates that the digital economy imposes a distinct siphon effect on the innovation of other cities within this range. It is in line with the nation-level characteristics but different from those of the eastern region. Moreover, the large spatial spillover range and siphonage range in the central and western regions for the impact of the digital economy on urban innovation have exacerbated the digital economy gap and lagged-behind urban innovation in the central and western regions. In this region, several capital cities, such as Chengdu, Chongqing, and Wuhan, even see their level of the digital economy and urban innovation higher than some coastal cities in the eastern region. However, this pattern of the digital economy and urban innovation, with a strong capital city as a

characteristic, is formed by siphoning the factors of resources from other small and medium cities in the central and western regions, objectively speaking, which widens the gap of the digital economy and urban innovation in the central and western regions.

After that, we looked at the northern region. In recent years, the economic differences between the north and the south in China have received increasing attention from scholars. The development gap between the north and the south has been a significant issue for China's economy. As shown in Table 13 and Figure 10, for direct effects, the values of the direct effects of the northern region's digital economy on urban innovation are all positive and significant, in line with the nation-level characteristics. For indirect effects, in the range of 50–350 kilometers, the digital economy has strong spatial spillover effects on urban innovation, indicating that the northern region's digital economy can substantially drive the innovation of other cities within this range. However, in the range of 700–2,000 kilometers, the indirect effects of the digital economy on urban innovation are generally negative and significant, which means the development of the local digital economy imposes a strong siphon effect on the innovation of peripheral cities within this range. In comparison with the nation-level results, the northern region is characterized by a shorter distance for spatial spillover effects and an ample space for the siphon effect, and the distance of the siphon effect in the northern region is not in a declining trend, which indicates that the siphon effect of the northern region's digital economy on urban innovation could occur in a larger range. The main reasons are the relatively weak impact of the northern region's overall digital economy on urban innovation capacity, the imbalanced regional development, and municipalities directly under the Central Government, especially Beijing and Tianjin, siphoning the factors of the digital economy and technological innovation resources from most areas of North China, leaving an extensive siphon range for the impact of the digital economy on urban innovation in the northern region.

Finally, we looked at the southern region. The digital economy is relatively well-established in the southern

TABLE 12: Spatial spillover distance of the impact of the central and western regions' digital economy on urban innovation.

Distance threshold (km)	Direct effect		Indirect effect		Distance threshold (km)	Direct effect		Indirect effect	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic		Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
50	1.232***	(5.15)	5.822***	(2.95)	1050	1.621***	(6.39)	-11.904***	(-3.48)
100	1.210***	(4.83)	14.749***	(3.06)	1100	1.742***	(6.86)	-11.981***	(-3.69)
150	1.093***	(4.37)	10.185**	(2.28)	1150	1.692***	(6.68)	-11.531***	(-4.12)
200	0.969***	(3.81)	5.302*	(1.69)	1200	1.760***	(6.88)	-11.041***	(-4.26)
250	1.106***	(4.39)	6.570*	(1.87)	1250	1.826***	(7.17)	-11.721***	(-3.88)
300	1.186***	(4.70)	5.057	(1.48)	1300	1.855***	(7.17)	-10.188***	(-3.87)
350	1.246***	(4.89)	2.836	(0.91)	1350	1.761***	(6.80)	-8.853***	(-3.73)
400	1.297***	(5.01)	3.235	(1.04)	1400	1.638***	(6.34)	-7.690***	(-3.63)
450	1.508***	(5.76)	2.936	(0.91)	1450	1.597***	(6.19)	-8.044***	(-3.19)
500	1.524***	(5.84)	1.984	(0.60)	1500	1.497***	(5.78)	-5.251**	(-2.44)
550	1.664***	(6.46)	-0.205	(-0.05)	1550	1.520***	(5.87)	-3.601*	(-1.93)
600	1.587***	(6.17)	-3.612	(-0.83)	1600	1.366***	(5.26)	-2.890*	(-1.79)
650	1.643***	(6.49)	-6.128	(-1.32)	1650	1.320***	(5.09)	-1.699	(-1.17)
700	1.610***	(6.37)	-6.999	(-1.58)	1700	1.243***	(4.77)	-1.104	(-0.86)
750	1.594***	(6.33)	-7.660*	(-1.95)	1750	1.323***	(5.14)	-0.517	(-0.44)
800	1.655***	(6.56)	-6.633**	(-2.10)	1800	1.340***	(5.24)	0.173	(0.16)
850	1.538***	(6.10)	-8.320***	(-2.75)	1850	1.524***	(5.97)	-0.337	(-0.31)
900	1.522***	(6.00)	-10.389***	(-3.12)	1900	1.642***	(6.39)	-1.024	(-0.85)
950	1.585***	(6.25)	-12.409***	(-3.20)	1950	1.551***	(6.12)	0.614	(0.51)
1000	1.596***	(6.32)	-14.328***	(-3.39)	2000	1.551***	(6.06)	1.837	(1.56)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

region, home to Internet giants Tencent and Alibaba. The economy on urban innovation are generally negative and

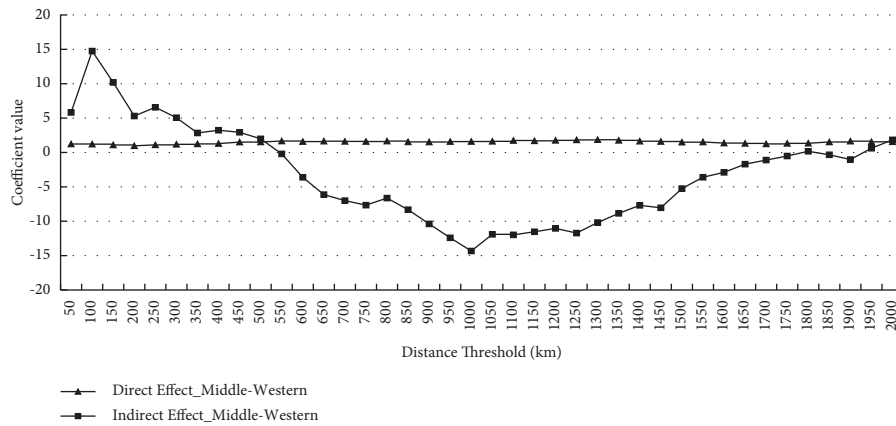


FIGURE 9: Spatial trends of the impact of the central and western regions' digital economy on urban innovation.

southern region is the leader in the digital economy in the country. As shown in Table 14 and Figure 11, for direct effects, the direct effects of the southern region's digital economy on urban innovation are all positive and significant at various thresholds. For indirect effects, in the range of 100–550 kilometers, the values of the indirect effects of the digital economy on urban innovation are positive and significant, which shows that the digital economy in the southern region can considerably drive the innovation of peripheral cities within this range. Compared with the northern region and the nation-level results, the southern region has a larger spatial spillover space, and the digital economy can reach larger peripheral areas. In the range of 650–2,000 kilometers, the indirect effects of the digital

significant, which indicates that the development of the digital economy in the southern region also imposes a strong siphon effect on the innovation of other cities within this range. The southern region sees the coexisting ranges of spatial spillover effects and the siphon effect of the digital economy on urban innovation. However, unlike the northern region, the southern region is characterized by a larger spatial spillover range and a smaller siphon effect range with a declining trend.

6. Conclusions and Policy Recommendations

6.1. Research Conclusions. The digital economy is a crucial direction for the future high-quality development of China's

TABLE 13: Spatial spillover distance of the impact of the northern region's digital economy on urban innovation.

Distance threshold (km)	Direct effect		Indirect effect		Distance threshold (km)	Direct effect		Indirect effect	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic		Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
50	0.968***	(3.34)	8.923***	(3.67)	1050	1.228***	(3.98)	-6.420***	(-4.21)
100	1.069***	(3.51)	20.306***	(3.90)	1100	1.428***	(4.65)	-7.860***	(-4.58)
150	0.941***	(3.13)	15.580***	(3.44)	1150	1.251***	(4.12)	-8.339***	(-4.49)
200	0.932***	(3.06)	14.270***	(3.17)	1200	1.242***	(4.14)	-9.865***	(-4.82)
250	0.899***	(2.99)	12.767***	(2.87)	1250	1.104***	(3.65)	-7.549***	(-3.90)
300	0.921***	(3.08)	8.160**	(2.12)	1300	1.122***	(3.64)	-6.218***	(-3.42)
350	1.018***	(3.38)	8.560**	(2.00)	1350	1.059***	(3.42)	-4.454***	(-2.66)
400	1.080***	(3.55)	4.226	(1.12)	1400	1.091***	(3.53)	-2.684*	(-1.70)
450	1.299***	(4.18)	0.044	(0.01)	1450	1.086***	(3.47)	-3.194**	(-2.20)
500	1.221***	(3.95)	3.476	(1.00)	1500	1.084***	(3.47)	-5.446***	(-3.92)
550	1.480***	(4.78)	3.908	(1.00)	1550	1.052***	(3.34)	-5.122***	(-4.22)
600	1.584***	(5.14)	-2.629	(-0.71)	1600	0.872***	(2.75)	-3.411***	(-2.92)
650	1.690***	(5.57)	-5.621	(-1.56)	1650	0.806***	(2.60)	-3.981***	(-3.66)
700	1.596***	(5.35)	-9.826***	(-3.16)	1700	0.805***	(2.59)	-3.883***	(-3.73)
750	1.583***	(5.26)	-7.146***	(-2.81)	1750	0.965***	(3.15)	-4.501***	(-4.47)
800	1.564***	(5.24)	-5.094**	(-2.12)	1800	0.979***	(3.19)	-3.812***	(-3.79)
850	1.412***	(4.62)	-5.617***	(-2.79)	1850	0.978***	(3.20)	-4.400***	(-4.37)
900	1.444***	(4.66)	-3.221*	(-1.78)	1900	1.086***	(3.58)	-5.333***	(-5.06)
950	1.439***	(4.68)	-2.939*	(-1.83)	1950	1.089***	(3.61)	-5.303***	(-4.96)
1000	1.351***	(4.31)	-4.379***	(-3.02)	2000	1.037***	(3.39)	-4.925***	(-4.50)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

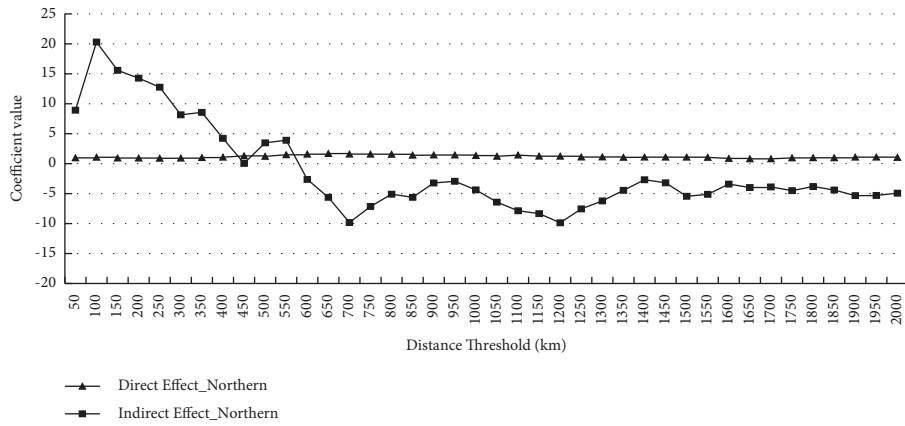


FIGURE 10: Spatial trends of the impact of the northern region's digital economy on urban innovation.

TABLE 14: Spatial spillover distance of the impact of the southern region's digital economy on urban innovation.

Distance threshold (km)	Direct effect		Indirect effect		Distance threshold (km)	Direct effect		Indirect effect	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic		Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
50	1.274***	(5.14)	3.240	(1.52)	1050	0.992***	(3.65)	-5.721*	(-1.87)
100	1.100***	(4.33)	7.123**	(2.30)	1100	0.985***	(3.59)	-5.860**	(-1.96)
150	1.140***	(4.46)	8.576**	(2.34)	1150	0.925***	(3.39)	-5.541**	(-2.06)
200	0.812***	(3.05)	11.568***	(3.66)	1200	0.999***	(3.64)	-7.213**	(-2.50)
250	0.884***	(3.30)	11.271***	(4.33)	1250	0.988***	(3.63)	-4.964**	(-2.20)
300	1.093***	(4.07)	16.043***	(4.37)	1300	0.933***	(3.42)	-3.392**	(-1.96)
350	1.135***	(4.19)	16.508***	(4.81)	1350	0.727***	(2.66)	-2.562**	(-2.15)
400	1.243***	(4.57)	20.724***	(5.82)	1400	0.862***	(3.16)	-1.698*	(-1.79)
450	1.275***	(4.62)	18.638***	(5.55)	1450	0.843***	(3.11)	-1.777**	(-2.15)
500	1.228***	(4.48)	12.721***	(4.37)	1500	0.793***	(2.91)	-0.949	(-1.49)
550	1.083***	(3.93)	6.174**	(2.23)	1550	0.870***	(3.23)	-0.964*	(-1.84)
600	1.103***	(4.11)	-2.619	(-0.86)	1600	0.884***	(3.27)	-1.009**	(-2.16)
650	1.234***	(4.62)	-5.272*	(-1.90)	1650	1.023***	(3.80)	-0.979**	(-2.23)
700	1.052***	(3.91)	-6.670**	(-2.35)	1700	0.957***	(3.54)	-0.904**	(-2.13)
750	0.871***	(3.27)	-7.546***	(-2.61)	1750	1.124***	(4.18)	-0.724*	(-1.83)
800	0.823***	(3.10)	-9.128***	(-2.94)	1800	1.119***	(4.11)	-1.201***	(-2.87)
850	0.716***	(2.68)	-10.419***	(-3.17)	1850	0.985***	(3.68)	-1.012**	(-2.38)
900	0.762***	(2.82)	-8.469**	(-2.51)	1900	1.077***	(4.03)	-1.274***	(-3.06)
950	0.832***	(3.05)	-7.889**	(-2.36)	1950	1.111***	(4.21)	-0.941**	(-2.18)
1000	0.944***	(3.47)	-4.970*	(-1.77)	2000	1.004***	(3.80)	-1.259***	(-3.21)

Note. ***, **, and * represent the significance level at the 1%, 5%, and 10% levels, respectively. The numbers in brackets are the test values *t*.

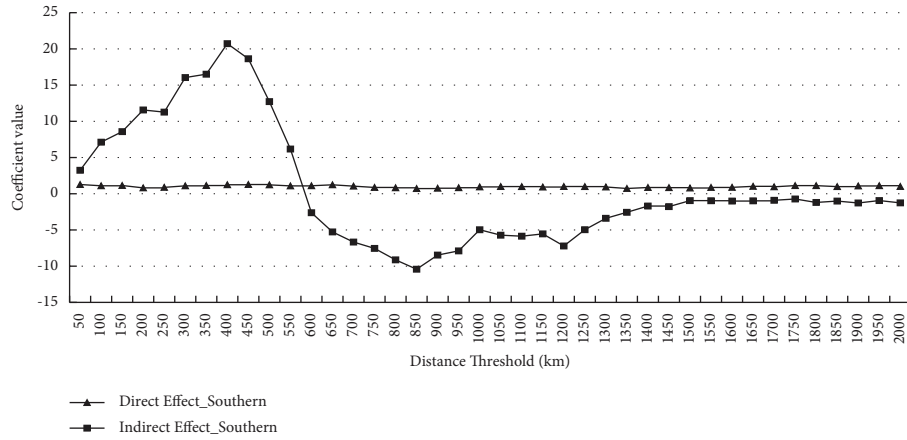


FIGURE 11: Spatial trends of the impact of the southern region's digital economy on urban innovation.

economy and an essential safeguard for propelling urban innovation to new heights and realizing innovation-driven development. In this context, we calculated the digital economy index and measured the level of urban innovation with patents per capita. Furthermore, we discussed the spatial implications and spillover effects of the digital economy on urban innovation from the spatial perspective and explored the mechanisms of the digital economy to influence urban innovation. We drew the following conclusions:

- (1) China's city-level digital economy and urban innovation see a significantly positive spatial correlation and the feature of spatial clustering, mainly presented as the H-H and L-L clusters, with pronounced

spatial differentiation. The level of the digital economy and urban innovation is higher in the western coastal regions of China, while the common cases in the central and western regions are the L-L cluster with a less developed digital economy and urban innovation.

- (2) The digital economy has a distinctly positive impact on urban innovation. The estimation results of spatial econometrics show that if the spatial effect is excluded, the impact of the digital economy on urban innovation will be overestimated. The spatial implications of the digital economy on urban innovation are reflected in the direct effects and indirect effects. The direct effects mean the development of

the digital economy will directly and considerably drive local urban innovation. The indirect effects mean the digital economy can not only directly boost the urban innovation in its region but imposes distinct spatial spillover effects that promote urban innovation of cities in peripheral regions. After addressing the endogeneity problem and conducting various robustness tests, the research conclusions remain robust and reliable.

- (3) The analysis of the mechanisms of the digital economy to influence urban innovation shows that the digital economy enhances local innovation capacity directly through promoting the concentration of human resources and increasing science and technology spending and drives the improvement of the innovation capacity in peripheral cities through the spatial spillover of human resources and science and technology spending. The effects of science and technology spending outweigh those of human resources. The policy effect in the central and western regions outperforms the eastern region, and the northern region outperforms the southern region. Regions with a relatively less developed digital economy and lower levels of urban innovation have the latecomer advantage.
- (4) The calculating results demonstrate that the digital economy may not always have a significantly positive spatial spillover on urban innovation. Within 500 kilometers, the digital economy's impact on other cities' innovation is primarily presented as positive spatial spillover effects. When it is beyond 500 kilometers, the negative siphon effect prevails. Regarding space, the spatial implications of the digital economy on urban innovation are characterized by the range of spatial spillover effects and the siphon effect. These two ranges are roughly divided by provincial boundaries. Therefore, we should explore the spatial differences of the impact and effects of the digital economy on urban innovation from the spatial perspective and in a comprehensive and objective way.

6.2. Policy Recommendations. With the research conclusions of this paper, we propose several policy recommendations for the future development of the digital economy and urban innovation, hoping to provide authorities with a reference for promoting the digital economy and boosting urban innovation.

Firstly, we should give due weight to the development of the digital economy and make substantial efforts to conduct digital infrastructure construction. Therefore, we should increase the investment in digital infrastructure construction, including but not limited to the investment and support for 5G technology, artificial intelligence (AI), industrial Internet, Internet of things, data centers, and cloud computing. We should improve the integration of digital technology into infrastructure construction, provide more convenient digital, information, and AI-enabled safeguards

for urban industrial upgrading and innovative and entrepreneurial activities, and drive urban innovation through the digital economy.

Secondly, we should pay adequate attention to the significance and urgency of innovative activities and continue to take urban innovation to the upper level. COVID-19 is continuing to spread around the world and dealing a severe blow to the global economy already marked by slow growth. In the future, the global economy will still be sluggish and even see the potential for a financial crisis. We should strengthen the efforts made to encourage and support innovative activities, offer incentives, such as tax incentives and government subsidies, to the innovative activities of enterprises and individuals, provide innovative activities and startups with the necessary financial support, and reduce the costs and risks of innovative activities and startups for all walks of life.

Thirdly, we should attach importance to human resources for the digital economy and urban innovation. Therefore, we should pay adequate attention to building a pipeline of talent, make more investments in all types of schools and research institutes, and encourage personal growth. Meanwhile, we should promote rational human mobility and mobilize human resources to move to less developed areas, such as the central and western regions. Governments should maximize the value of various human resources and encourage people to engage in activities to develop the digital economy and promote urban innovation.

Lastly, we should be fully aware of the differences of the digital economy and urban innovation among different regions and take actions to mitigate the spatial differentiation of the digital economy and urban innovation. It should raise concerns from governments at all levels, and efforts should be made to minimize the spatial mismatch of various resource factors. In particular, we should mobilize the flow of surplus factors of production from the eastern region to the central and western regions to relieve the shortage of factors of production and then achieve a better spatial match for resource factors, maximizing the spatial economic benefits.

Data Availability

The data used to support the findings of this study are available from the first and corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Research Article

Effects of Land Use/Cover Change on the Ecosystem Service Values in the Greater Bay Area of China Accounting for Spatiotemporal Complexity

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With the rapid development of the economy, the land use/cover change (LUCC) in the Greater Bay Area (GBA) has undergone tremendous changes, which have had directly negative effects on ecosystem functions and services. The development of sustainable land use strategies to quantitatively evaluate ecosystem services is required. Based on multitemporal land use data (2005, 2010, 2015, and 2020), the equivalent coefficients table method was used to assess the ecosystem service values (ESVs), and the impact of LUCC on ecosystem services was analyzed. A future land use simulation (FLUS) model and multiscenario simulations were employed to predict land use change in 2030. Our results indicated that the loss of ESVs decreased by 14.29 billion yuan from 2005 to 2020. The spatial distribution of the high-value ecosystem services was concentrated around the peripheral area of the northern regions in the GBA, and those areas had less land use development and human activity. Compared with those in 2020, the total ESVs of the business-as-usual (BAU) scenario, socioeconomic development (SED) scenario, and cultivated protection priority (CPP) scenario in 2030 decreased, while they increased in the ecological protection priority (EPP) scenario. In the CPP scenario, regulating, supporting, provisioning, and cultural services increased slightly, but they decreased in the other scenarios. The patterns of LUCC were the main reasons for the decrease in ESVs, such as the loss of land with high ecological value. Additionally, a four-quadrant analysis is introduced to determine which land use simulation will be expected to be adopted by the government. The findings of this study provide valuable information for decision-making and policy development in the coastal zones and for the sustainable management of ecosystems.

1. Introduction

With the rapid expansion of industrialization and urbanization, the population has grown to unprecedented levels, and natural resources are constantly being exploited [1], leading to the increasing encroachment of natural ecosystems in the last century. To counteract the increasing global pressure on ecosystems and improve the supply of natural resources [2, 3], the concept of ecosystem services (ESs) has been proposed, and research on ecosystem services has gained widespread attention [4, 5]. The term “natural services” was first used academically by Westman [6] to measure “How much are nature’s services worth?” and, simultaneously, the term “ecosystem services” was officially

introduced by Ehrlich and Mooney [7]. Two pioneering studies on ecosystem services and natural capital were published in 1997 [8, 9]. Since then, ecosystem services have sparked a discussion, and the evaluation of ESs has become a central issue in decision-making and land management [4].

Ecosystem services refer to the natural environmental conditions and functions that are formed and maintained by the ecosystem and developed for human survival. These services are the benefits obtained by human beings, directly or indirectly, from ecosystem functions [9, 10], and they are divided into four categories: provisioning, regulating, supporting, and cultural services [11, 12]. Seventeen types of ecosystem service coefficients for 16 biomes were first proposed by Costanza et al. [9, 13]. These new methods can

be applied for evaluating ecosystem service value (ESV), which is defined as the estimation of the marginal value of ecosystem services [14]; uncertainties in these coefficients have been studied [15]. In 2014, the evaluation of global ESVs was updated by Costanza et al. [10] based on the same methods applied in 1997. Since then, most scientific studies have referred to or improved Costanza's methods to estimate ESVs on different scales, such as the provincial scale, regional scale, national scale, and global scale [2, 16]. The Chinese ESV coefficient was revised by Xie et al. [12] to include 11 service types according to China's ecological characteristics. This classification is adopted in the present study, and the new revised coefficient is used to estimate the ESV that refers to local characteristics.

The sustainable development of the social economy depends on the sustainable supply of ecosystem services [17]. However, the world has faced environmental pollution and the increasing exploitation of ecosystems [18]. Some severer cases of ecosystem destruction associated with land use systems and different functions in specific areas have reached or exceeded the ecosystem carrying capacity and even become irreversible. Land use change/cover (LUCC) is a crucial way in which human activities affect ecosystems [5, 19]. LUCC alters the structure and function of ecosystems, and the supply of ecosystem products and services influences ecosystem patterns and processes [20, 21]. High-intensity human activities, including urban expansion and land development, have enhanced the LUCC process worldwide [22, 23], which has impacted ecosystems and exacerbated the loss of ESV. The ecological benefit losses greatly impacted ecosystem services and caused imbalances [19]. Because there are time lags between land use change and ecosystem responses [24], land use legacies affect ecosystem service provisions. Therefore, an understanding of the impact of LUCC on ecosystem service helps decision-makers to minimize the negative consequences of LUCC or to relieve the ecological pressure through targeted management measures. Analysis of the past dynamics of LUCC [25] can help researchers anticipate the potential effects in future land use simulations and reveal tradeoffs [2]. Consequently, research on the effect of LUCC on ecosystem services has attracted increasing attention [1].

The spatial distribution of ESVs in response to LUCC has been studied [26]. Huang et al. [27] used the InVEST model to analyze the impact of LUCC on ESV. The ESV loss caused by LUCC exhibited significant spatial heterogeneity due to the spatial difference in land use [28]. In recent decades, a series of land use simulation models with good accuracy have been developed, such as the logistic-CA [29] model, cellular automata-Markov (CA-Markov) model [30], conversion of land use and its effects at small regional extent (CLUE-S) model [31], and artificial neural network-cellular automata (ANN-CA) model [32]. Subsequently, the future land use simulation (FLUS) model based on the traditional CA model was developed by Liu et al. [33] and was shown to have higher simulation accuracy than other models. The FLUS model has become a major tool in ES research and can be implemented on various spatial scales and regions to analyze urban growth boundary simulation [17, 19, 34],

flood risk assessments [35], typical developed areas [5], mountain regions [36], and metropolitan regions [37]. Although socioeconomic and geographic conditions have been included as factors in the FLUS model [38], few studies have considered the background climate factor, which has significant effects on LUCC. The climate factor is therefore addressed in this study, and POIs are also selected.

The Greater Bay Area (GBA) is one of the major coastal areas in China and a crucial pivotal region connecting the development of the Belt and Road. The region has experienced complex land use changes due to rapid urbanization and the high-intensity development of human activities [39]. Therefore, it is a good case study for assessing the impacts of LUCC on ecosystem services over long periods for the following reasons. A large proportion of the population (<https://www.stats.gov.cn/>) greatly benefits from providing highly diverse ecosystem services typical of coastal regions. In addition, coastal ecosystems and their related ecosystem services are highly susceptible to LUCC and climate change. In this study, we focused on the GBA. The main objectives of this study were to assess the ESVs, predict the future distribution of LUCC using multiscenario simulation analysis based on the FLUS model, and estimate the variations in ESV resulting from the impacts of LUCC in the GBA.

The innovations of this study are as follows. First, we used a future land use simulation model to evaluate the ESVs. The advantages are that the FLUS model can process the complex competition and interactions among the different land use types. Second, we focused on assessing the effect of social and economic factors, but climate, facilities, and other environmental factors in land use prediction were also considered. Finally, we developed a four-quadrant analysis to determine which land use simulation is expected to be adopted by the government and, thus, provide scientific decision-making support for sustainable land use and ecosystem management in the GBA.

2. Materials and Methods

2.1. Study Area. The GBA is located at 111°12'E to 115°35'E and 21°25'N to 24°30'N (Figure 1). The GBA lies in the fragile and complicated ecological environment of the southeast coastal region in China. It extends over an area of 56000 km² with various topographies, such as mountains (low mountains and hills), plains (alluvial plain and delta plain), and islands. The GBA has a subtropical monsoon climate with an annual average temperature of approximately 21.4–22.4°C, an annual average precipitation of 1808 mm, and an annual average sunshine hours of 2000 h (<https://data.cma.cn/>).

The GBA is composed of nine prefecture-level cities of Guangdong Province and the two special administrative regions (Hong Kong and Macao) in the Pearl River Delta Region. Like other coastal regions, the GBA is an important economic zone, with a relatively concentrated population totaling 86.40 million people and increasingly concentrated industries, with a total GDP of 11.3 trillion yuan in 2020 (<https://www.stats.gov.cn/>).

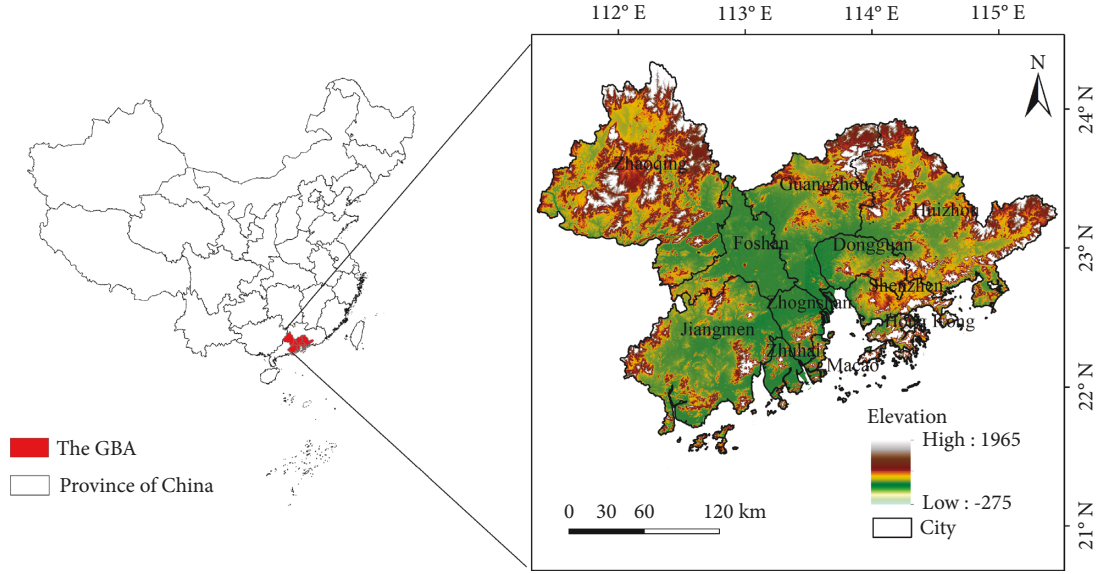


FIGURE 1: Location of the Greater Bay Area.

TABLE 1: Data sources in this study.

Data aspect	Data content	Data declaration
Terrain	DEM	Raster (12.5 m grid)
	Aspect	
	Slope	
Soil	Soil type	Sand content, silt content, and clay content
Climate	Annual average temperature	2006–2015
	Annual average precipitation	
	Potential crop	
Environmental factors	NDVI	—
	Ecological protection	Ecosystem protection region
Social economy	GDP	Raster (1 km grid)
	Population	
	Town	
	Residential	Vector (shapefile format)
	Railway	
	Traffic	
Facilities	Water	Public and other facilities
	POI	

With the rapid development of urbanization and industrialization around the GBA, increasingly frequent human activities, rapid urban sprawl, and gradually increasing regional inequality, land use has changed significantly and led to excessive development and utilization activities [5, 39]. At the same time, the ecological environment has been put under increasing pressure, resulting in continuous declines in the ecosystem service functions. Thus, it is necessary to assess changes in ESVs and simulate ESVs in response to LUCC in the future.

2.2. Data Sources and Land Classification. We collected historical land use data (2005, 2010, 2015, and 2020) and driving factor data (Table 1), which were obtained from the Resources and Environment Science and Data Center, Chinese Academy of Sciences (30 m resolution) ([https://](https://www.resdc.cn/)

www.resdc.cn/). The land use data were used for LUCC multiscenario simulation analysis and ESV assessment. In this study, wetlands were listed separately [40], so that the types of LUCC were reclassified into seven categories: farmland, forestland, grassland, water body, wetland, built-up land, and unused land (Table 2). The dynamic information (Table 3) on land use over a 15-year period was calculated using ArcGIS software. Then, we obtained a transition matrix that represented the quantitative transition between different land use types.

According to the results of previous research and considering the availability of data [17, 19], the spatial driving factor dataset for LUCC multiscenario simulations was selected, as shown in Table 1. The digital elevation model (DEM), with a 12.5-meter resolution, served as the basis for data on terrain heights and the calculation of slopes and aspects. Data on the soil characteristics (e.g., clay content, silt

TABLE 2: Classification of land use in the GBA.

Category	Category definition
Farmland	This includes paddy field and nonirrigated farmland
Forestland	This includes organic forest, shrubbery, thin stocked land and others woodland
Grassland	This includes three coverage types: high, medium, and low
Water body	This includes natural and artificial rivers, fishery reservoirs, and lakes
Wetland	This includes marshland and shallows
Built-up land	This includes urban land residential land, rural residential land and other built-up land
Unused land	This includes sand, saline and barren lands, others

TABLE 3: Land use/cover patterns in the GBA.

LUCC	Area (km ²)				Proportion (%)				Area change (km ²)			
	2005	2010	2015	2020	2005	2010	2015	2020	2005–2010	2010–2015	2015–2020	2005–2020
Farmland	13349.45	12817.85	12563.53	12253.22	23.84	22.89	22.43	21.88	−531.61	−254.32	−310.31	−1096.23
Forestland	30721.53	30460.74	30153.78	30073.14	54.86	54.39	53.85	53.7	−260.79	−306.96	−80.65	−648.4
Grassland	1162.94	1116.6	1256.1	1201.18	2.08	1.99	2.24	2.14	−46.34	139.5	−54.92	38.24
Water body	4105.64	4006.98	3901.23	3954.59	7.33	7.16	6.97	7.06	−98.66	−105.74	53.35	−151.05
Wetland	150.97	119.74	122.42	98.38	0.27	0.21	0.22	0.18	−31.23	2.68	−24.04	−52.59
Built-up land	6491.95	7467.6	7993.56	8413.55	11.59	13.34	14.27	15.02	975.66	525.95	420	1921.61
Unused land	17.53	10.5	9.38	5.94	0.03	0.02	0.02	0.01	−7.03	−1.12	−3.44	−11.58

content, and sand content), temperature, precipitation, gross domestic product (GDP), and population were provided by the Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences. Socioeconomic data, including town data, residential data, railway data, traffic data, water system data, and facilities data (POI), were collected from open-source data retrieved from OpenStreetMap (OSM). A unified coordinate transformation was performed with ArcGIS. Socioeconomic data and facility data were calculated by Euclidean distance analysis. The spatial reference of the WGS_1984 coordinate system was constructed for matching land use data and driving factor data.

Statistical datasets on ecosystem services, including grain output per unit area and total sown area of farm crops, were obtained from the National Bureau of Statistics, China Statistical Yearbook, Guangdong Statistical Yearbook, and the statistical yearbooks of various cities in the GBA. In addition, some policy documents were obtained from government reports for the GBA.

2.3. Ecosystem Service Valuation. The equivalent coefficients table method, which is one of three main ESV evaluation methods [41], is more intuitive and suitable for the assessment of ESVs because it has fewer data requirements on the regional and global scales. The values per unit area of ecosystem service in this study were revised in reference to previous studies [42] based on the method of regional corrections on cropland. The formula is defined as follows:

$$\theta = \frac{Q}{Q_0}, \quad (1)$$

$$E_i = \theta \times E_{i0},$$

where θ is the revision factor. Q and Q_0 are the annual average food production of cropland in the GBA and China, respectively. E_i represents the revision equivalent factor for land use type i , while E_{i0} represents the standard equivalent factor which is quoted in Xie et al.[12] for land use type i of farmland, forestland, grassland, water body, wetland, built-up land, and unused land.

Because the food production function of cropland determined the equivalent ESV coefficient, the economic value of the average natural food production of cropland per hectare per year was a critical indicator. Generally, natural food production is equal to 1/7 of the actual food production [43]. We calculated the annual average food production of cropland in the GBA and China in 2020 and obtained values of approximately 5500 kg/hm² and 5600 kg/hm², respectively, and then determined the standard equivalent factor. Based on the average net profit per unit area of the major foods (rice and soybeans), the average ESV of one equivalent value for the GBA was 2215.61 RMB yuan hm^{−2}·yr^{−1}. The unit area values of some land use/cover types were calculated based on this equivalent coefficients' table, in which the service value coefficient of built-up land was given as 0 [19]. Thus, the value tables of the ecosystem services per unit area of different land use types were obtained (Table 4). The ESV, including each land use type per hectare, was calculated, based on the following equations:

$$\begin{aligned} ESV_i &= \sum_i A_i \times V_{ij}, \\ ESV_j &= \sum_j A_i \times V_{ij}, \\ ESV &= \sum_i \sum_j A_i \times V_{ij}, \end{aligned} \quad (2)$$

TABLE 4: Ecosystem service value per unit area for different land use/cover types in the GBA (yuan/hm²).

Primary classification	Secondary classification	Farmland	Forestland	Grassland	Water body	Wetland	Unused land
Provisioning services	Food supply	2952.96	1780.47	1519.91	1737.04	1107.36	0.00
	Raw material supply	195.42	4103.76	2236.44	499.40	1085.65	0.00
	Water supply	-5710.51	2127.87	1237.64	18000.06	5623.67	0.00
Regulating services	Air quality regulation	2410.14	13505.47	7860.10	1671.90	4125.47	43.43
	Climate regulation	1237.64	40386.13	20779.32	4972.27	7816.67	0.00
	Waste treatment	369.12	11746.72	6861.30	12050.70	7816.67	217.13
	Regulation of water flows	5905.93	25165.35	15220.80	221993.49	52610.54	65.14
Supporting services	Maintenance of soil	21.71	16436.73	9575.42	2019.31	5015.70	43.43
	Maintenance of nutrient cycle	412.55	1259.36	738.25	151.99	390.83	0.00
	Biodiversity conservation	455.98	14960.24	8706.91	5536.81	17088.11	43.43
Cultural services	Aesthetic inspiration	195.42	6557.32	3843.20	4103.76	10270.24	21.71

where ESV_i , ESV_j , and ESV refer to the ESV of the type i ecosystems, the ability category of ESV_j , and the total ESV , respectively. A_i is the area (in hm²) of the type i ecosystem, and V_{ij} (yuan/hm²) denotes the value coefficient for land use type i and ecosystem service function type j .

2.4. Spatial Simulation of Land Use Change. LUCC simulation models are effective and reproducible tools for analyzing the causes and consequences of land use patterns assuming various scenarios [33]. The FLUS model was first applied to simulated LUCC in mainland China from 2000 to 2010 [33]. The FLUS model was developed by introducing a self-adaptive inertia and competition mechanism into the cellular automata (CA) model to predict land use changes [33, 44]; the Markov chain (MC) approach was adopted to predict the scale of land use and multilayer artificial neural networks (ANNs) were used to estimate the probability of occurrence of different land use types. In this study, we used GeoSOS-FLUS software to develop both a geographic simulation and optimization system (GeoSOS) and a FLUS model. GeoSOS-FLUS software is a powerful tool to predict multiple LUCC scenarios by coupling human and natural effects. It can be used to make LUCC simulations more convenient and efficient [36]. It is important for decision-makers to predict future land use changes and dynamic LUCCs for multiscenario simulations. The general structure of the FLUS model is illustrated in Figure 2.

2.4.1. Prediction Type of Land Use. The pixel's future type was predicted using the Markov chain model. The transfer probability matrix of land use types [45] was computed from the previous state at time t to the land use state at time $t + 1$ [46]. In this study, ten years was selected as the initial forecast unit to obtain the land use change, and the land use type in 2020 was predicted. The Kappa coefficient and figure of merit (FOM) were used to evaluate modeling accuracy to better compare our simulation results in 2020 with those of previous studies in 2020. Then, the land use type in 2030 was predicted by inputting historical data into the FLUS model. We also predicted multiscenario simulations in 2030. The model stopped outputting the results when it achieved the

iteration target; otherwise, the land use demand was not met, and the model iterated 300 times in the forecast year.

2.4.2. Land Use Change Simulation Using Cellular Automata (CA). The CA simulation was implemented in two steps. Step 1: an artificial neural network (ANN) is used to train and estimate the probability of occurrence of each specific pixel of land use types. Step 2: a reliable self-adaptive inertia and competition mechanism is designed to identify the competition and interactions among different land use types. The change in land use type was obtained through the high transformation of the probability of occurrence during the CA iteration; for example, a specific pixel either retains the current land use type or is transferred into another land use type. A schematic framework of the CA model is presented in Figure 2.

Artificial neural networks are typically used to capture the nonlinear relationship between factors that are dependent on independent variables. It fits the complicated relationships between input data and predicted targets through a number of learning-recall iterations [47] and is widely used in studies of land use change. In this study, DEM, aspect, slope, soil type, temperature, precipitation, potential crop, NDVI, ecological protection, GDP, population, distance to town, distance to residential area, distance to railway, distance to traffic, distance to water, and POI were selected as potential driving factors of LUCC (Table 1). The land use transfer matrix was determined, and the probability of occurrence of land use types was estimated. The expected output and the current output were compared by randomly selecting the primary weights [48] and then predicting the futures land use type. In general, an ANN is composed of three layers: an input layer, a hidden layer, and an output layer network. Its formula is as follows:

$$\begin{aligned}
 sg(p, t, k) &= \sum_n W_{n,k} \times \text{sigmoid}(\text{net}_n(p, t)) \\
 &= \sum_n W_{n,k} \times \frac{1}{1 + e^{-\text{net}_n(p, t)}},
 \end{aligned} \tag{3}$$

where $sg(p, t, k)$ is the probability of pixel conversion from the original land use type to the target land use type k at

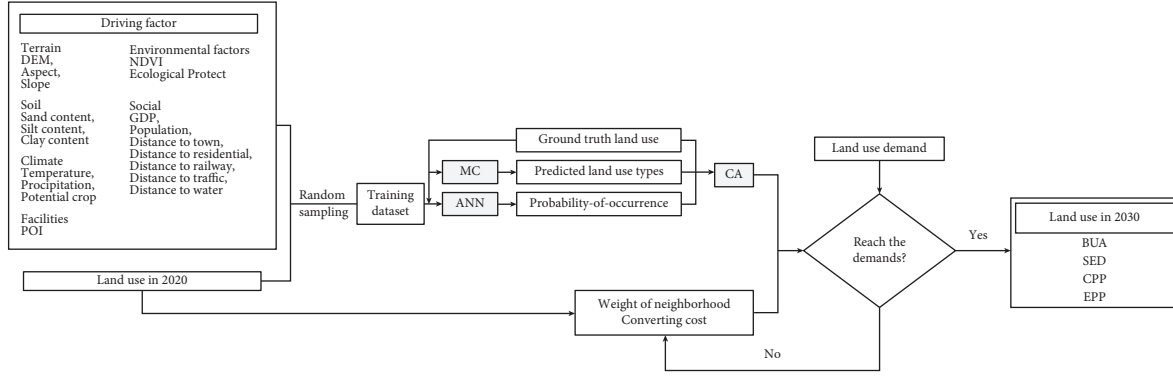


FIGURE 2: Schematic framework of future land use simulation.

iteration time t ; $W_{n,k}$ is an adaptive weight between the input layer and the hidden layer; sigmoid is the excitation function from the hidden layer to the output layer; and $net_n(p, t)$ is the signal received by in the hidden layer n from the pixel p at time t .

The ANN model was developed to establish the relationship between the probability of occurrence surface for a specific land use type and the given spatial factors [33]. Whether the pixels of land use type are converted to a specific land use type not only is consistent with the probability of occurrence but also is related to other variable components accounting for different development statuses over the prediction period. Therefore, the probability of occurrence is combined with the conversion cost, neighborhood condition, and the competition and interactions of different land use types to estimate the combined probability for each land use pixel.

2.4.3. Multiscenario Land Use Prediction. The CA model determines the pixel land use type according to the pixel s previous state at a microscale, the neighbor pixel state, and the land use transfer rules [17]. The neighborhood weight value in CA describes the neighbor interaction between different land use types [17, 49]. In this study, a 3×3 Moore neighborhood model was adopted, and the weight of the neighborhood of each land use type ranged from 0 to 1; the larger the weight is, the stronger the expansion ability of the land use type is [46]. The conversion cost is defined as the difficulty of converting from the current land use type to another land use type. The conversion cost values are in a binary matrix consisting of zeros and ones, where zero means that the transfer of the land use from the row to the column type is not allowed, while one means that the transfer is allowed [34].

With the LUCC characteristics and the current situation of social and economic development in the GBA, we considered four scenarios: business-as-usual (BAU), socioeconomic development (SED), cultivated protection priority (CPP), and ecological protection priority (EPP). The four scenarios on the land use transfer matrix in 2030 were calculated according to the transfer probability matrix of land use types from 2010 to 2020. GeoSOS-FLUS software was used to calculate the land use adaptability probability

based on the land use data and driving factors of LUCC (e.g., DEM, aspect, slope, soil type, temperature, precipitation, potential crop, NDVI, ecological protection, GDP, population, distance to town, distance to residential area, distance to railway, distance to traffic, distance to water, and POI). Then, the spatial distribution data of LUCC for the BAU, SED, CPP, and EPP scenarios were obtained.

3. Results

3.1. Changes in Land Use/Cover

3.1.1. Temporal Analysis of LUCC. The proportion of land use/cover types is as shown in Table 3. Forestland was the predominant land use type in the GBA in 2005, 2010, 2015, and 2020, accounting for 54.86%, 54.39%, 53.85%, and 53.70%, respectively, and its proportion exhibited a continuous decline. Farmland accounted for 23.84%, 22.89%, 22.43%, and 21.88%, respectively, and these types also appeared to undergo a sustained slow decline in 2005, 2010, 2015, and 2020. The water area declined continuously. Moreover, the proportion of built-up land exhibited a continuously increasing trend, accounting for 11.59%, 13.34%, 14.27%, and 15.02%, respectively. Grassland and wetland tended to fluctuate from 2005 to 2020, initially decreasing, then increasing, and finally decreasing. The proportion of unused land was the smallest, and it decreased, accounting for only less than 0.03% of the GBA.

From 2005 to 2020, built-up land exhibited the largest change in the GBA, with a total net area increase of 1921.61 km² (Table 3). The net area changes in farmland and forestland were larger, followed by those of water area and wetland. Finally, the change in net area of unused land was the smallest. The area of land use/cover types showed varying characteristics during different phases. From 2005 to 2010, the areas of farmland and forestland declined significantly, with decreases of 531.61 km² and 260.79 km², respectively, while built-up land had the most significant increase (957.66 km²). From 2010 to 2015, the forestland area showed the greatest decreases (306.96 km²). The area decrease of farmland and water areas was 254.32 km² and 105.74 km², respectively. The area of grassland increased (139.50 km²) and that of wetland slightly increased (2.68 km²). Built-up land exhibited a continuously

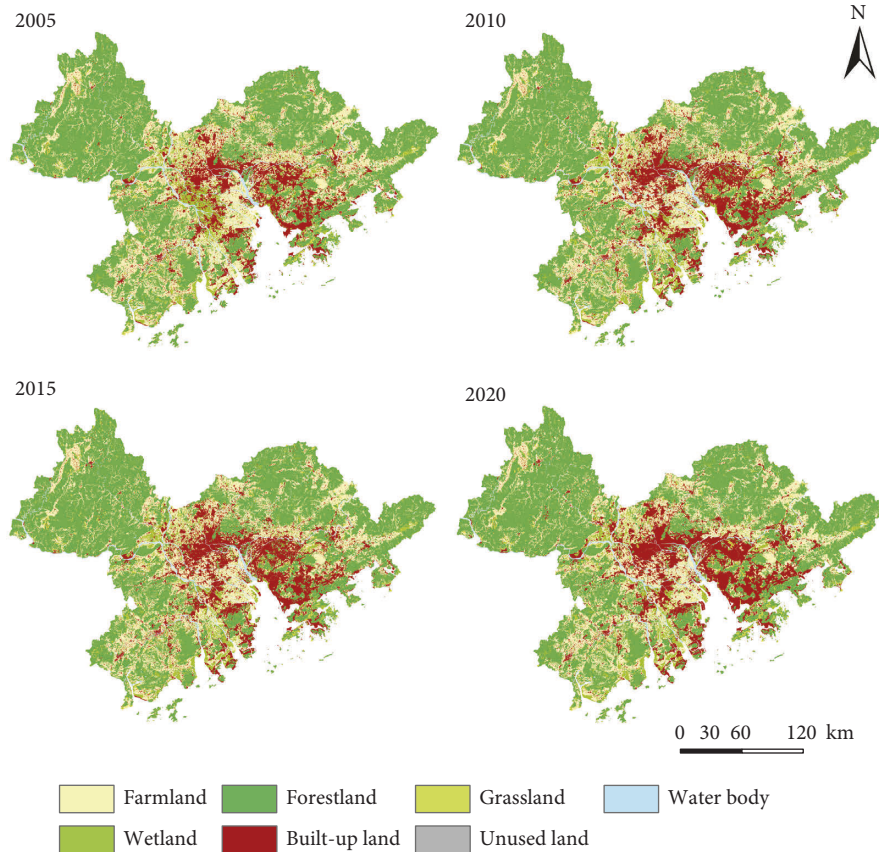


FIGURE 3: Spatial distribution of land use/cover types in the GBA.

increasing trend, with an area of 525.95 km². From 2015 to 2020, the area of farmland decreased the most, followed by that of forestland, grassland, and wetland, while the water area increased.

The change rates of the land use/cover types showed varying characteristics during different periods (Table 3). In 2005–2020, farmland, forestland, and water area showed stages of slow decline, while unused land and wetland decreased more rapidly, accounting for 66.10% and 34.84%, respectively. However, built-up land increased the fastest (29.60%).

3.1.2. Spatial Patterns of Land Use/Cover Change. The spatial distribution of land use/cover types in the GBA is shown in Figure 3. The primary land use types were forestland and farmland in the GBA. Forestland was mainly distributed in the western, northwestern, and eastern regions. Farmland was found in the central, southwestern, and eastern regions, including Guangdong, Foshan, Zhongshan, Jiangmen, and Huizhou. Built-up land was concentrated in the central region, which had a high level of urbanization, such as Guangdong, Shenzhen, Hong Kong, and Macao. Grassland was scattered throughout the GBA. Water areas were mainly distributed in the northern region of the GBA.

3.1.3. Transformation Patterns of LUCC. The total conversion area of land use/cover types occurring in the GBA from

2005 to 2020 reached 6242.17 km². The transformed land use types were mainly farmland, forestland, water area, and built-up land, which accounted for 39.78%, 21.69%, 18.67%, and 15.36% of the total transformed area, respectively. These land use types were mainly converted into built-up land, farmland, forestland, and water area.

To illustrate where the main conversion of land use occurred between 2005 and 2020, Figure 4 shows the spatial distribution of the main land use changes. Built-up land showed a significant increase of 45.00% and mainly occupied farmland and forestland, with area increases of 1502.2 km² and 723.07 km², respectively. Farmland declined by 2483.32 km², and this area was mainly converted into built-up land, water area, and forestland. The water area was mainly changed into farmland and built-up land, with areas of 553.41 km² and 492.31 km², respectively. A small amount of wetland and grassland was transformed and converted to forestland, built-up land, and farmland. The proportion of unused land was the lowest and it was mainly transformed into wetland and forestland. Finally, the transformations of land use/cover types were caused by human activities, one of the most significant driving factors.

3.2. Changes in Ecosystem Service Values

3.2.1. Temporal Analysis of Ecosystem Service Values. With the high-quality development of industrialization and urbanization in the GBA, constructed land is constantly

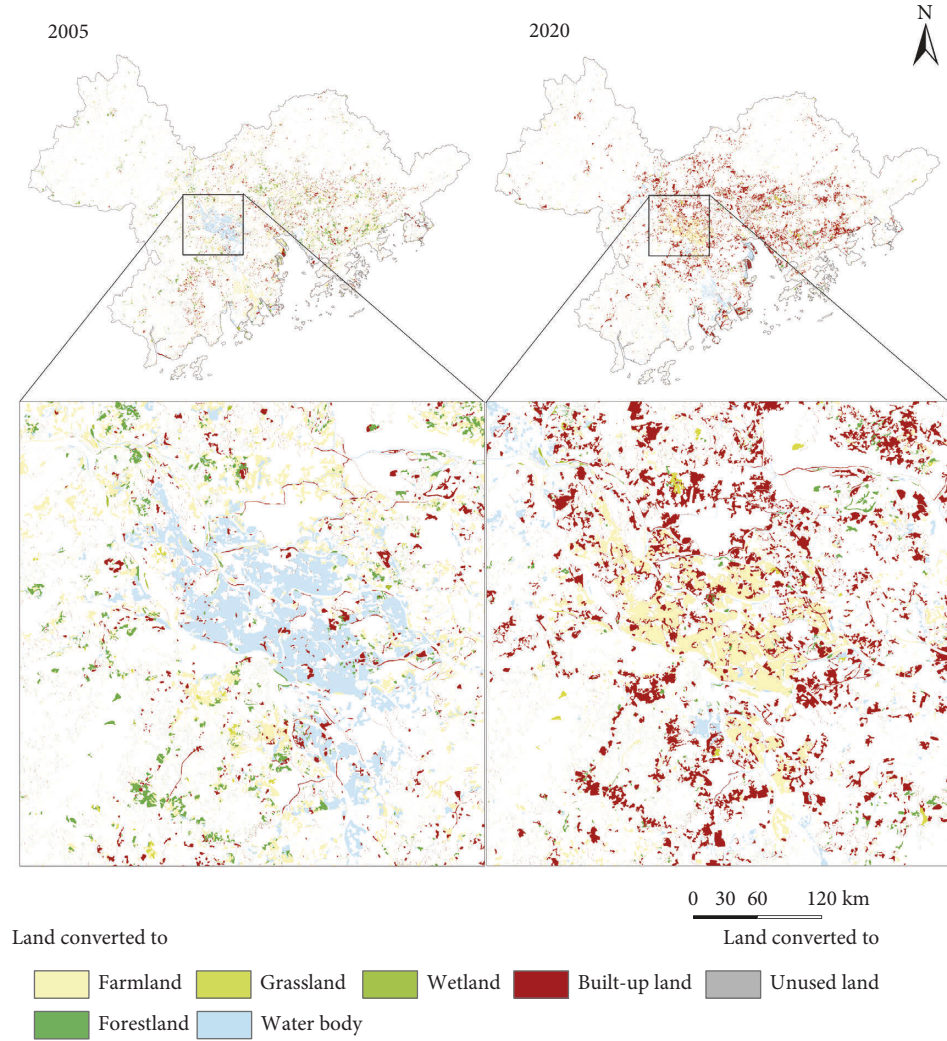


FIGURE 4: Distribution of the conversion of land use/cover types in the GBA.

TABLE 5: Changes in the ecosystem service value of different land use/cover types in 2005, 2010, 2015, and 2020 (10^8 RMB yuan, %).

LUCC	Farmland	Forestland	Grassland	Water body	Wetland	Unused land	Total
2005	112.75 2.02	4240.47 75.97	91.38 1.64	1119.76 20.06	17.05 0.31	0.01 0.00	5581.43
2010	108.26 1.97	4204.48 76.35	87.74 1.59	1092.85 19.85	13.52 0.25	0.00 0.00	5506.86
2015	106.12 1.95	4162.11 76.44	98.70 1.81	1064.01 19.54	13.83 0.25	0.00 0.00	5444.77
2020	103.50 1.90	4150.98 76.33	94.39 1.74	1078.56 19.83	11.11 0.20	0.00 0.00	5438.54

expanding in urban and rural regions, and the expansion of construction related to urbanization, industry, and transportation has resulted in the occupation of forestland, water area, and farmland, representing the primary drivers of the reductions in ESVs. The value of the ecosystem services in the GBA in 2005, 2010, 2015, and 2020 is shown in Table 5 and Figure 4. The total ESVs were approximately 558.14 billion yuan in 2005, 550.69 billion yuan in 2010, 544.48

billion yuan in 2015, and 543.85 billion yuan in 2020, exhibiting a trend of continuous decline. The value of the ecosystem services provided by different land types was different. Forestland contributed the most, accounting for more than 75% of the total ESV, followed by water area, which accounted for approximately 20%. Among land use/cover types, the ESV losses of forestland and water area were significant, with decreases of 8.95 billion yuan and 4.12

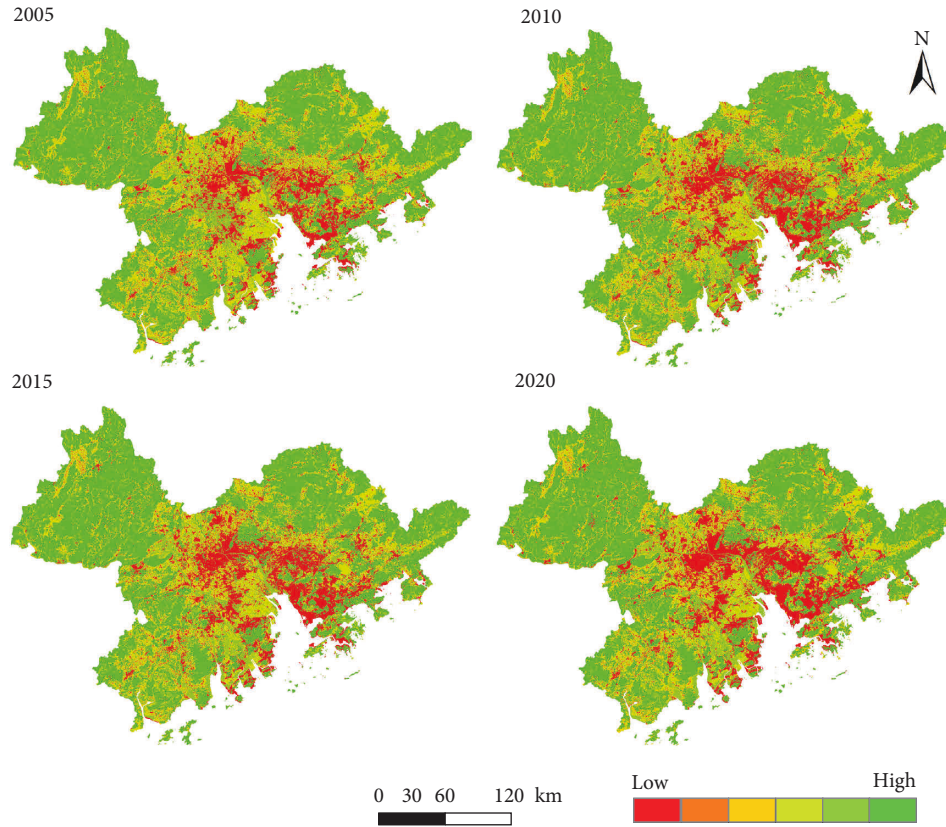


FIGURE 5: Spatial change in the distribution of ESV in the GBA in 2005, 2010, 2015, and 2020.

billion yuan, respectively, followed by those of farmland and wetland, which decreased by 92.60 million yuan and 59.40 million yuan, respectively. The ESV loss of unused land was the lowest, with a decreasing value of 0.05 million yuan. In contrast, the ESV of grassland increased by 30.05 million yuan, accounting for less than 2% of the total ESV.

3.2.2. Spatial Changes in Ecosystem Service Values. Figure 5 also shows the spatial distribution of the ESV change. The high-value areas of ecosystem services were concentrated in almost every peripheral of the northern regions in the GBA; those areas had less land use development and human activity and were mainly located in Zhaoqing, Huizhou, and Jiangmen. Conversely, the low-value areas of ecosystem services were distributed in the central regions of the GBA, including Guangdong, Dongguan, Zhongshan, Hong Kong, and Macao; those areas were subjected to intense human activity and frequent land use change, especially the expansion of constructed land.

To determine which type of land transition that had a major effect on the total ESV change, we produced a transition matrix of ESV change between 2005 and 2020. The increasing and decreasing changes in ESV are shown in Figure 6, and, in general, the loss of ESVs was greater than the increasing value of ecological services. The areas of decreased ESVs were distributed throughout the entire GBA, and the greatest losses were distributed in Foshan city, while

the areas of increased ESVs were scattered in the central region of the GBA, such as Zhuhai city.

3.2.3. Changes in Different Ecosystem Service Values. From 2005 to 2020, the regulating services contributed the most, accounting for the highest proportion (>70%) of ecosystem services. They were followed by supporting services, accounting for approximately 20%, while provisioning services and cultural services accounted for the lowest proportion of the total ESV, approximately 10%.

Regulating services, supporting services, and cultural services showed a continuous declining trend, while provisioning services showed first a minor decrease and then a slight increase, as shown in Figure 6. From 2005 to 2020, the primary ecosystem service types, including regulating services, supporting services, provisioning services, and cultural services, experienced ESV losses of 10.80 billion yuan, 2.38 billion yuan, 56.60 million yuan, and 54.80 million yuan, respectively.

In terms of the ecosystem service subtypes, the regulation of water flows contributed most to the total ESV, followed by climate regulation, maintenance of soil, biodiversity conservation, air quality regulation, waste treatment, and aesthetic inspiration. In contrast, maintenance of the nutrient cycle contributed the least. The ESV of the water supply exhibited an increasing-decreasing-increasing trend. The regulation of water flows experienced an

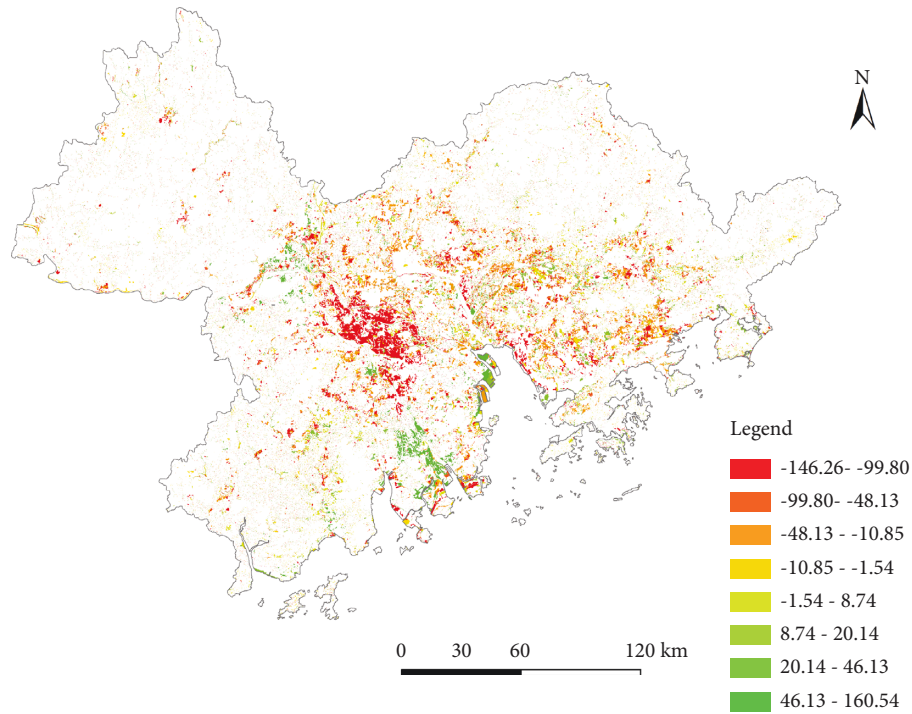


FIGURE 6: Spatial distribution of the ESV change caused by land use transition from 2005 to 2020. Positive numbers in the legend indicate increased ESVs and negative numbers indicate decreased ESVs.

initial decrease and then increase. The ESVs of all other ecosystem service subtypes decreased during all periods (Figure 7).

3.3. Future Changes in LUCC and EVS

3.3.1. LUCC in 2030. The ROC results are shown in Table S1. The ROC values were larger than 0.74, indicating that there was a good fit for each land type. Furthermore, the Kappa coefficient and the overall accuracy of land use simulation under the BAU scenario were 88.29% and 92.58%, respectively, which were used to assess the accuracy of the simulation results by comparing the differences between ground-truth land use and simulated land use in 2020. The FOM was 0.2535, which is a high accuracy value. In this study, multiscenario simulations of land use were carried out, including BAU, SED, CPP, and EPP (Figure 8). The results showed that the change in land use types was consistent with the spatial regional distribution (e.g., the distribution of built-up land) without any large deviation in spatial location, but there were differences in local areas. Compared with 2020, the change area of each land use type was considerable in 2030, and the degree of overall land use fragmentation was more significant.

To identify the main conversion types, we extracted the transformation of land use types from 2020 to 2030 from the land transfer matrix based on the BAU, CPP, SED, and EPP scenarios (Table 6, Tables S2–S5). The results showed that most of land use types underwent conversion, including farmland, built-up land, forestland, and water area.

In the BAU scenario, the areas of built-up land and grassland were 484.33 km² and 80.75 km², respectively, while the areas of farmland, water area, and forestland were 451.46 km², 66.02 km², and 48.50 km², respectively. The increase in built-up land was mostly due to the occupation of farmland, and the change in land use was consistent with that represented in the land transfer matrix; therefore, built-up land increased sharply by 60.62%, while the farmland declined by 70.37%. Under the SED scenario, to continuously meet rapid economic and social development, the demand for land increased. There was a rapid development of urban sprawl, which expanded from the periphery of the original urban boundary, and built-up land significantly increased (total area 459.40 km²), while the area of grassland increased only slightly. However, the forestland rapidly decreased (361.71 km²) followed by decreases in water area, farmland, and wetland and a slight decline in unused land. The expansion of built-up land resulted from the conversion of forestland, farmland, and water area, and these results were consistent with the land transfer matrix. In the CPP scenario, farmland played an important role in maintaining national food security. Within the framework of the national security system, the goal is to control the least cultivated areas and protect the basic farmland preservation area. The area of farmland increased the most (64.58 km²) and that of built-up land increased only slightly (29.37 km²). Forestland decreased the most, with a total area of 154.08 km². Forestland was converted to expand farmland, and grassland was converted to urban construction in the land use transfer matrix. In the EPP scenario, there was less pressure on

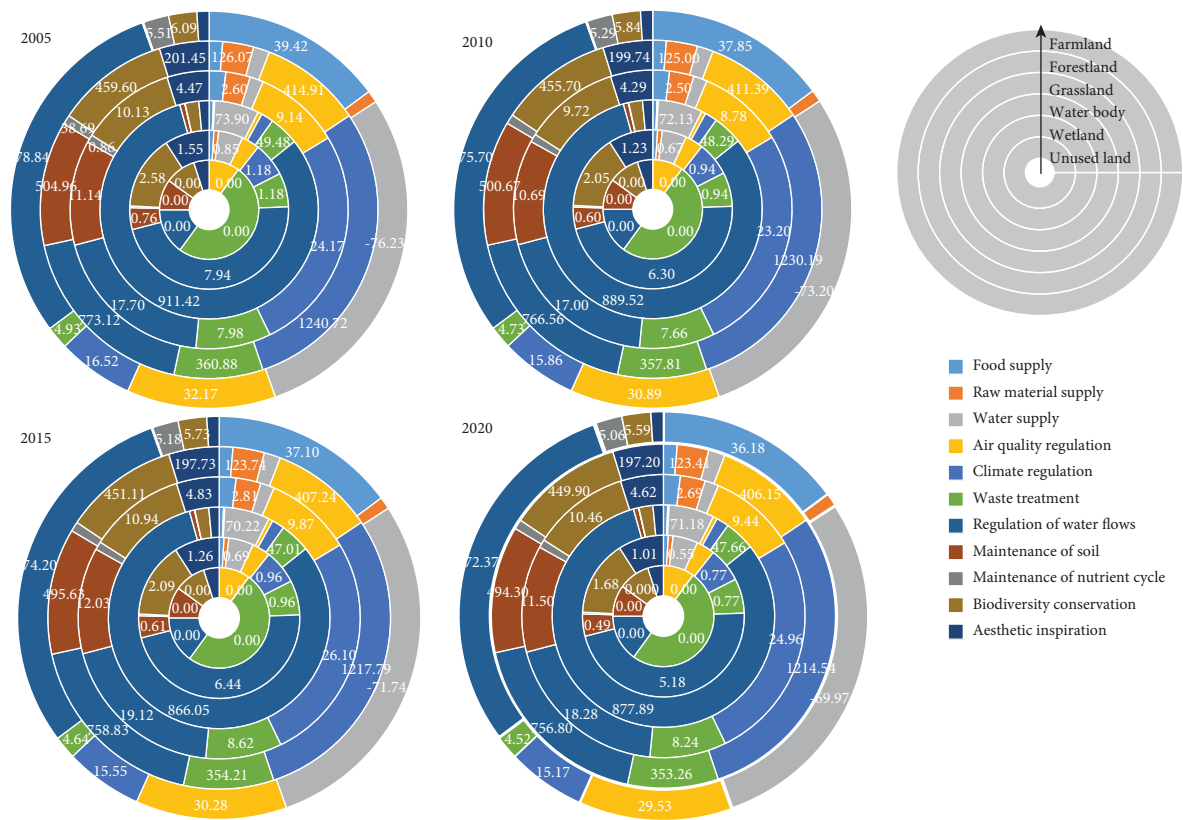


FIGURE 7: Ecosystem service subtype values of different of land uses in the GBA.

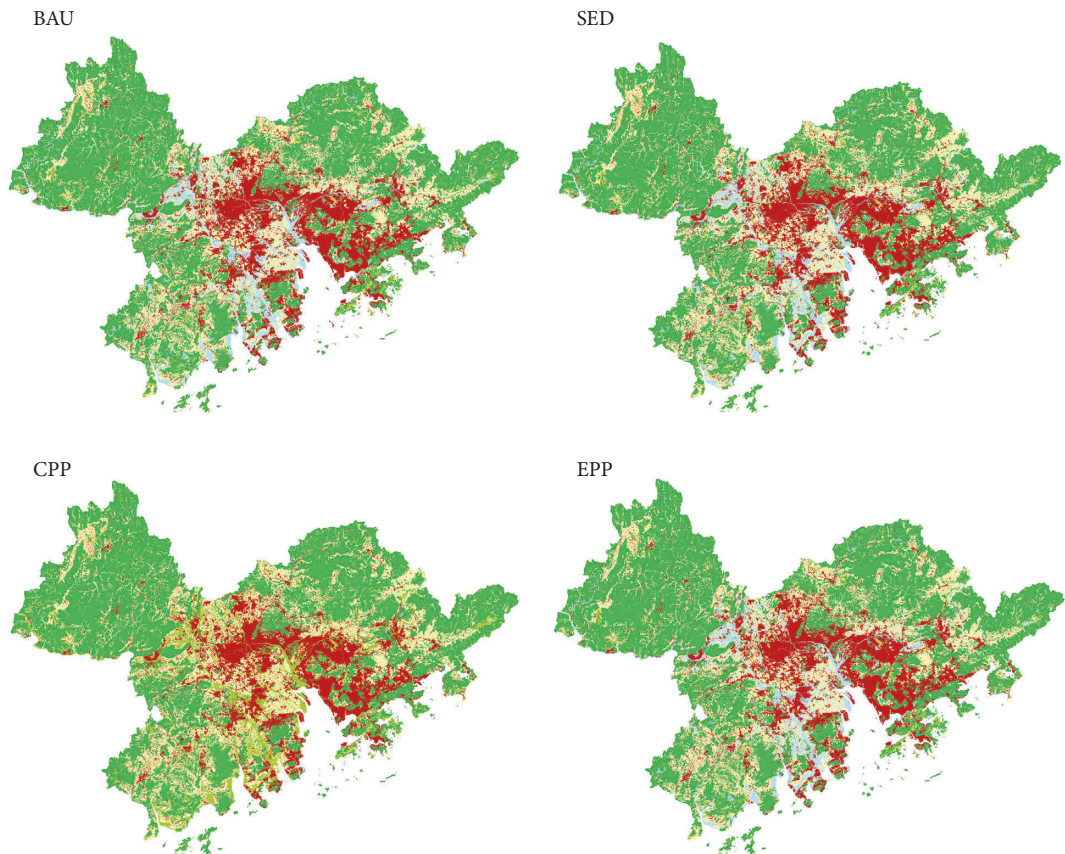


FIGURE 8: Spatial distribution of land use/cover types in the GBA under different scenarios.

TABLE 6: LUCC in the GBA in different scenarios.

	BAU	CPP	SED	EPP	2020
Farmland	11798.50	12314.54	12228.77	11798.54	12253.22
Forestland	30026.00	29920.41	29712.78	30121.59	30073.14
Grassland	1281.54	1281.53	1204.59	1220.50	1201.18
Water body	3889.25	3940.15	3889.25	3989.79	3954.59
Wetland	99.29	95.25	85.17	101.07	98.38
Built-up land	8899.48	8444.52	8874.55	8764.92	8413.55
Unused land	5.95	3.60	4.89	3.60	5.94

TABLE 7: ESVs of the GBA in 2030 based on different scenarios (10^8 yuan).

Primary classification	Secondary classification	BAU	SED	CPP	EPP	2020
Provisioning services	Food supply	97.11	97.69	98.53	97.37	98.53
	Raw material supply	130.44	129.05	130.13	130.75	130.58
	Water supply	68.67	65.37	66.39	70.61	67.24
Regulating services	Air quality regulation	450.94	447.08	450.82	451.92	452.14
	Climate regulation	1273.98	1260.15	1270.58	1277.09	1275.09
	Waste treatment	413.50	409.34	413.03	415.43	414.45
	Regulation of water flows	1713.41	1706.16	1724.89	1737.30	1730.52
Supporting services	Maintenance of soil	514.41	508.46	512.77	515.61	514.55
	Maintenance of nutrient cycle	44.26	43.98	44.34	44.35	44.45
	Biodiversity conservation	488.97	483.56	487.83	490.45	489.52
Cultural services	Aesthetic inspiration	221.10	218.69	220.68	221.92	221.45
Total		5416.79	5369.55	5420.00	5452.80	5438.54

ecological land, such as forestland, water area, and grassland. Compared with 2020, the area of farmland declined, with a total reduction of 451.42 km^2 , while other land use types, including forestland, grassland, water area, and wetland, showed increases in area of 47.09 km^2 , 34.51 km^2 , 19.70 km^2 , and 2.79 km^2 , respectively. The ecological land provided high-quality service functions, although the area of farmland decreased the most and the area of built-up land increased the most.

3.3.2. Changes in ESVs in 2030. The changes in ESVs in the GBA under multiple scenario simulations in 2030 are presented in Table 7. The ESVs showed a downward trend in the BAU, SED, and CPP scenarios, with a total decrease in value of 2.18 billion yuan, 1.85 billion yuan, and 6.90 billion yuan, respectively. The ESV showed an upward trend in the EPP scenario, with a total increase of 1.43 billion yuan. In terms of the type of ecosystem service, in the BAU, SED, and CPP scenarios, the values of the regulating services, supporting services, provisioning services, and cultural services decreased compared with those in 2020, while they increased slightly in the EPP scenario.

The ESVs in different simulated scenarios were significantly different due to different land use types (Tables S2–S5). In the BAU scenario, the decline in the total ESV was attributed to the decrease in the ESVs of farmland, with a loss of 2.57 billion yuan, and the change in other land use types led to a small increase or decrease in ESVs. In the SED scenario, the loss of ESVs was derived from the increase

in the area of built-up land and decrease in the area of farmland, with total values of 3.47 billion yuan and 3.27 billion yuan, respectively, followed by those of forestland, grassland, and wetland, with decreases in ESVs of 0.13 billion yuan, 5.9 million yuan, and 1.5 million yuan, respectively. However, an increase in ESVs resulted from a slight increase in water area, with a total value of 1.4 million yuan. In the CPP scenario, the decrease in farmland was remarkably restrained, and the loss in ESVs was also significant, which increased 1.03 billion yuan, and the other land use types (e. g., forestland and water area) were converted to grassland and wetland, which increased the values of ecological services. In the EPP scenario, the increasing ESVs originated from the contributions of water area, forestland, and grassland, with the total values of 0.96 billion yuan, 0.54 billion yuan, and 0.22 billion yuan, respectively. This is because the protection of the ecological environment led the ESVs to significantly increase due to limitations on development activities and the partial restoration of damaged habitats.

4. Discussion and Conclusions

4.1. Discussion

4.1.1. Impact of LUCC on ESV. The change in land use was caused by the interaction between human activities and the ecological environment and led to the change in the ecological environment. The changes in patterns of land use and land cover types were affected by factors such as population

growth, urbanization, land use policy, biology, climate change, and soil [50–52], which included the natural environment, local conditions, socioeconomics, and policy orientation, and were important driving factors of the geographical environment and socioeconomic factors that affected the quality and quantity of land use change. For instance, changes in land use types were triggered by population growth and urbanization [53], such as the conversion of agricultural land to settlements. Therefore, the impact of LUCCs on ecosystem services is very complex. These changes significantly impacted ecosystem services and led to a change in the provision of functions [54, 55], and the losses in ESVs caused by land use change were experienced on different regional scales [53]. Therefore, it has been suggested that land use patterns, land management, and land use planning also affected ESV change. It is important to quantify and evaluate the impact of land use/cover change on ESV and its changes, and this is necessary for the sustainable development of land resources and ecological environment protection.

In line with other studies, our results indicated that rapid urban sprawl resulted in a vast loss of ESV via land use changes in China, especially in coastal regions [17, 19]. The GBA is a typical representative of coastal regions with fragile ecological environments. Land use types tended to be out of balance, which had an impact on ESVs under the dual effects of climate change and human activities. In addition, in recent decades, intensive development activities, such as urban sprawl and the construction of urban land, have accelerated profound LUCCs in the GBA. These changes have significantly impacted the ESVs. Hence, the impact of LUCCs on ecosystem services is ultimately a result of the relationship between land use development and ecological protection. We propose a four-quadrant analysis method for determining which land use simulation will be expected to be adopted by the government. In the four-quadrant analysis, the rapid expansion of urban construction indicates land use development, while less pressure on ecological land indicates ecological protection. The distribution of the multisenario simulations is presented according to land use conversion and ESV transfer change (Tables S2–S5) (Figure 9).

The positive and negative effects on ESVs were revealed by multisenario simulations in the four-quadrant analysis, and the impacts on the landscape in terms of spatial expansion were different in different ecological regions. Changes in ESVs resulting from the decrease in farmland and built-up land were similar in the BAU and SED scenarios, which showed high land use development and low ecological protection in the HL quadrant. One reason is that farmland was occupied by the expansion of urban construction, and the ESVs exhibited a downward trend. A second reason is that legacy effects impacted the change in ESVs [56, 57]. In our study, we investigated the changes in ecosystem services in response to LUCC. The changes in the ESVs declined in the BAU and SED scenarios due to the continuous expansion of urban land, and the loss of ecological services in the SED scenario was higher than that in the BAU scenario, as there was a high speed of urbanization

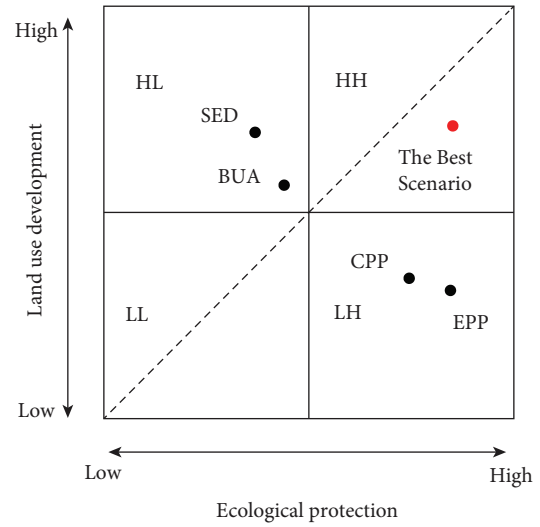


FIGURE 9: Relationship between land use development and ecological protection under different scenarios in four-quadrant analysis. The four quadrants are low land use development and low ecological protection (LL), low land use development and high ecological protection (LH), high land use development and high ecological protection (HH), and high land use development and low ecological protection (HL). Red indicates the best scenario, which not only improves the land use development but also considers ecological protection.

and rapid urban sprawl in the future. We believe that socioeconomic changes are the dominant driver of changes in ESVs [19]. In the CPP scenario, the ESVs for LUCC decreased the least, which showed low land use development and high ecological protection in the LH quadrant. Measures should be taken to protect farmland. On the one hand, the transformation of land use change should ensure a higher-level, higher-quality food supply, and a more efficient and more sustainable food security system at the regional level. On the other hand, land use should prevent the conversion of farmland into nongrain crop production areas and stabilize food production. The EPP scenario was the same as the CPP scenario, which is shown in the LH quadrant. Ecological environment protection should be considered in future land use change initiatives. The greatest conversion would be to forestland, grassland, and water area, increasing the ESVs in the multisenario simulations.

The spatial spillover effects of land use changes on ESVs are significant and differ among different regions with different economic levels. There have been frequent changes in land use in the highly urbanized and economically important regions; for example, farmland, forestland, and water area have been converted to built-up land, promoting urbanization, and leading to more significant spatial spillover effects. The spatial distribution of land use led to the spatial heterogeneity in the loss of ESV. Furthermore, the ecological effects of land use change were also ignored by land use management and land use planning in China and caused by ecological environment deterioration [58] and the loss of ESVs. Our objective was to determine how to allocate and develop land use without compromising ecological

sustainability so that the synergistic effect of urban high-quality development and ecological civilization construction (shown in red in Figure 9) will be generated.

In response to population growth, intensification of human activities, government policies, and initiatives that aim to improve the economy of the country without considering the environmental consequences [59], we recommend that the spatial effects of ESV changes be considered in response to the impact of LUCC on ESVs in the GBA. With economic and social development stage transformation, the land use transition in this area should be carefully controlled and, facing the degradation of ecosystem services, we should provide reasonable guidance for land use development.

4.1.2. Management Implications. Future spatiotemporal changes in LUCC and ESV were predicted through multi-scenario simulations, and the results showed potential effects on long timescales in the GBA. This study will help to understand critical tradeoffs between ecosystem services caused by LUCC and provide valuable information for decision-making and policy development.

The loss of ESV has significant spatial heterogeneity, caused by the spatial difference in land use. To break the “Matthew effect” of ecosystem services, the low value of ecosystem services should therefore be prioritized for protection. We suggest that the characteristics and synergistic effect of different driving factors should be considered to optimize the ecosystem and control ecological risks, especially for low ESVs. The impact of complex human activities on ecosystem services made us adopt differentiated and diversified regulating strategies. The government should comprehensively consider the ESV changes in land use and emphasize the spatially explicit extent of the ecological environment effect in the GBA.

In addition, land use patterns are a critical way to protect ecosystem services, which should coordinate with local geographic conditions and socioeconomic development in multisenario simulations. With the principle of the symbiotic development of land use development and ecological protection, the GBA needs to improve the spatial agglomeration of urban constructed land, balance the occupation and supplementary use of cultivated land, and maintain the high-value ecosystem service of ecological spaces. These are in response to a strategy for ecological civilization construction to improve the harmony between nature and human activities, which led to the publication of the Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area in 2018. Recently, the local government attempted to build an ecological compensation mechanism, following the principle that developers are responsible for protecting the environment and users must compensate for damages they cause. The ecological compensation mechanism should be further improved through ESVs and ecological protection costs and will be an important route for exploring ecological protection work.

4.1.3. Limitations and Future Works. Several limitations of the study should be considered. The first limitation of this study is associated with the ESV valuation method. In the ecosystem service valuation process, value coefficients are assigned to each land use type; in this study, the value coefficients used were those of Xie et al. [12] and the adopted local modified ecosystem services coefficients. However, with the social and economic development, there should also be differences in the understanding of ecological service value. Furthermore, with the rapid urbanization process, the demand for land resources should also affect ecological service functions. Therefore, the revising factors of social economic and resource scarcity could be considered with the value coefficient of ecological services. The second limitation is that the selection of driving factors could affect LUCC. Logically, these representative factors should have an important influence on simulation accuracy and directly affect the probability of occurrence of land use types. Several factors were considered in the study, such as geographical factors, environmental factors, socioeconomic factors, and POI. However, there was a lack of government-related decision-making factors, which may have led to uncertainties in land use simulation. Consequently, the introduction of the decision-making factors of land use-related stakeholders will enhance the scientific and comprehensive spatial simulation through the bottom-up analysis of natural carrying capacity and the top-down analysis of territorial spatial structure order. Urban expansion can be characterized by low speed and compact and sustainable growth under decision-making intervention. In addition, the accuracy and confidence level of the analyzed results would be more significant in future simulation research.

In future studies, we will test the applicability of higher-resolution simulations and focus on comparative experiments between the simulation results among more comprehensive restricted factors. Driving factors have relatively different impacts on land use, and the weights of different types of driving factors must be assigned. Future work may include adding the driving factor weights to the FLUS mode. The FLUS model transition rules should also be considered, as those rules may change over a long period. We hope to address this challenge in future works.

4.2. Conclusions. The spatiotemporal evolution characteristics of the impacts of LUCC on ecosystem services in the GBA by 2030 were analyzed in the multisenario simulations, and the following conclusions were drawn.

In 2005–2020, forestland and farmland were the predominant land use/cover types, and their proportions continued to decline. Forestland was mainly distributed in the western, northwestern, and eastern regions, and farmland was found in the central, southwestern, and eastern regions. The water area declined continuously in the northern region of the GBA. In contrast, the proportion of built-up land increased continuously with high urbanization and economic levels as a consequence of sacrificing

farmland, forestland, and water area, and it was concentrated in the central region. The proportion of grassland and wetland tended to fluctuate, initially decreasing, then increasing, and finally decreasing.

During 2005–2020, ESVs continuously declined and decreased significantly by 14.29 billion yuan. The ESV per unit area showed a significant decline, which was largely associated with a decrease in farmland and an increase in built-up land. Forestland contributed the most to the total ESV (>75%), and those areas experienced great land use transitions and human activity. The high-value ecosystem services were concentrated around the peripheral area of the northern regions in the GBA.

Compared with 2020, the total ESV in the SED, BAU, and CPP scenarios in 2030 decreased, while it increased in the EPP scenario. The transformation of land use change was the main reason for the decrease in ESV. For example, most land use types will be converted, changing to or from farmland, built-up land, forestland, and water area.

Data Availability

The data used to support the findings of this study can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

Table S1. The ROC of logistic regression. Table S2. The change of land use and ecosystem service value in BUA scenario in 2030. Table S3. The change of land use and ecosystem service value in SED scenario in 2030. Table S4. The change of land use and ecosystem service value in CPP scenario in 2030. Table S5. The change of land use and ecosystem service value in EPP scenario in 2030. (*Supplementary Materials*)

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Research Article

On Class Difference in Educational Aspirations and Educational Expectations: A CUCDS-Based Social Analysis

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Educational aspirations under an ideal state and educational expectations based on reality have an important impact on children's academic development, but distinct differences between them exist. On the basis of distinguishing the differences between the two, using the national data of Tsinghua University's China Urbanization and Child Development Survey (CUCDS), this article endeavors to explore the inequality of educational aspirations and expectations from the perspective of class and urban-rural areas, and lay out the influencing factors of educational aspirations, expectations, and the difference between them. It is found that Chinese parents generally have high aspirations for their children's education. There is no distinct class difference in "high hopes for children's bright future." However, in the sense of educational expectations, there are distinct class differences, which are deeply rooted in socioeconomic status and closely related to education level, family type, family structure, and family economic status, as well as children's academic performance.

1. Introduction

Numerous studies have confirmed the significant role of educational background on socioeconomic status acquisition [1–3]. Therefore, educational inequality holds the key to problems such as class consolidation and intergenerational transmission of poverty. Educational inequality comprises multiple levels, besides inequality in educational attainment; inequality in educational expectations is also an important factor. However, past research studies failed to distinguish between "aspirations" and "expectations," and the former is based on subjective ideals, while the latter derives from objective reality. Given the two may have distinct measurement differences, research conclusions without distinction between the two are often in doubt. Thus, at least two problems arise—whether those factors passing the significance test affect the "aspiration based on subjective ideals" or "expectation based on objective reality?" Is it

"educational aspirations" or "educational expectations" that are more closely related to class?

To clarify these issues, this study divides parents' expectations for their children's education in more detail and endeavors to apply national data from China Urbanization and Child Development Survey (CUCDS) to explore the disparity between parents' aspirations and parents' expectations from the perspectives of class and urban or rural areas and find out the factors contributing to the difference. The specific questions to be answered are as follows: in current China, the differences and influencing factors of different classes of children's education aspirations; and the differences and influencing factors of different classes' education expectations. Supposing that educational aspiration is an ideal, expectation an alternative to the final education acquisition, the author is in an endeavor to analyze the factors hindering the realization of educational expectations of different classes.

2. Concept Definition and Literature Review

2.1. Concept Definition. “Modern Chinese Dictionary” to the explanation of “expectation” is waiting for the future of things or people with hope [4]. But this explanation does not state that “expectation” is merely a subjective hope or an expected vision of the future based on current reality. In fact, in daily life, the understanding of the word “expectation” also varies from person to person. Some people understand it more from the perspective of ideal hope, while some people hold that it is an expectation based on actual conditions. As for parents’ expectations for their children’s education (hereinafter referred to as parents’ education expectations), if not strictly defined in the survey and research, some people may think that it is the level that they hope their children’s education can achieve under ideal conditions, while others may hold that it is the expectation that children can reach the educational level in consideration of the actual situation. Obviously, these are two different concepts, and the relevant research conclusions obtained by integrating them indiscriminately under the “educational expectations” may be in doubt. In view of this, in practical research, a strict distinction should be made between educational aspirations and expectations, and the distinction between the two should first be reflected in the meticulous measurement of aspirations and expectations during data collection.

In this study, parents’ educational aspirations refer to the level that parents want their children to achieve in an ideal state. While Parents’ educational expectations refer to the parents’ expected estimation of their children’s educational attainment based on objective conditions, which include not only macrolevel educational settings, but also family and individual children’s conditions. We are well aware that in Chinese people’s perceptions, ideals based on objective reality are often confused with ideals based on subjectivity; that is, it is difficult to accurately identify attitudes in questionnaires. Therefore, on the one hand, a detailed distinction in the questionnaire design is vital, and the question that “what degree do you want your children’s education to achieve in the most ideal situation?” may be more accurate to measure parents’ education aspirations; meanwhile, the question like “sometimes, children may not be able to achieve the education level we hope for, what level of education do you expect children to really achieve?” may be more appropriate to parents’ educational expectations. On the other hand, efforts should be made to train the questionnaire interviewers to ensure their accurate and clear explanation of the difference between the two concepts to the respondents.

Educational attainment is the ultimate educational level. The relationship among educational aspirations, educational expectations, and educational attainment can be roughly illustrated in Figure 1.

Educational aspiration is one end, the ideal, and education acquisition is the other, the reality; between the ideal and the reality is the educational expectation. Theoretically speaking, the gap between ideal and reality may be very large or small, or even zero, that is, the union of ideal and reality;

as it is with ideal and reality, the distance between educational aspirations, expectations, as well as educational attainment may be very large or small or even the three may correspond exactly. In reality, there are always many factors that may hinder the acquisition of education, and there is often a gap between ideal and reality. As rational people, we can often foresee possible obstacles and correctly predict the gap between ideal and reality. Therefore, education expectations and education acquisition tend to be closer. Based on this, it is feasible to use the difference between educational aspirations and expectations as the difference between ideal and reality in this study to explore the factors that hinder the realization of ideals in the case of being unable to obtain the final education level data. However, it should also be acknowledged that educational expectations are also different from the final educational attainment. This is reflected not only in the results, but also in the meaning of expectations; that is, expectations still have the meaning of hope, although they are less idealized than aspirations. Therefore, in a sense, educational expectations also have similar effects to aspirations and play an important role in educational attainment; family and personal factors that affect educational aspirations may also affect expectations.

2.2. Literature Review. Instead of strictly differentiating educational aspirations and expectations, the existing research studies combine “expectations based on subjective ideals” and “expectations based on objective reality” under the term “educational expectations.” Taking the continuation of the use of the term in existing studies into consideration, it is customary that the term “educational expectations” is still employed in the literature review of this article. However, it should be clear that the “educational expectations” here are in fact a combination of “educational aspirations” and “educational expectations,” which are strictly distinguished in this article.

2.2.1. Parents’ Educational Expectations and Their Children’s Educational Attainment. In the research on the influencing factors of educational attainment, aspiration is often proved to be an important intermediary mechanism between family socioeconomic status and the academic performance and educational attainment of their children, which functions in the way that it impacts the educational aspirations of important people to them such as their parents, thereby influencing children’s educational expectations, which will ultimately contribute to their children’s academic performance and educational attainment [5–9]. Studies on parents’ participation in their children’s studies have found that, compared with “communication,” “supervision,” as well as “participation in school activities,” “educational aspirations” is the most closely related to children’s academic performance [10]. The “Plowden Report” pointed out that compared with the family material environment and school factors, parental attitudes account more for their children’s academic performance [11]. Some scholars even regard educational aspirations as the most effective variable for predicting educational attainment [12]. So, how do parents’

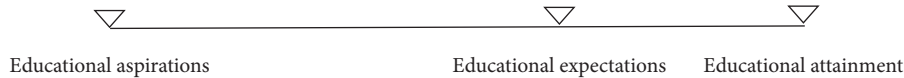


FIGURE 1: Educational aspirations, educational expectations, and educational attainment.

educational aspirations affect their children's academic accomplishments and educational attainment?

The Pygmalion effect clearly shows the mechanism of teachers' aspiration: teachers' high aspirations for students are passed on to students through positive attitudes and more praise, interaction, and other behaviors, which stimulates students' motivation and enthusiasm for learning. Positive feedback makes teachers more enthusiastic and gives more care to students. Such a virtuous circle pushes students' academic performance toward the desired direction, and finally, self-predictions can be realized [13].

The functional logic of parent aspirations is similar to teacher's ones, which can be summarized as parents' educational aspirations are closely related to their attitudes and behaviors. Higher educational aspirations often result in positive attitudes and supportive behaviors. Meanwhile, positive attitudes, in terms of encouragement, praise, and recognition, can be transformed into children's motivation and confidence in learning, helping to sharpen up academic performance; supportive behaviors will be transformed into more attention and support for children's academic studies, such as positively overcoming the difficulties encountered in the learning process together with their children, be willing to buy learning materials for children and encouraging them to participate in extracurricular tutoring classes, and actively communicating with school teachers, etc., which will also contribute to the improvement of academic performance [14, 15]. Pibquart and Ebeling's empirical research paper assessed systematically concurrent and longitudinal associations between parental educational expectations and child achievement, and factors that mediate the effect of expectations on achievement. The research found that associations between parental educational expectations and child achievement were partially mediated by children's educational expectations, child academic engagement, academic self-concept, and parental achievement-supportive behaviors [16].

However, the same aspirations are not always able to produce the same results, and the positive attitudes and supportive behaviors along with high educational aspirations also vary according to different conditions of those who are studied, and despite holding high educational aspirations for their children, some less educated or poorer parents who are in lack of resources may fail to communicate or give support timely and effectively as they desire due to their conditions. In other words, what really plays a role in the improvement of children's academic performance is not the "aspiration" in ideal, but the "expectation" in reality and the actual support in the attitude and behavior together with it, which are closely related to socioeconomic status and class. So, what are the factors that affect parents' educational expectations?

2.2.2. Factors Affecting Parents' Educational Expectations.

Studies have shown that many factors affect parents' educational expectations, including cultural traditions, the disparities in national/regional educational conditions, labor market conditions at the macrolevel, as well as family socioeconomic status, parents' educational level, children's academic performance or cognitive ability, and children's gender in microlevel. Some studies have attributed the high educational expectations of Asian parents to their children to traditional Confucian cultural traditions [17], and some studies have explored the impact of different educational systems and labor markets on educational expectations [18]. Since more research studies are (were) carried out under the same macrobackground, the microfamily background and children's characteristic factors are (were) more tested.

Among them, family socioeconomic status and parents' educational level are recognized as two vital factors affecting educational expectations [5, 9, 19–22]. The logic runs like parents with superior socioeconomic status, especially parents with higher education levels, are more aware of the role of education in obtaining individual status and maintaining the continuation of the family's superior status, so they pay more attention to the education of their children and hold a higher expectation for their children to get a higher level of education [5, 20]. However, a study based on the data of China's migrants found that family economic status did not affect parents' educational expectations, while children's academic performance, parents' education level, and life experience were the leading factors influencing parents' educational expectations [23]. A study using data from the "China Education Tracking Survey" not only found that different dimensions of family socioeconomic status have different effects on parents' educational expectations, but also found that there are gender differences in these effects. For boys, parents' education, occupation, and family cultural capital will have a positive impact on parents' educational expectations, but the family's economic level will have a negative impact; for girls, parents' educational level and family cultural capital will have a positive impact on parents' educational expectations, and the effect of occupation and family economic status is not significant [24]. Gofen believes that there is no difference in the educational expectations of parents from all walks for their children. They all hope that their children can go to college. The difference lies in their ability to accomplish expectations. Regarding the effect of gender, most studies believe that the educational expectations of Chinese parents have boy preferences and attribute this to the influence of cultural concepts [22, 25]; there are also some studies that do not support the gender preference in educational expectations [26]. The reason may be the popularization of education and the declining birth effect caused by the one-child policy.

2.2.3. The Potential Gap between Educational Aspirations and Expectations. The reason why so many research studies apply aspiration and expectation indiscriminately is that both concepts with the same meaning—possible selves. Because possible selves are not necessarily derived from empirical realities, there is always a potential gap between aspired-to selves, which the possible selves they want to become, and expected selves (the possible selves), which they believe they will become [27]. Since educational expectations are more realistic and highly susceptible to external cues, they are often lower than aspirations, particularly among disadvantaged groups [28, 29]. Therefore, it is of great significance to explore the external factors of the gap between educational aspirations and expectations to explain why the educational aspirations cannot be realized, for education intervention and school reform, and then for the upward mobility of children from disadvantaged groups. But this kind of research is rare in China.

2.2.4. Review of Existing Research. There have been some findings in existing research on the influencing factors of parent education expectations, but there are still some areas that need to be enriched. First, there is no strict distinction between educational aspirations and expectations, especially the study of Chinese society. Educational aspiration is the hope for the education level of their children in an ideal state. Although it is related to the class they belong to, they can more often than that get rid of the limitations of socioeconomic status. This is also why existing surveys often found that parents of different classes have the same educational expectation for their children.

Secondly, because “final educational attainment” data are more difficult to collect than “academic achievement,” the existing researches are likely to focus more on the impact of educational expectations on academic performance, while less attention has been paid to the relationship between educational expectations and final educational attainment. Although academic performance is closely related to the final education attainment, in reality, there are also many occasions that children with good academic performance cannot reach a higher education level due to various factors. Therefore, the two cannot be treated as the same. And the use of retrospective questionnaires (e.g., “Did your parents expect you to go to college when you were a teenager?”) is susceptible to the respondent’s current social status or educational achievements in collecting answers to educational expectations. Thus, the award situation arises in which the respondents are intended to blur the difference between educational expectations in childhood and adolescence, thereby affecting the reliability and validity of the measurement. In this way, in order to analyze the relationship between educational expectations and educational attainment, we must first solve the problem of data collection or the measurement of two variables.

Given the above considerations, based on national data, this study, by introducing the “education expectations” variable and regarding it as a substitute for “education acquisition,” endeavors to explore the influencing factors of

education aspirations and educational expectations, and the disparities between them so as to learn more about the elements affecting the realization of ideals, that is the family and personal factors resulting in the difference between educational aspirations and expectations.

3. Data, Variables, and Analysis Methods

3.1. Data. The data used in this study is derived from the China Urbanization and Child Development Survey (CUCDS) conducted by the China Economic and Social Data Center of Tsinghua University in 2012. The survey adopted a multistage stratification scheme and the PPS sampling method. In Mainland China, 500 villages were randomly selected from 28 provincial administrative units and 147 districts and counties except for Qinghai, Tibet, and Hainan, and then, field mapping was used to enumerate the probabilities. The sampling method and the Kish table sampling method are applied to sample households and household members, respectively, and conduct tests and interviews with 3–15-year-old children and their main caregivers in the sampled households. Children who meet the age requirements are required to take language, math, and English proficiency tests; the main caregiver needs to answer the “caregiver questionnaire” that covers all aspects of the child’s growth.

3.2. Variables

3.2.1. Dependent Variables. Parents’ educational aspirations and expectations. The options of parents’ educational aspirations were set as elementary school, junior high school, technical secondary school or vocational high school, high school, college, undergraduate, master, and doctorate. College education is a basic condition for finding a good job in contemporary China. Therefore, there is a clear difference between people who received college education and who did not receive college education in people’s minds. On the other hand, although we made very detailed measured both educational aspirations and expectations, the proportion of respondents with a college degree below is small, especially the educational aspirations, which is less than 5%. Based on the above analysis, educational aspirations are simply divided into “university education expectations” = 1 and “nonuniversity education expectations” = 0. The option setting and reassignment methods of parents’ educational expectations are the same as educational aspirations.

The gap between educational aspirations and expectations (hereinafter referred to as the gap between aspirations and expectations). In order to maximize the use of data, educational aspirations and expectations variables were reassigned as follow: “primary school” = 6 years; “junior high school” = 9 years; “secondary school or vocational high school” = 11 years; “high school” = 12 years; “college degree” = 15 years; “bachelor degree” = 16 years; “master degree” = 19 years; and “doctor degree” = 22 years. The value of the variable after assignment is 6–22. The larger the value (absolute value), the greater the difference between aspirations and expectations. A negative value indicates that the

TABLE 1: Frequency distribution of educational aspirations and expectations.

Educational aspirations/expectations	Frequency		Percentage		Percentage difference
Primary school	7	14	0.2	0.4	-0.2
Junior high school	35	220	1.0	6.2	-5.2
Secondary school/Vocational high school	14	104	0.4	2.9	-2.5
High school	114	631	3.2	17.7	-14.5
College degree	63	227	1.8	6.3	-4.5
Bachelor degree	2540	2105	71.1	58.9	12.2
Master degree	243	113	6.8	3.2	3.6
Doctor degree	557	158	15.6	4.4	11.2
Total	3573	3573	100.0	100.0	

Notes. The former frequency is the educational aspirations, and the latter frequency is the educational expectations; percentage difference refers to the percentage difference between educational aspirations and expectations.

expectation is less than the aspiration; a positive value indicates that the aspiration is greater than the expectation; 0 indicates that the aspiration is consistent with the expectation. See Table 1 for educational aspirations, expectations, and the gap between the two.

Table 1 shows that parents' educational aspirations for college education account for 95.2%, high school and below education aspirations are only 4.8%; parents' educational expectations for college education account for 72.9%, nonuniversity education expectations are 27.1%, and the difference between college education aspirations and college education expectations is 22.3%. The gap is distinct.

3.2.2. Independent Variables and Control Variables. The independent variables of this study are family socioeconomic status, family structure, family type, and cognitive level. The socioeconomic status of the family is explored by analyzing the following three variables: father's education level, father's occupation category, and family income per capita to represent the family's cultural capital, social capital, and economic capital. The family structure is measured by the variable of the number of children aged 0–15 years; the difference in family types is reflected by the child type variable. All children in this study are classified into four categories: left-behind children in rural areas, children in complete families in rural areas, migrant children, and urban children. Left-behind children refer to children under the age of 16 years who have stayed in rural areas for more than one month because their parents (both or one of them) go out for work or business; migrant children refer to those under the age of 16 years and have been living in urban areas with their migrant parents or business parents (both or one of them) for one month, while their household registration remains in rural area; children with complete rural families refer to children with rural household registration who live with nonmigrant parents in rural areas; urban children refer to children with urban household registration. This study uses the test scores of Chinese, mathematics, and English ability of children as the basis for measuring the level of their cognitive level so as to explore their impact on educational aspirations, expectations, and the gap between them. The gender of the children is the control variable. The descriptive

statistics of independent variables and control variables are shown in Table 2.

3.2.3. Analysis Method. Because educational aspirations and expectations are dichotomous variables, this study uses the logit regression model to analyze its influencing factors; while the gap between aspirations and expectations is a continuous variable, this study uses the linear regression model to analyze its influencing factors.

4. Analysis Results

4.1. Analysis of Factors Influencing Educational Aspirations. In Table 3, Model 1 adds the child's gender, child type, father's education level, the number of children aged 0–15 years in the family, family income per capita, and language cognition scores. The statistical results show that the father's education level and language recognition scores have a significant impact on parents' educational aspirations.

Specifically, the father's education level has a significant impact on educational aspirations. The higher the father's education level, the more distinct the college education aspirations for their children. Educational aspirations for college education of parents with junior high school, senior high school, and equivalent education, junior college education, or above are, respectively, 1.508 times ($e^{0.411}$, $p < 0.05$), 1.671 times (only reaching the significance level of 0.1), and 8.758 times compared with parents with primary education and below. Education level has a vital impact on educational aspirations, which is consistent with the conclusions of most existing studies. Meanwhile, children's language cognition scores have exerted an important impact on parents' educational aspirations. For every 1-point increase in language cognition level, the probability that parents have college education aspirations for their children increases by 1.042 times ($p < 0.001$).

Replace the Chinese cognitive scores in Model 1 with mathematical cognitive scores to get Model 2, and the conclusions obtained are the same as those of Model 1. The variables that have a significant impact on educational aspirations are still the father's education level and cognitive level. The higher the education level of the parents, the more distinct the college education aspirations of their children,

TABLE 2: Descriptive statistics of independent and control variables.

Variables	Weighted mean/ratio
Child type	
Left-behind children	0.20
Complete family children	0.38
Migrant children	0.16
Urban children	0.26
Father's education level	
Elementary school and below	0.25
Junior high school	0.46
High school and equivalent	0.21
University and above	0.08
Father's occupation	
Farmers and manual workers	0.37
Service personnel and skilled workers	0.37
Clerks, private entrepreneur, or self-employed industrialists	0.17
Management and professional and technical staff	0.09
Number of children of 0–15 years in the family (pcs)	1.55 (0.82)
Per capita household income in 2011 (thousand dollars)	11.27 (16.85)
Language cognitive level	100.16 (15.08)
Mathematical cognitive level	100.26 (15.11)
English cognitive level	99.99 (14.95)
Gender of the child (1 = male)	0.54

Notes. $N = 3573$, may not be 3573 due to partial exclusion of missing values from the sample; standard deviation in parentheses; cognitive level is the transformed standard score.

and the higher the children's mathematical cognitive scores, the more distinct the parents' college education aspirations.

The cognition level in Model 3 is English, and the conclusions obtained are different from Model 1 and Model 2. The father's education level does not reach a significant level, and only the children's English cognition level has a significant impact on educational aspirations. It displays like that for every 1-point increase in children's English cognition level, the probability that parents have college education aspirations for their children increases by 1.032 times.

Combining three models, it can be arguably stated that family type, family social capital, family economic capital, and family structure have no significant impact on educational aspirations, which is inconsistent with people's assumptions. Compared with parents of left-behind children in rural areas, other types of parents' college education aspirations are more advantageous; compared with parents of farmers and manual workers, parents of other occupations, especially parents of managers and professional technicians, have more advantages in their children's university education aspirations; compared with parents with low incomes, the educational aspirations of college education for their children of parents with high incomes are more advantageous; compared with parents with many children, the aspiration of college education for parents with fewer children is more advantageous. This may indicate that the important role of education has reached a consensus among all classes, and it is for this reason that the ideal educational aspirations do not show class differences.

The control variable gender has no significant effect, indicating that there is no significant difference in gender about whether parents have college education aspirations for their

children or not and showing that education for men and women has achieved equality at the level of parents' aspirations.

4.2. Analysis of Factors Influencing Educational Expectations.

Educational expectation is a predictive estimate of the level of education that children may reach. There are both similarities and distinct differences between educational aspirations and expectations. The analysis strategy is to include the same variables as the influencing factors of educational aspirations in the logit model to examine the influencing factors of educational expectations.

The statistics show that the following factors such as child type (i.e., family type), father's education level, number of children in the family, family income per capita, and cognitive level have a significant impact on parents' educational expectations; the impact of children's gender on parents' educational expectations has not reached a significant level; fathers occupation shows different effects in different models (see Table 4).

Specifically, in terms of family types, compared with parents of left-behind children, parents of migrant children, parents of rural complete families, and parents of urban children have more distinct college education expectations for their children. Taking Model 4 for example, the other three types of parents' educational expectations for their children's college education displayed advantages as 1.384 times, 1.441 times, and 3.059 times than that of parents of left-behind children.

The father's education level has a significant impact on educational expectations. The higher the education level, the more distinct the parents' expectations for their children's college education. This is evident in the three models.

TABLE 3: Logit regression analysis of educational aspirations.

Variables	Model 1		Model 2		Model 3	
	B	SE	B	SE	B	SE
Gender (female as reference)	0.187	0.171	0.116	0.173	0.157	0.219
Type of children (left-behind children as reference)						
Children in rural complete families	0.107	0.204	-0.012	0.209	0.001	0.258
Migrant children	0.305	0.291	0.132	0.297	0.747	0.407
Urban children	0.552	0.318	0.491	0.322	0.644	0.406
Father's education level (elementary school and below as reference)						
Junior high school	0.411*	0.186	0.374*	0.191	0.269	0.241
High school and equivalent	0.513	0.278	0.330	0.281	0.079	0.332
University and above	2.170*	1.006	1.933	1.001	1.010	1.026
Father's occupational category (farmers and manual workers as reference)						
Service personnel and skilled workers	0.031	0.198	0.000	0.201	0.340	0.249
Clerks, private entrepreneur, or self-employed industrialists	-0.011	0.290	-0.046	0.294	0.180	0.350
Management and professional and technical staff	-0.202	0.449	-0.018	0.446	1.770	0.976
Number of children aged 0-15 years in the family	-0.106	0.095	-0.122	0.093	-0.236	0.124
Per capita household income in 2011 (thousand dollars)	0.002	0.011	0.005	0.011	-0.006	0.008
Cognitive level	0.041***	0.006	0.040***	0.007	0.031***	0.007
Constant term	-1.337*	0.617	-1.079	0.690	-0.202	0.804
	-2LL = 1151.623, Pseudo $R^2 = 0.082$, Prob > $\chi^2 = 0.000$, N = 2888		-2LL = 1122.268, Pseudo $R^2 = 0.071$, Prob > $\chi^2 = 0.000$, N = 2843		-2LL = 727.376, Pseudo $R^2 = 0.073$, Prob > $\chi^2 = 0.000$, N = 1744	

Notes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 4: Logit regression analysis of educational expectations.

Variables	Model 4		Model 5		Model 6	
	B	SE	B	SE	B	SE
Gender (female for reference)	0.130	0.088	0.001	0.088	0.179	0.111
Child type (left-behind children for reference)						
Children in rural complete families	0.325**	0.106	0.295**	0.107	0.209	0.136
Migrant children	0.366**	0.140	0.477***	0.146	0.374*	0.174
Urban children	1.118***	0.156	1.061***	0.158	1.453***	0.211
Father's education level (elementary school and below for reference)						
Junior high school	0.494***	0.096	0.470***	0.097	0.509***	0.123
High school and equivalent	0.829***	0.139	0.947***	0.148	0.594***	0.172
University and above	2.657***	0.552	2.554***	0.551	2.145**	0.684
Father's occupational category (farmers and manual workers for reference)						
Service personnel and skilled workers	-0.073	0.101	-0.093	0.101	0.027	0.127
Clerks, private entrepreneur, or self-employed industrialists	-0.287*	0.139	-0.145	0.145	-0.232	0.173
Management and professional and technical staff	0.197	0.254	0.237	0.253	1.295***	0.405
Number of children aged 0-15 years in the family	-0.242***	0.052	-0.226***	0.053	-0.341***	0.070
Per capita household income in 2011 (thousand dollars)	0.031***	0.007	0.032***	0.007	0.026**	0.009
Cognitive level	0.029***	0.003	0.026***	0.003	0.021***	0.004
Constant term	-2.669***	0.339	-2.272***	0.349	-1.748***	0.423
	-2LL = 3292.314,		-2LL = 3187.933,		-2LL = 2063.8722,	
	Pseudo R^2 = 0.150,		Pseudo R^2 = 0.145,		Pseudo R^2 = 0.155,	
	Prob > χ^2 = 0.000,		Prob > χ^2 = 0.000,		Prob > χ^2 = 0.000,	
	N = 2888		N = 2843		N = 1744	

Notes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The number of children in a family reflects the structure of the family and also reflects the “dilution” of family resources. One more child will share the limited family resources. Therefore, in theory, the more children in the family, the less the parents need for their children’s college education. On the contrary, parents with fewer children have more distinct expectations for their children’s college education. This has been confirmed in the three models. Thus, it can be seen that the number of children in a family is an important factor influencing parents’ educational expectations.

Family income per capita reflects the economic status of the family, which is an important factor that affects parents’ education expectations. Taking Model 4 for example, for every 1,000 yuan increase in family income per capita, the probability of parents having college education expectations increases by 1.032 times.

Children’s cognitive level or academic performance is an important factor that affects parents’ educational expectations. The higher the children’s cognitive level, the greater the probability of parents having college education expectations. For example, every time children’s language cognition score increases by 1 point, the probability of parents’ college education expectations for their children increases by 1.030 times. The same goes for mathematics and English cognitive level.

It is worth mentioning the father’s occupation category. In the English cognitive model (model 6), the advantage of managers and professional technicians for their children’s university education reached 3.651 times that of farmers and manual workers ($p < 0.001$). It shows that compared with farmers and manual workers, the English scores of the

children of management and professional technicians are generally better.

The gender of children has no significant impact on parents’ educational expectations, which reflects a certain extent that in terms of gender education has achieved equality at the level of parents’ expectations.

Based on factors influencing education aspirations and educational expectations, there is a clear difference between the two. Under ideal conditions, it is acknowledged that parents tend to hold higher aspirations for their children’s education, regardless of the family’s economic status, the number of children in the family, the type of family, the gender of children, etc. However, in reality, parents’ educational expectations are affected both by family economic capital, family social capital, family cultural capital, family structure, and the family type, and by children’s academic performance.

4.3. Analysis of Factors Influencing the Disparity between Aspiration and Expectation. Rather than educational aspiration as an ideal, expectation is closer to reality. The gap between the two reflects the degree of realization of the ideal. The larger the gap, the greater the distance between the ideal and reality; the smaller the gap, the closer the ideal is to reality. Generally speaking, educational aspirations are always higher than expectations (very few cases where educational aspirations are higher than expectations are excluded). In order to make full use of the data, the study re-assigns the educational aspirations and expectations to the value of 6–22 years, so that the difference between the educational aspirations and expectations of the cases involved

TABLE 5: Multiple linear regression analysis of the disparity between aspirations and expectations.

Variables	Model 7		Model 8		Model 9	
	B	SD	B	SD	B	SD
Gender (female as reference)	−0.032	0.093	0.059	0.095	−0.040	0.117
Child type (left-behind children for reference)						
Children in rural complete families	0.037	0.127	0.053	0.129	0.245	0.166
Migrant children	−0.163	0.160	−0.197	0.164	−0.050	0.200
Urban children	−0.705***	0.153	−0.668***	0.156	−0.773***	0.199
Father's education level (elementary school and below for reference)						
Junior high school	−0.250*	0.115	−0.244*	0.117	−0.225	0.146
High school and equivalent	−0.216	0.147	−0.199	0.151	0.033	0.183
University and above	−0.200	0.231	−0.169	0.235	−0.233	0.290
Father's occupational category (farmers and manual workers for reference)						
Service personnel and skilled workers	0.204	0.113	0.191	0.115	0.220	0.143
Clerks, private entrepreneur, or self-employed industrialists	0.049	0.148	−0.008	0.152	0.159	0.187
Management and professional and technical staff	0.334	0.203	0.249	0.205	0.099	0.249
Number of children aged 0–15 years in the family	0.150*	0.060	0.182**	0.060	0.177*	0.079
Per capita household income in 2011 (thousand dollars)	−0.011***	0.003	−0.010**	0.004	−0.007#	0.004
Cognitive level	−0.018***	0.003	−0.021***	0.003	−0.013***	0.004
Constant term	3.936***	0.370	4.126***	0.369	3.203***	0.453
	$R^2 = 0.047$, $F = 12.21^{***}$, $N = 3238$		$R^2 = 0.053$, $F = 13.37^{***}$, $N = 3153$		$R^2 = 0.047$, $F = 7.75^{***}$, $N = 2074$	

Notes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

in the analysis is a continuous variable ranging from 0 to 16, which can be analyzed by the employment of the multiple linear regression model. The analysis results are shown in Table 5.

Model 7 is the result of incorporating variables such as gender, child type, father's education level, father's occupation category, number of children in the family aged 0–15 years, family income per capita, and language cognitive level. Compared with Model 7, Model 8 and Model 9 replace the mathematics cognitive level and the English cognitive level for the language cognitive level, respectively.

Model 7 shows that the main factors affecting the disparity between aspiration and expectation are language cognition, family income, number of children in the family, and family type; the effects of gender, father's education level, and father's occupation category are insignificant. Specifically, under the premise that other conditions remain the same, every time the children's language cognition score increases by one point, the gap between aspiration and expectation decreases by 0.018 years; every time the family income per capita increases by 1,000 yuan, the gap reduced by 0.011 years; under the premise that other conditions remain unchanged, for every increase in the number of children in the family, the gap increases by 0.15 years; under the premise that other conditions remain unchanged, the gap between aspiration and expectation of urban children's parents is 0.705 years smaller than that of parents of left-behind children on average. The difference between parents of migrant children, parents of children from rural complete families, and parents of left-behind children has not reached a significant level. It is worth mentioning that in terms of the father's education level and the father's occupation category, although the gap between aspirations and expectations of

parents with high education levels is smaller compared with the low-educated parents, only those with junior high school education have reached a significant level. There is no significant relationship between the level of occupation and the size of the gap between aspiration and expectation, indicating that the difference between aspiration and expectation is not closely related to education level and professional status.

The conclusions of Model 8 and Model 9 are the same as those of Model 7. At the individual level, children's cognitive scores have an important impact on the gap between aspiration and expectation. The higher the cognitive score, the smaller the gap; at the family level, the gap between the aspiration and expectation is closely related to family economic capital, while family social capital and family cultural capital show no significant effect. The gap between the aspiration and expectations of parents of urban children is significantly smaller than that of parents of left-behind children in rural areas.

5. Limitations

Some limitations of the present analysis have to be mentioned. First, due to the limitation of data, variables confirmed in some empirical studies, such as academic motivation, self-regulating behaviors, academic self-perception, and attitudes toward teachers, have not been included in the model when analyzing the influencing factors, so the study cannot be fully compared with the existing studies. Second, studies have shown that educational aspirations and expectations change at different time points [30, 31]. In the study, educational aspirations and expectations have been modeled as a single point in time.

However, findings based on such analyses provide limited guidance toward the formation of intervention and policy [32]. Finally, in this article, educational aspirations and expectations are treated as dummy variables. Although the classification reflects the overall distribution trend of the data, the result is rough after all. More detailed classification techniques should be applied to conduct more accurate research.

6. Conclusion

Rather than the confusion of the two terms “aspiration based on subjective ideal” and “expectation based on objective reality” in existing studies, this study strictly distinguishes them. The former is called educational aspiration and the latter educational expectation. Based on the above, this study endeavors to analyze educational aspiration, expectation, and the factors influencing the disparity between them by using national sample data, and the following conclusions are drawn.

6.1. No Distinct Class Difference in Terms of Educational Aspiration. Although educational aspiration is not completely divorced from reality, it is arguably more of a wishing ideal. Therefore, when people have reached a consensus on the important role of education, the aspiration in an ideal state is free of many constraints. The study found that there is no significant effect between occupation category, economic income, family type, family structure, and the college education aspiration, except that father's education level and children's academic performance have significant impacts on it; that is, parents with high education levels are more likely to have college education aspiration for their children. Parents of their children with good academic performance are more likely to have college education aspirations for their children. Given the data 95.2% of the university education aspiration, it can be understood that Chinese parents universally have higher educational aspirations for their children, and there is no distinct class difference in parents' “high expectation for their children's bright future.”

6.2. Distinct Class Difference in Term of Educational Expectation. Compared with educational aspiration, the educational expectation is significantly more constrained. In addition to the impact of the education level and family type, it is also closely related to family structure and family economic conditions. Moreover, children's academic performance or cognitive level contributes a lot to parents' educational expectations. Therefore, if there is no distinct class difference in educational aspiration, the class difference is distinct in the sense of educational expectation. Children's academic performance or cognitive level has an important influence on parents' educational expectations, which seemingly makes educational expectations break through the limits of the class. However, compared with the disadvantaged class, children of the superior class have better academic performance and higher cognitive test scores. The

reality shows that it is still difficult to get rid of the influence of class [33, 34].

6.3. Realization of Educational Expectation Being Deeply Ingrained into the Socioeconomic Status. The gap between aspiration and expectation is the distance between ideal and reality. Analyzing its influencing factors is to dig out factors hindering the realization of ideals. The study found that the main factors affecting the realization of parents' educational expectations are family economic status, family structure, family type, and children's cognitive level. The logic of the role of family economic conditions is not difficult to understand. Although there are high expectations for children's education, the limited economic conditions may eventually lead to the failure to achieve the desired education level. The number of children in a family affects the realization of educational expectations. It can be understood from the perspective of resource dilution. Under certain resource conditions, the consequence of sharing resources among multiple people is a decrease in the average education level. On the whole, compared with families with left-behind children, urban families have richer economic resources, fewer children, and parents with higher education levels. Therefore, the realization of their educational expectation is greater than that of families with left-behind children. Children's academic performance or cognitive level has an important influence on the realization of expectations because, under the principle of merit-based admissions, academic performance is a key factor in educational triage. Better academic performance and higher cognitive levels more certainly ensure better education.

The above research findings mean that in the analysis of influencing factors of educational aspiration and expectation, it is not the best choice to use the family socioeconomic status variable in general, and the influence of family background should be analyzed from a more specific dimension.

The cognitive level of children has an important impact on educational aspiration, expectation, and especially the realization of educational expectations. It means that in recognition of the fact that education has an important role to play in the status acquisition, some families in poor economic conditions and with children having great academic performance may overcome the limitations of economic conditions and try to support their children to obtain a higher level of education, thereby breaking the intergenerational transmission of disadvantaged classes and realizing upward social mobility.

Data Availability

The data used to support the findings of the study can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Research on the Evolutionary Game Model and Stable Strategy of Urban Management Law Enforcement

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As a form of the informal economy, countries around the world have different policies towards street vendors. This paper constructs a law enforcement game model composed of the Chengguan, street vendors, and urban residents in China. Based on the evolutionary game theory, we achieved the evolutionary stable equilibrium points under complying with different constraint conditions by solving the replicator dynamic equations of parties in the dynamic system. Through the gradual stability analysis of the equilibrium point, the stable strategy of the evolutionary game can be calculated. It is found that the flexible law enforcement behavior of urban management departments plays an important leading role in urban street governance. Flexible law enforcement not only requires macro policy arrangements but also tests the executive wisdom of street bureaucrats.

1. Introduction

Under the rapid urbanization and social structure changes, China's urban street space is presenting a fragmented structure and gathering diversified social demands. A large number of landless peasants, laid-off workers, and freelancers poured into the streets to make a living by setting up stalls to sell products, which brought the order of urban streets out of control. In 1997, China's first urban management law enforcement was formally established to strengthen the management of street vendors. As street bureaucrats, officers of urban management law enforcement (they have a famous name "Chengguan" in China) have played a significant role in maintaining urban street orders [1] and protecting social and public interests. However, they also have been criticized for their unsound system, simple methods, and extensive behavior [2]. For a long time, the relationship between Chengguan and vendors has been like a cat-and-mouse game [3], which is a typical contradictory relationship.

Chengguan represents the executor of urban management rules and regulations. Street vendors are usually the group of law enforcement target. Surrounding residents are

directly or indirectly affected by law enforcement activities. There is a general agreement that the control and elimination of street vendors will lead to an increase of living costs, especially for low-income groups [4–6].

Most previous studies have explored the relationship between Chengguan and street vendors [7–9], our study discloses conflicts among three parties: Chengguan, street vendors, and surrounding residents. The demands of Chengguan, residents, and street vendors are not one-dimensional, including but not limited to: the interest relationship between one subject and the other two, and the interests within each other. Therefore, the interaction between Chengguan and vendors will affect the evaluation of public policy behavior from surrounding residents. This paper attempts to construct a three-party game relationship model among Chengguan, street vendors, and urban residents. The main objective of the study is to seek the equilibrium point and stable conditions of the tripartite game, so as to provide a rational solution for street governance in Chinese cities.

The rest of this study is organized as follows: we present the literature review in Section 2. Section 3 constructs the evolutionary game model of urban management law

enforcement. Section 4 discusses the evolutionary stability of the game model. Section 5 analyzes the scenario of the evolutionary games. Section 6 describes the conclusions and contributions of this study.

2. Literature Review

Street vending is regarded as an old and significant occupation in cities all over the world [10]. The research on street vendors usually includes multiple disciplinary perspectives, such as sociology, politics, geography, food science, economics, public health, urban planning, and so on [11]. In the existing research on vending, the primarily discuss is the conflicts between street vendors and the government [12, 13].

In many developing countries like China, Thailand, and Columbia, street vending forms an important part of urban economies, and most street vendors operate outside state regulation [14]. Selling wares on the streets is considered a way to make a living for the people at the bottom [8, 15, 16]. By making available ordinary articles of everyday use for a comparatively less price, street vending is regarded as one of the most visible occupations in the cities. Igudia [17] proposed that street vending also has positive benefits for consumers, including financial gains, maintaining social relations, and compensating for the formal economy. But the problem is how to balance the management of public space with the need for street vendors to support livelihoods. Unfortunately, there are very few cities succeeding in it [18].

The spatial politics of vending have received plenty of attention among the contemporary scholars [6, 19–21]. Turner et al. [22] examine the strengths and complexities of street vendors' everyday experiences. They find that street vendors are often targeted by state officials for fines or bribes. In most scenes of Chinese city daily life, the resulting vendor–Chengguan conflicts dramatize state power in public and carry the latent danger of crowd violence in response [23].

Street vending around the world continues to serve as market places with, and more often without, the consent of authorities [24, 25]. One mainstream explanation is that the local government tends to view street vendors as inefficient, disorderly, and unsanitary, which are opposed to the desired national image [26]. Li et al. [11] examined and compared the spatiotemporal patterns and occurrence mechanisms of street vending events from both the urban managers' "top-down" and the urban residents' "bottom-up" points of view.

But we have to admit that street vending also has negative impacts on urban society. These impacts usually have two folds: first of all, from the perspective of the citizens, street vendors usually pay less attention to food safety, and the operation process usually has sanitation hazards [27, 28]. At the same time, vending activities usually bring about some nuisance issues such as noise and smoke, which affect the appearance of neighborhoods and residents' daily lives [29]. Trafialek et al. [30] found many noncompliances in the street food vendors' hygienic practices through a survey. Secondly, in the government's position, the occupation of public space, traffic jams, influence on the

appearance of the city, and unfair competition with formal businesses are significant issues caused by street vending.

Street vendors are often seen as an element to be purged in the whole world. Between the 1980s and 1990s, the tendency to reduce the street vendors' presence spread, in compliance with the neoliberal urban governance model promoted in the United States and later introduced to many developing countries [31–34]. Therefore, the recent public discourse on security have stimulated street trade criminalization and the adoption of exclusionary policies in a lot of developing countries [35].

According to analyzes of vendors' rights, interests, and strategies for coping with the eviction that affected their livelihood, Boonjubun [36] focused on street vendors' survival strategies in Bangkok and analysed various forms of conflicts over the streets. Ojeda and Pino presented [37] an in-depth view of social and spatial conflict identified by street vendors themselves and revealed the socio-spatial dispute over the use of public space.

From the existing literature, there is still a great debate on street vendors. Due to the complexity of street vendors, we need to re-examine the relationship between urban management and vendors from a dynamic point of view.

Referring to the calculation methods of Weixin Yang et al. [38, 39] and the evolutionary game of Ying Zhu et al. [40], especially the evolutionary game analysis of urban traffic environment governance made by Jun yi Liu et al. [41], this paper attempts to construct a multiparty dynamic game model to deconstruct the daily behavior of vendors and analyze the final evolutionary stable strategy of urban governance.

However, different from the existing literature, in view of the complexity of vendor governance, we do not think that strict law enforcement is a good choice. The complexity includes the conflict between Chengguan and street vendors, the huge number of street vendors in China's cities, and the ongoing reform of China's administrative law enforcement. Therefore, by constructing a three-party game model, this paper focuses on analyzing the strategic choices of Chengguan, residents, and vendors, that is, the stable point of the game system. Finally, we can get the most beneficial governance scheme for Chinese streets. Consequently, the innovation of this paper is to use the existing evolutionary game model to analyze the strategic actions of multiple subjects in China's urban streets. We believe that to maintain the stability and vitality of the social system, flexible rather than strict law enforcement is a realistic choice for Chengguan.

3. Research Hypotheses and Evolutionary Game Model

3.1. Evolutionary Game Participants. Some scholars focus on analyzing the relationship between state and citizens, insofar as the two are often seen to clash over how public street space is to be utilized [33, 42]. However, in the actual scene of daily life, the participation of residents will affect the relationship between urban management and vendors. Residents' positive or negative evaluation of vendors will affect the behavior

choice of urban management - loose or strict law enforcement. The participants in our evolutionary game include Chengguan, street vendors, and consumers. The three groups have their own strategic space. The strategic space of Chengguan is {Law enforcement, Not Law enforcement}, which means under various pressures, Chengguan may adopt different strategies to deal with vendors. The strategic space of street vendors is {Vending, Not Vending}, which means vendors can adopt different strategies to cope with the eviction law enforcement on their livelihood. The strategic space of residents is {Purchase, Not Purchase}, meaning residents' purchase behavior will be affected by many factors, such as price, safety, convenience, and so on.

3.2. Basic Assumptions of Evolutionary Game Model. Based on the three subjects and their respective strategic spaces, the following assumptions are made.

Assumption 1. Assuming that the probability of Chengguan choosing "Law Enforcement" is x , then the probability of not is $(1 - x)$; the probability of the street vendors choosing "Not Vending" is y , then the probability of "Vending" is $(1 - y)$; the probability of residents choosing "Not Purchase" at mobile stalls is z , then the probability of "Purchase" is $(1 - z)$.

Assumption 2. When Chengguan chooses "Law Enforcement," there will be a warning effect on street vendors. Penalty mechanisms such as fines and confiscations reduce the number of vendors, thereby improving the city's image, and the positive impact on urban governance is a . Chengguan's law enforcement will lead to the reduction of mobile stalls in urban streets. Residents who are accustomed to buying goods at stalls will complain about the behavior of eviction and punishment from Chengguan as d . Residents who do not buy items at the stalls have good feedback on the proper law enforcement behavior of the Chengguan as b , but they will have negative feedback on scant enforcement of Chengguan, and the negative effects such as complaints and bad reviews are set as c . In addition, the cost of Chengguan's enforcement on street vendors is set to be e .

Assumption 3. When street vendors choose to spread out goods for sale in a booth, they will receive income f . The loss caused by the Chengguan's punishment is g . The negative impact of street vendors on the city's image is h .

Assumption 4. For urban residents, shopping at stalls will give them a sense of satisfaction due to convenience and benefits. This sense of satisfaction is set to be m . However, Chengguan's law enforcement may have mediated adverse effects on ongoing transactions. For example, consumers have already paid the money but the items are confiscated by the Chengguan, resulting in losses, or facing the nervousness and discomfort caused by the Chengguan's law enforcement. Such negative effects are recorded as n .

3.3. Payoff Matrix of the Tripartite Game Model. In the case of the Chengguan having obligations to maintain the street order, all players incur different costs depending on the strategies adopted. Regarding the above assumptions, the payoff matrix of players is shown in Table 1.

4. Evolutionary Stability Analysis

4.1. Replicator Dynamic Equations of Players. According to the evolutionary game theory, we let the expected return of Chengguan choosing "Law Enforcement" be U_a , and let the expected return of choosing "Not Law Enforcement" be U_b . Then, we can obtain the expected return of Chengguan that "Law Enforcement" and "Not Law Enforcement" as follows:

$$\begin{aligned} U_a &= byz + (-d) \cdot y(1 - z) + (a + b)(1 - y)z + a(1 - y)(1 - z), \\ &= dyz - (d + a)y + bz + a, \\ U_b &= eyz + ey(1 - z) + (e - c)(1 - y)z + e(1 - y)(1 - z), \\ &= cyz - cz + e. \end{aligned} \quad (1)$$

The average expected return is as follows:

$$U_x = xU_a + (1 - x)U_b. \quad (2)$$

Therefore, according to the dynamic equation of Malthusian, the replicator dynamics equation of Chengguan's strategy is

$$\begin{aligned} \frac{dx}{dt} &= x(U_a - U_x) = x(1 - x)(U_a - U_b) \\ &= x(1 - x)[(d - c)yz - (d + a)y + (b + c)z + a - e]. \end{aligned} \quad (3)$$

Let U_c represent the expected return of street vendors if they choose "Not Vending" and U_d represent the expected return of street vendors if they choose "Vending." We can obtain the expected return of street vendors as follows:

$$\begin{aligned} U_c &= 0 \cdot xz + 0 \cdot x(1 - z) + 0 \cdot (1 - x)z + 0 \cdot (1 - x)(1 - z) = 0, \\ U_d &= (-g)xz + (f - g)x(1 - z) + 0 \cdot (1 - x)z + f(1 - x)(1 - z) \\ &= -gx - fz + f. \end{aligned} \quad (4)$$

Let U_y represent the average expected return of street vendors that can be written as follows:

$$U_y = yU_c + (1 - y)U_d. \quad (5)$$

The replication dynamic equation of street vendors' strategy can be expressed as follows:

$$\frac{dy}{dt} = y(U_c - U_y) = y(1 - y)(U_c - U_d) = y(1 - y)(gx - f + fz). \quad (6)$$

Let U_e represent the expected return of residents if they choose "Not Purchase" and U_f represent the expected return of residents if they choose "Purchase." We can obtain the expected return of residents as follows:

TABLE 1: Payoff matrix of the tripartite game.

Chengguan	Vendors	Residents	
		not purchase z	purchase $(1 - z)$
Law enforcement x	Vending $(1 - y)$	b	$-d$
		0	0
	Not vending y	0	0
		$a + b$	a
Not law enforcement $(1 - x)$	Vending $(1 - y)$	$-g$	$f - g$
		$-h$	$m - h - n$
	Not vending y	e	e
		0	0
Not law enforcement $(1 - x)$	Vending $(1 - y)$	0	0
		$e - c$	e
	Not vending y	0	f
		$-h$	$m - h$

$$\begin{aligned}
U_e &= 0 \cdot xy + (-h)x(1 - y) + 0 \cdot (1 - x)y \\
&\quad + (-h)(1 - x)(1 - y) = hy - h, \\
U_f &= 0 \cdot xy + (-h - n + m)x(1 - y) + 0 \cdot (1 - x)y \\
&\quad + (-h + m)(1 - x)(1 - y) \\
&= nxy - nx + (h - m)y - h + m.
\end{aligned} \tag{7}$$

The average expected return for consumers is

$$U_z = zU_e + (1 - z)U_f. \tag{8}$$

The replication dynamic equation of street vendors' strategy can be expressed as follows:

$$\begin{aligned}
\frac{dz}{dt} &= z(U_e - U_z) = z(1 - z)(U_e - U_f) \\
&= z(1 - z)(nxy - nx + my - m).
\end{aligned} \tag{9}$$

The replicator dynamic (3), (6), and (9) constitute a three-dimensional dynamic system as follows:

$$\begin{cases}
F(x) = \frac{dx}{dt} = x(1 - x)[(d - c)yz + (-d - a)y + (b + c)z + a - e], \\
F(y) = \frac{dy}{dt} = y(1 - y)(gx - f + fz), \\
F(z) = \frac{dz}{dt} = z(1 - z)(-nxy + nx + my - m).
\end{cases} \tag{10}$$

4.2. Evolutionary Stability Strategy of Players. According to the replicator dynamic equations of the model, the probability of "Law Enforcement" by Chengguan $x(t)$, the probability of "Not Vending" by vendors $y(t)$, and the probability of "Not Purchase" by residents $z(t)$ all depend on time, and $x(t), y(t), z(t) \in [0, 1]$. In the system, we let $F(x) = 0, F(y) = 0, F(z) = 0$, the dynamical system has eight local equilibrium points of adopting pure strategies as follows:

$$\begin{aligned}
A_1 &= [0, 0, 0], A_2 = [0, 0, 1], A_3 = [0, 1, 0], A_4 = [0, 1, 1], \\
A_5 &= [1, 1, 1], A_6 = [1, 0, 1], A_7 = [1, 1, 0], A_8 = [1, 0, 0].
\end{aligned}$$

4.2.1. The Evolutionarily Stable Strategy of One Group. The dynamical system may have three equilibrium points where one group adopts a pure strategy:

$$\begin{aligned}
A_9 &= [m/n, 0, -a - e/b + c], A_{10} = [f/g, a - e/d + a, 0], \\
A_{11} &= [B_1, 1, d + e/d + b]
\end{aligned}$$

in the equilibrium point A9.

$$0 < m/n < 1, 0 < -a - e/b + c < 1;$$

in the equilibrium point A10.

$$0 < f/g < 1, 0 < a - e/d + a < 1;$$

in the equilibrium point A11.

$$0 < B_1 < 1, 0 < d + e/d + b < 1.$$

4.2.2. The Evolutionarily Stable Strategy of Two Groups. The dynamical system may have three equilibrium points where two-party groups adopt a pure strategy:

$$A_{12} = [1, 1, B_2], A_{13} = [0, 1, B_3], A_{14} = [0, B_4, 1].$$

$$\text{Among them, } 0 < B_2 < 1, 0 < B_3 < 1, 0 < B_4 < 1.$$

If the dynamical system satisfies $F(x) = 0, F(y) = 0, F(z) = 0$, and the values of x, y , and z are not 0 or 1, we can obtain the following equation:

$$\begin{cases}
C(x_1, y_1, z_1) = (d - c)yz - (d + a)y + (b + c)z + a - e = 0, \\
D(x_1, y_1, z_1) = -gx + f - fz = 0, \\
E(x_1, y_1, z_1) = -nxy + nx + my = 0.
\end{cases} \tag{11}$$

4.2.3. The Hybrid Strategy Analysis. The three-dimensional dynamical system (10) may have a hybrid adoption strategy equilibrium point: $A_{15} = [x_1, y_1, z_1]$.

We solve equation (11) and obtain the following equation:

$$\begin{cases} x_1 = \frac{m}{n}, \\ y_1 = \frac{(b+c)(1-gm/fn) + a - e}{(d-c)(1-gm/fn) - d - a}, \\ z_1 = 1 - \frac{gm}{fn}. \end{cases} \quad (12)$$

So the equilibrium point A_{15} is $[m/n, (b+c)(1-gm/fn) + a - e / (d-c)(1-gm/fn) - d - a, 1 - gm/fn]$.

4.3. Stability Analysis of Equilibrium Point. According to the first theorem of Lyapunov requirements for system stability:

(1) x_e is unstable

One eigenvalue of the Jacobian matrix $\text{Re}(\lambda_k) > 0$, or the eigenvalues of $\text{Re}(\lambda_k) = 0$ have multiple roots;

(2) The asymptotic stability of x_e

All eigenvalues $\text{Re}(\lambda_k) < 0$ in the Jacobian matrix;

(3) The Lyapunov stability of x_e

All eigenvalues of the Jacobian matrix $\text{Re}(\lambda_k) \leq 0$, and the eigenvalues of $\text{Re}(\lambda_k) = 0$ have no multiple roots.

Regarding the above-given conditions, 15 equilibrium of the system formula (10) can be judged. Calculating the Jacobian matrix of system (10), equation (13) can be obtained as follows:

$$\begin{bmatrix} (1-2x)[(d-c)yz - (d+a)y + (b+c)z + a - e] & x(1-x)[(d-c)z - d - a] & x(1-x)(dy - cy + b + c) \\ gy(1-y) & (1-2y)(-gx + f - fz) & fy(1-y) \\ z(1-z)(n - ny) & z(1-z)(-nx + m) & (1-2z)(-nxy + nx + my - m) \end{bmatrix}. \quad (13)$$

Then, we can calculate the eigenvalue of the Jacobian matrix corresponding to each equilibrium point of equation (10) through equation (13). The main equilibrium point can be shown in Table 2.

5. Scenario Analysis of the Evolutionary Games

Through the group evolution model and the asymptotic stability of the equilibrium point of the three-party game among Chengguan, street vendors, and residents, the stable strategy of the evolutionary game is obtained. Under different stability conditions, all participants in urban streets will adopt their own strategies which eventually tend to be stable. Next, we will analyze the three situations that tend to be stable in order to find the optimal urban street governance scenario.

5.1. Chaotic Street Order. In this scenario, Chengguan chooses “Not Law Enforcement,” street vendors choose “Vending,” and the residents have consumption behavior, that is, $A_1 = (0, 0, 0)$. In this scenario, the condition that must be met is $a - e < 0$, which means the cost of law enforcement is greater than the social benefits brought by law-enforcement. In the practice of urban governance, when the cost of public governance is higher than the public benefit, it means that there is a problem with the governance mechanism. People do not recognize the law enforcement behavior of Chengguan. Therefore, Chengguan eventually tends not to enforce the law, vendors go to the streets, and residents then choose to purchase, so that the urban streets enter a vicious circle. To avoid this, Chengguan should reasonably control the cost of law enforcement and appropriately increase social benefits, so that the condition $a - e < 0$ is not established. It can be

concluded that the evolution path of the system will not tend to the evolutionary stable point of $A_1 = [0, 0, 0]$.

5.2. Fragile Informal Economy due to Strict Law Enforcement. When Chengguan chooses “Law Enforcement,” street vendors choose “Not Vending,” and the residents have no consumption behavior, that is, $A_5 = [1, 1, 1]$, the condition $-b + e < 0$, $-g < 0$ must be satisfied. At this scenario, the cost of Chengguan enforcement is less than the social reputation formed by urban residents for enforcement. At the same time, Chengguan will make fines when investigating and dealing with vendors, which will lead to the loss of street vendors. The behavior of the Chengguan tends to be severely law enforcement, the vendors tend not to vend, and the residents cannot consume. Although this is the optimal strategy from the perspective of the system model, it is significantly different from the actual situation of China. According to data from the seventh census released in 2021, by the end of 2020, China’s urban population will be over 901 million, accounting for 63.89% of the total population. The floating population in China is 376 million, and the number of flexible employment has reached 200 million. With such a large floating population and flexible employment, strict law enforcement against vendors will lead to many consequences, so it is not feasible. Consequently, the evolutionary path of the system will not tend to the stable point of condition 3.

5.3. Flexible Law Enforcement. In this scenario, Chengguan enforces the law to street vendors, but street vendors and consumers both participate in, that is, $A_8 = [1, 0, 0]$, and the condition $-a + e < 0$, $g - f < 0$, $n - m < 0$ must be satisfied. The law enforcement cost is less than the social benefits. At

TABLE 2: Eigenvalues and asymptotic stability conditions of the Jacobian matrix.

Equilibrium points	Eigenvalues λ_1	Eigenvalues λ_2	Eigenvalues λ_3	Asymptotic stability condition
A1 = (0, 0, 0)	$a - e$	f	$-m$	$a - e < 0$
A2 = (0, 0, 1)	$b + c + a - e$	0	$-m$	Unstable point
A3 = (0, 1, 0)	$-d - m$	f	0	Unstable point
A4 = (0, 1, 1)	$b - e$	0	0	Unstable point
A5 = (1, 1, 1)	$-b + e$	$-g$	0	$-b + e < 0$; $-n < 0$
A6 = (1, 0, 1)	$-b - c - a + e$	n	$-n + m$	Unstable point
A7 = (1, 1, 0)	$d + e$	$-g + f$	0	Unstable point
A8 = (1, 0, 0)	$-a + e$	$g - f$	$n - m$	$-a + e < 0$; $g - f < 0$; $n - m < 0$

this time, on the basis of scenario 1, the social benefits are reasonably increased. Therefore, Chengguan has changed the decision-making behavior and actively participated in the governance of urban streets. However, the income of the vendors is greater than the fines punished by the Chengguan, so vendors will choose to continue to set up stalls on the streets, but due to the enforcement behavior of Chengguan, there will be a “cat-and-mouse” scene, that is, when Chengguan appears at streets, the vendors will quickly flee, or conflict behavior occurs. For residents, the benefits brought by the purchase behavior at the stall are greater than the adverse effects, so they will eventually tend to purchase. The urban street governance has been better improved due to the active participation of Chengguan, but due to the behavior of street vendors, there will be violent conflicts and chaos in urban management law enforcement. Therefore, Chengguan’s law enforcement behavior needs to have appropriate flexibility, so that the three parties of the Chengguan, street vendors, and residents can maintain in a dynamic, stable, and balanced state.

6. Conclusions

We use the evolutionary game replication equation to construct an evolutionary game model of urban street governance with Chengguan, street vendors, and consumers as the main players of the game, and analyze the evolutionarily stable strategy of the system. For decades, street vendors have been considered as marginal individuals who passively practice their activities [31]. But our research shows that the stability of the equilibrium point of a single group is not only affected by itself but also affected by the other two groups. According to the evolutionarily stable state obtained through the scenario analysis, the law enforcement of Chengguan plays an important leading role in the urban street governance. But the important thing is maintaining appropriate and flexible policies to reserve a certain living space for street vendors, which tests the law enforcement wisdom of the street bureaucrats.

Therefore, the flexible law enforcement of Chengguan is of great significance. On the one hand, it satisfies the efficiency pursuit of urban development and realizes the overall effective and orderly street space. On the other hand, it also accommodates the livelihood needs of the bottom groups, which will alleviate the poverty of them to a certain extent. In the process of rapid urbanization in China, there has not been a large number of slums like in some developing

countries. Although this is a phenomenon with multiple causes and effects, the transfer of the right to earn a living space for the bottom groups is one of the reasons. Although informal employment such as vendors and tricycle workers infringes upon the spatial order of the city, it provides survival opportunities for a large number of low skilled groups who are excluded or failed in urban vocational competition. Our research results are consistent with these studies, mainly conducted in the global South, having emphasized the role of the street vendors’ agency, highlighting the strategies of resistance and negotiation they employ to confront exclusionary policies and guarantee their right to work in street [34, 42, 43].

In fact, the newly revised “Administrative Punishment Law of the People’s Republic of China” in 2021 clearly stipulates the rule of “first violation without punishment” for urban management law enforcement “those who violate the law for the first time and have minor harmful consequences can not be punished.” This is a very beneficial institutional innovation. “First violation without punishment” is a reasonable tolerance that conforms to the spirit of the law and belongs to law enforcement using noncoercive means such as persuasion and education. This will not only help reduce resistance but also conduce to improving the efficiency of law enforcement. Therefore, in the normal management of street vendors, the boundaries of street space should be constantly adjusted in the process of the game. The power-right structure of street space should evolve gradually with the change of urban social space. Finally, the overall harmony and stability of urban public space in the rapidly changing environment of China can be realized by these manners.

Data Availability

The data used for the numerical analysis are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Structural Evolution of Regional Firm Network System under the Influence of Industrial transfer: A Case Study of the Refrigeration Industrial Cluster of Minquan County

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The transplanted firm is an important force to promote the network evolution and cluster transformation and upgrading of the undertaking firm. From the micro-analytic perspective of firm network, this paper puts forward a theoretical framework with “relationship-network-evolution” as the main line. Taking the refrigeration industry cluster in Minquan County of China as a case study and keeping the firm networks of economic relation, technical cooperation, and social communication firm network in 2009, 2013, and 2017 as the research objects, this paper analyzes the structure and evolution characteristics of regional firm network system, proposes the degree and effect of the local embeddedness of transplanted firms, and discusses their differences between international and interregional transplanted firms. The results revealed that: (1) the local embeddedness of transplanted firms significantly promotes the development of refrigeration industry network. (2) The network power of large-scale transplanted firms in the cluster is increasing day by day, and the network presents a multi-core trend. (3) The local embeddedness of some transplanted firms is not high, and the overall connectivity of the network is not strong. (4) Network intermediary nodes have strong heterogeneity, and the intermediary role of some large transplanted firms in the network needs to be improved. (5) The three network systems have similar structural characteristics, and social capital plays an important role in the local embeddedness of transplanted firms and the development of regional firm network. (6) Compared with international transplanted firms, interregional transplanted firms are more adaptable in terms of local embeddedness. The research results provide a reference for the construction of similar industrial clusters in China and other developing countries.

1. Introduction

In China's social and economic construction, there are relatively prominent problems of urban-rural development differences and unbalanced and insufficient regional development. In the past 20 years, China's domestic industrial transfer from the eastern coastal areas to the inland central and western regions is greatly important for narrowing regional differences and promoting coordinated development [1, 2]. The transplanted firms from the eastern coastal areas carry the flow of capital, technology, and information, and their local embeddedness brings valuable opportunities for industrial development, technology learning, transformation, and upgrading in the central and western regions,

and can enhance the related diversity of the local clusters. It helps to break the rigidity and lock-in state of traditional industrial clusters, so the local embeddedness of transplanted firms can be regarded as the “windows of location opportunity” for undertaking the transformation and upgrading of local clusters. At present, China's domestic industrial transfer is still in a relatively rapid development stage. The vast central and western regions are trying to guide the transplanted firms to achieve local embeddedness and build a compact and efficient regional production and innovation network to promote the mid- to high-end connection between regional industries and global value chains (GVCs), so as to create more competitive characteristic industrial clusters.

Seen from the existing theoretical research and economic practice, the local embeddedness of the transplanted firms can promote the industrial development and economic prosperity to a certain extent, but there are also problems that some transplanted firms are difficult to embed locally, and some clusters are not highly developed. First, due to the “space of place” and “institution thickness,” it will face a mismatch in terms of technology, structure, space, and system, thus limiting the global-local production network connection [3, 4]. Second, due to the high mobility of global capital, once the local environmental viscosity is reduced, the problem of “migratory economy” or “footloose embeddedness” may arise [5, 6]. Third, if the transplanted firms adopt the strategy of “club convergence,” the phenomenon of “cathedrals in desert” and “enclave economy” will be formed [7, 8]. Fourth, due to the instinct to maintain “network power,” transplanted firms often adopt the strategy of technical blockade, thus falling into the local “low technology trap” and “poverty growth” [9, 10]. It should be pointed out that the discussion on the above issues is mainly based on the research on global industrial transfer represented by FDI. At present, there are also studies focusing on the local embeddedness of domestic transplanted firms and the interactive coupling between the transplanted and local firms [11, 12], but the comparison of the local embeddedness, regional networking behavior and mechanism of global and domestic transplanted firms still need to be strengthened.

Therefore, based on the perspective of firm network analysis at the micro-scale, this paper puts forward a theoretical framework with “relationship-network-evolution” as the main line, and then, takes the refrigeration industrial cluster in Minquan County, Henan Province, which is located in the central region of China, as a research case. A large amount of first-hand data of connections among firms have been obtained by investigating, the firm network system of the cluster for economic relation, technical cooperation, and social communication in 2009, 2013, and 2017 is established, and then, the social network analysis method (SNA) is employed to analyze the network structure and its evolution characteristics of regional firms, determine the degree and effect of local embeddedness of transplanted firms, and discuss whether there are also embeddedness difficulties and failures in the process of local embeddedness of domestic transplanted firms, in order to provide decision-making reference for local governments to formulate scientific and reasonable industrial undertaking policies and cluster cultivation policies. The detailed chapters are shown as below. The first part is the introduction, the second part gives the theoretical framework, the third part presents the data sources and analytical method, the fourth part analyzes the proposed regional firm network structure and evolution, and the fifth part concludes this paper.

2. Theoretical Framework

The research on the local embeddedness of transplanted firms began in the 1960s, and the early studies mainly focused on the construction of industrial linkages

between transnational corporations (TNCs) and host countries [13]. In the 1990s, the concept of “embeddedness” was absorbed into the theoretical framework of new economic geography in several turns of research direction [14, 15], and economic geographers began to pay more attention to the relationship construction, institutional constraints, and cultural influences in the local embeddedness of transplanted firms [16–18]. After the 21st century, the Manchester School proposed the theory of global production networks (GPNs) [19–21], and more studies began to analyze the global and local strategic coupling from the perspective of GPN [22, 23]. At present, the research hotspots from the perspective of economic geography mainly include the network construction between transplanted and local firms [24], technology spillover and learning innovation [25], the role of social capital [26, 27], etc., Observation angles include economic embeddedness, technological embeddedness, social embeddedness, political embeddedness, cultural embeddedness, institutional embeddedness, cognitive embeddedness, etc., [28].

There are many entry points for the research on the local embeddedness of transplanted firms, “firm network” is a very effective research perspective at the micro-scale [29–31]. Therefore, based on the industrial cluster theory, global production network theory, and embeddedness theory, a theoretical framework was constructed with “relationship-network-evolution” as the main line (Figure 1). Industrial transfer is essentially a process of “industry/firm-region” interaction. With the gradual local embeddedness of the transplanted firms, the product supply and demand, technical cooperation, and social exchanges will be established. With these relationships as links, and firms and related institutions as nodes, an interactive network will be formed, and the connection between local and global production networks will be realized. With the advancement of the local embeddedness of transplanted firms and global embeddedness of local clusters, the regional firm network will show unique structural and evolutionary characteristics, and the regional industry will also achieve a rise and transition in the global value chain. At present, there are relatively few researches on industrial transfer based on the perspective of “firm network,” and there is a lack of clear understanding of the embeddedness process and mechanism of the transplanted firms. The theoretical framework and empirical research based on this framework can make up for the insufficiency of existing research.

3. Data Sources and Analytical Method

3.1. Data Collection. Minquan County is located in Henan Province in the central region of China. The refrigeration industry is a traditional and iconic industry in Minquan County. In the 1980s, there were only limited number of local firms, which formed the early stage of the refrigeration industry cluster in Minquan County. Since 2010, a large number of firms have transplanted from the eastern coastal areas. At present, the number of transplanted firms accounts

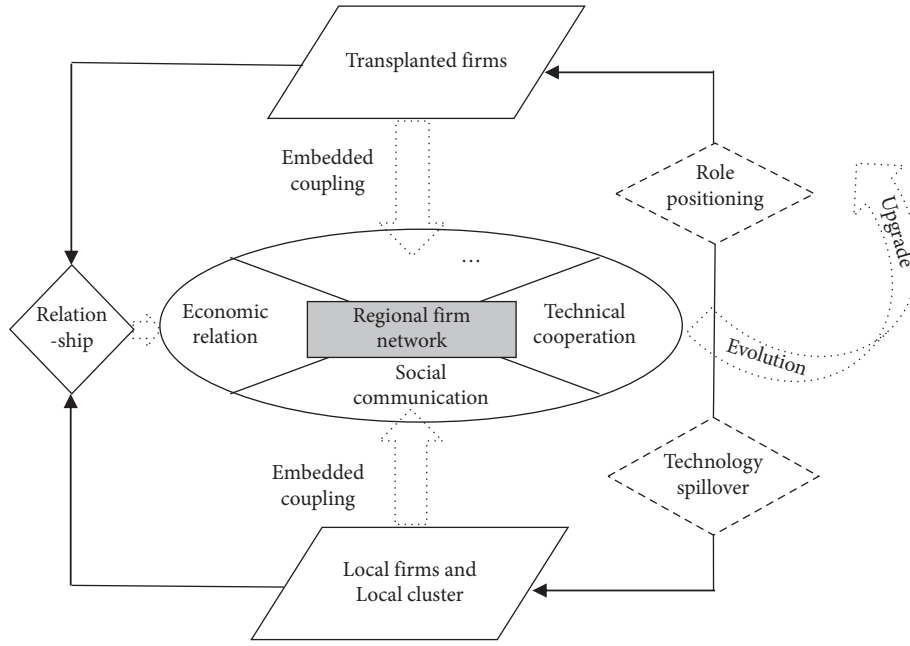


FIGURE 1: Theoretical framework of this Study.

for more than 60% of the total number of firms in the cluster, and they are from other regions in China, distinct obvious regional and industrial characteristics. Therefore, it is very suitable for the research on the local embedding of inter-regional transplanted firms. The data mainly originated from two rounds of research on the Minquan refrigeration industrial cluster from July to October 2014 and from November to December 2017. After 2017, the number of new firms in the cluster was relatively small. In addition, the COVID-19 had a great impact on the operation of the cluster in 2020, including the connection between firms. The data after 2020 is not suitable for comparison with previous data. So, no new research was conducted in the later period. It extracts the economic relation, technical cooperation, and social communication firm network of the cluster in 2009, 2013, and 2017 in the survey. Economic relation mainly refers to upstream and downstream supply relationships, subcontracting or OEM production between firms. Technical cooperation mainly refers to joint research and development of new products, patent transfer, technical assistance, etc., between firms. Social communication mainly refers to informal contacts between firms, including personal friendships among business owners, personal exchanges, etc., According to the annual report of the Industrial Cluster Management Committee in Minquan County, there were 15 firms in 2009, including 1 firm settled in Minquan refrigeration industry cluster through industrial transfer, and 14 local firms in Minquan. In 2013, there were 39 firms, including 23 transplanted firms and 16 local firms. From 2013 to 2017, 11 new firms were added and 6 closed down; therefore, there were 44 firms in total in 2017 (Table 1), including 17 firms that transplanted whole machine (T1), 10 firms that transplanted supporting equipment (T2), 9 local firms of whole machine (L1), and 8 local firms of supporting equipment (L2).

3.2. Construction and Extraction of Network System. First, the firm relationship data within the cluster obtained by the survey was verified and processed. The connection between firms was reserved and assigned a value of 1 only when confirmed by both parties; otherwise, it was assigned a value of 0. In the analysis of the survey data of the firm contacts, only the firm A and B believe that there is a certain connection between them, such as a technical cooperation relationship, the connection can be confirmed. In other words, if the firm A believes that it has a technical cooperation relationship with B, but the firm B does not think that it has a technical relationship with A, we do not think there is a technical relationship between A and B in this paper. This is done to ensure the objectivity of firm contacts. By sorting out the survey results, the symmetric relationship matrix of economic relation, technical cooperation, and social communication among firms within the cluster at each time section is finally constructed, and a network of undirected and weightless economic relation, technical cooperation, and social communication (Figure 2) among the Minquan refrigeration firms in 2009, 2013, and 2017 was extracted.

3.3. Measurement Analysis of Network System. The purpose of firm network system analysis is to examine the structural characteristics and evolution laws of network systems, identify important nodes, and interpret the similarity of network systems. Examining the overall structure of the network system is mainly based on node degree distribution, centripetal-centrifugal structure, and network centralization. Examining network accessibility is mainly based on node degree, network density, and average shortest length path. Identification of broker is mainly based on the betweenness centrality of the nodes. Analysis of the evolution law of the network system during the research period is

TABLE 1: General situation of the firms in the refrigeration industrial cluster of Minquan county.

Classification no.	Origin	Product	Number of firms	Firm name
T1	Transplanted	Whole machine	17	BS, WB, AKMDQ, HM, HKDL, XXH, XY, KMR, LK, HG, ZX, KBE, KW, AKM LCC, ASDDRSQ, ASDDJSJ, JT
T2	Transplanted	Supporting equipment	10	CX, AJ, SY, MH, HY, SNDQ, XD, XLPJ, ZC, HX
L1	Local	Whole machine	9	AX, JX, XP, ZB, XL, BXLCC, SC, YT, DLB
L2	Local	Supporting equipment	8	BH, GB, HKPJ, HKDQ, JXPJ, LL, SB, YF

mainly based on the number of nodes, node degree distribution, core nodes, and the change of broker [32–34].

In addition, in order to simultaneously analyze the structural similarity of economic relation, technical cooperation, and social communication network systems, and as well as to analyze whether they have similar evolutionary laws, this paper also proposes a model to measure the similarity of network systems. Assuming that there are undirected and weightless networks X and Y , the nodes of the two are exactly the same, but the connection relationship in the network system may be different, so the similarity measure formula of the two network systems is as follows:

$$S_{XY} = \frac{\sum_{i \neq j}^n \sqrt{(X_{ij} - Y_{ij})^2}}{n(n-1)}. \quad (1)$$

In the formula, S_{XY} is the similarity of the network system X and Y , X_{ij} is the connection between the nodes i and j in the network X , Y_{ij} is the connection between the nodes i and j in the network Y . If there is a connection between the nodes in the undirected and weightless network, X_{ij} and Y_{ij} are equal to 1; otherwise, they are equal to 0. n is the number of nodes. The value of S_{XY} is between 0 and 1. A value of 0 indicates that the network X is exactly the same as Y , and a value of 1 indicates that the two do not have any identical network connections.

4. The Structure and Evolution of Firm Network

On the basis of constructing the firm network within the cluster, the social network analysis method was employed to focus on analyzing the connectivity and coreness of the Minquan refrigeration firm network, identifying the intermediary nodes of the network and judging the local embeddedness of the transplanted firm. It also analyzes the structural similarity between economic, technological, and social networks, and explores the process, mechanism, and effect of the local embeddedness of transplanted firms.

4.1. The Overall Connectivity of the Network System Is Not Strong, Showing a Centripetal-Centrifugal Structure. On three timestamps, the density of Minquan refrigeration industry network is less than 0.20, and the average shortest path is more than 2 (Table 2), indicating that the interconnection between network nodes is relatively sparse, the network development is not perfect, and the “relationship proximity” between the firms

is low. The most obvious is the technical cooperation network. The technical cooperation network density in the three periods is less than 0.10, indicating that the technical connection strength between the firms is less than one-tenth of the fully connected network. Furthermore, the average shortest path of the technical cooperation network during the study period is constantly increasing, indicating that the technical cooperation network still has a trend of gradual sparseness.

In Table 3, the network node degree value of the Minquan refrigeration firm has a very large difference on three timestamps, and the node degree distribution shows a layering phenomenon. The degree distribution probability approximately shows “rightward inclined long-tailed distributions,” and low degree value nodes occupy a larger proportion in the network. It shows that the network development is unbalanced, and most of the firms have low degree value and are more dependent on the core node firms in the network. At the same time, it shows strong centripetal-centrifugal distribution characteristics, and the density difference between the two areas is very large. For example, the densities of the core areas of economic relation, technical cooperation, and social communication networks were 0.44, 0.35, and 0.64, respectively, and the densities of the fringe areas in 2017 were 0.07, 0.04, and 0.09, respectively.

4.2. The Local Embeddedness of Some Transplanted Firms Are Not High. From the centripetal-centrifugal distribution of transplanted firms, it can be seen that most of the transplanted firms are located in the fringe area or the centripetal-centrifugal junction area, and the number of firms located in the core area is very small. In 2017, there were 10 firms located in the core area in the three types of networks, of which there were still only 2 transplanted firms; there were 18 firms located in the fringe areas in the three networks, and 14 of them were transplanted firms. Therefore, most of the transplanted firms have not entered the core circle of the Minquan refrigeration industry network, and the degree of embeddedness in the network is not high.

In order to deeply analyze the reasons for the insufficient local embeddedness of the transplanted firms, the number of firm connections between and within each category for T1, T2, L1, and L2 is calculated and normalized in the three networks, respectively (that is, the ratio of the actual number of connections to the theoretical maximum number of connections). It can be seen from Figure 3 that in terms of

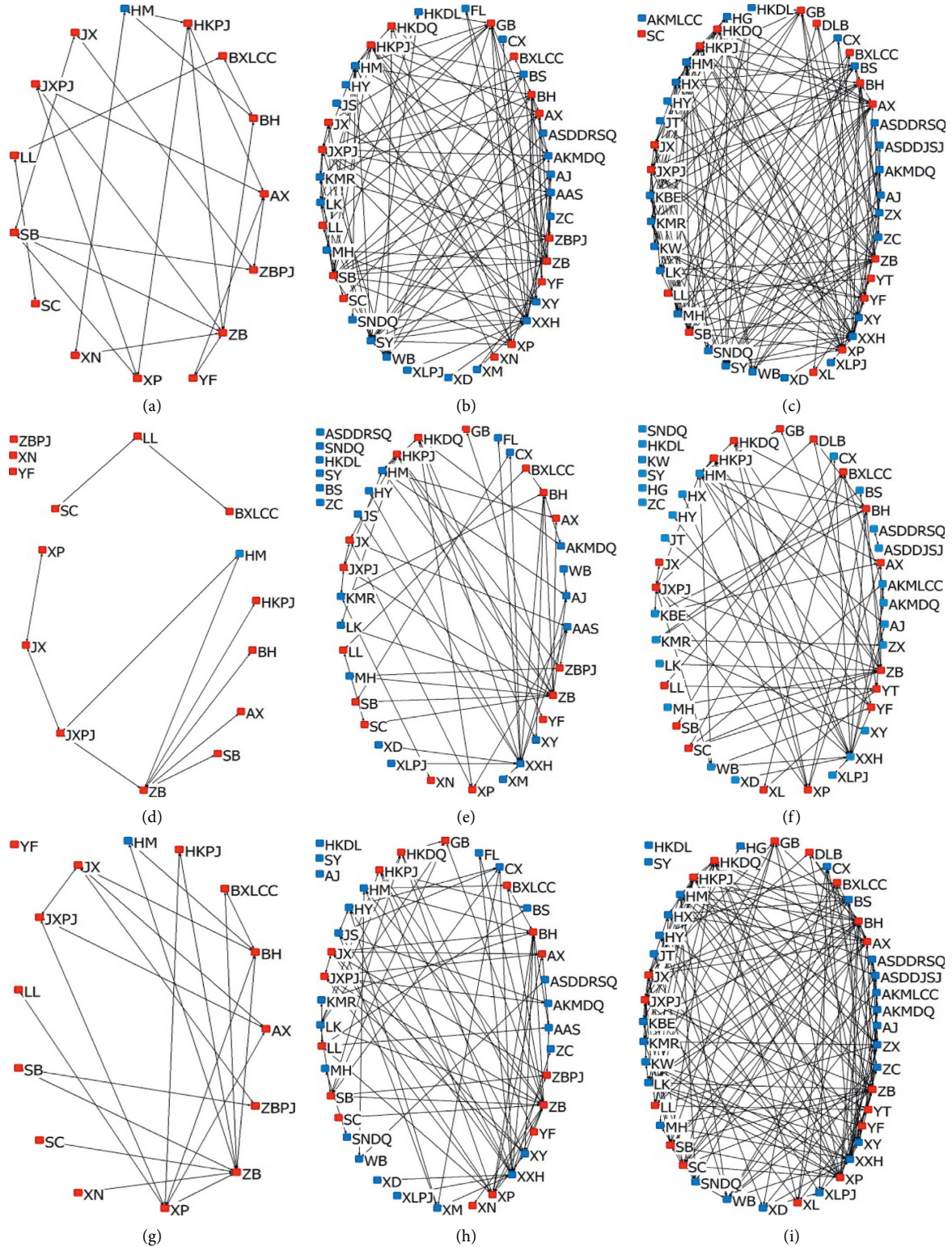


FIGURE 2: Relationship network of refrigeration firms in Minquan county. (a) Economic relation network in 2009. (b) Economic relation network in 2013. (c) Economic relation network in 2017. (d) Technical cooperation network in 2009. (e) Technical cooperation network in 2013. (f) Technical cooperation network in 2017. (g) Social communication network in 2009. (h) Social communication network in 2013. (i) Social communication network in 2017.

economic relation, both 2013 and 2017 showed the characteristics of $L1-L2 > T1-L2 > T1-T2 > T2-L1$, indicating that the economic relations between transplanted and

surrounding firms were relatively weak. In terms of technical cooperation, both 2013 and 2017 showed the characteristics of $L1-L1 > L1-L2 > T1-L2 > T1-T2 > T1-L1 > T2-L1 > T2-L2$,

TABLE 2: Density and average shortest path of refrigeration firms network in Minquan County.

	2009			2013			2017		
	Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication
Density	0.20	0.10	0.19	0.14	0.07	0.10	0.16	0.07	0.17
Average shortest length path	2.66	2.08	2.07	2.45	2.71	2.52	2.30	2.93	2.17

TABLE 3: Node degree value of refrigeration firms network of Minquan County.

Classification No	Firm name	2009			2013			2017		
		Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication
T1	AAS	—	—	—	5	4	4	—	—	—
T1	AKMDQ	—	—	—	7	2	2	6	2	7
T1	AKMLCC	—	—	—	—	—	—	0	4	3
T1	ASDDJSJ	—	—	—	—	—	—	2	1	6
T1	ASDDRSQ	—	—	—	1	0	1	3	1	6
T1	BS	—	—	—	5	0	2	8	2	8
T1	HG	—	—	—	—	—	—	6	0	2
T1	HKDL	—	—	—	3	0	0	7	0	0
T1	HM	3	2	2	11	6	5	11	10	12
T1	JT	—	—	—	—	—	—	1	1	1
T1	KBE	—	—	—	—	—	—	7	3	4
T1	KMR	—	—	—	6	3	2	9	4	5
T1	KW	—	—	—	—	—	—	5	0	5
T1	LK	—	—	—	5	2	5	7	1	9
T1	WB	—	—	—	7	1	2	9	4	9
T1	XXH	—	—	—	14	11	12	17	13	19
T1	XY	—	—	—	6	2	6	4	1	6
T1	ZX	—	—	—	—	—	—	6	2	9
T2	AJ	—	—	—	4	4	0	3	2	1
T2	CX	—	—	—	1	2	5	3	2	5
T2	FL	—	—	—	2	1	2	—	—	—
T2	HX	—	—	—	—	—	—	12	1	6
T2	HY	—	—	—	1	1	4	1	1	5
T2	JS	—	—	—	1	1	5	—	—	—
T2	MH	—	—	—	3	2	1	11	1	4
T2	SNDQ	—	—	—	2	0	1	6	0	5
T2	SY	—	—	—	15	0	0	15	0	0
T2	XD	—	—	—	1	1	1	1	1	5
T2	XLPI	—	—	—	1	1	1	1	1	5
T2	XM	—	—	—	2	1	4	—	—	—
T2	ZC	—	—	—	1	0	1	5	0	6
L1	AX	4	1	3	7	2	4	12	4	12
L1	BXLCC	2	1	2	2	2	3	3	5	6
L1	DLB	—	—	—	—	—	—	3	3	4
L1	JX	2	2	4	5	4	6	9	1	12
L1	SC	1	1	1	2	2	1	0	4	9
L1	XL	—	—	—	—	—	—	2	2	5
L1	XP	3	1	6	7	3	9	10	6	14
L1	YT	—	—	—	—	—	—	2	5	4
L1	ZB	6	6	8	9	11	14	12	10	17
L2	BH	3	1	5	10	6	9	11	8	16

TABLE 3: Continued.

Classification No	Firm name	2009			2013			2017		
		Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication	Economic relation	Technical cooperation	Social communication
L2	GB	—	—	—	10	1	4	8	2	7
L2	HKDQ	—	—	—	4	5	5	7	5	13
L2	HKPJ	4	1	2	10	6	5	15	4	14
L2	JXPJ	3	3	3	12	4	6	14	8	13
L2	LL	2	2	1	2	2	4	3	2	7
L2	SB	4	1	2	15	2	6	14	2	10
L2	XN	2	0	1	1	1	1	—	—	—
L2	YF	2	0	0	3	1	1	9	5	4
L2	ZBPJ	3	0	2	7	3	4	—	—	—

*Some firms have no data in 2009 and 2013 because these factories were built after 2009 or 2013, and some firms have no data in 2017 because those firms were closed down by 2017.

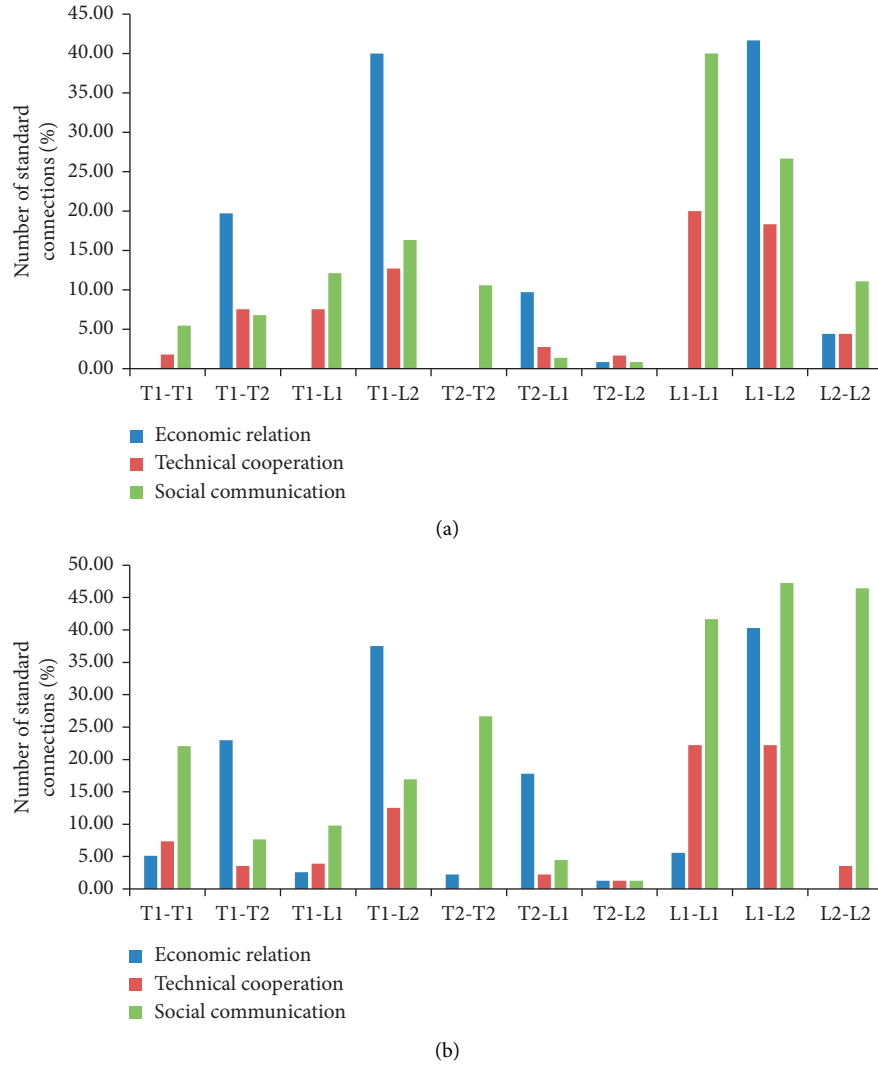


FIGURE 3: Number of standard connections for different types of firms in 2013 and 2017.

indicating that the technical cooperation between transplanted and surrounding firms were also relatively weak. In terms of social communication, the characteristics of $L1-L1 > L1-L2 > T1-L2 > L2-L2 > T1-L1 > T2-T2 > T1-T2$ were presented in 2013, and the characteristics of $L1-L2 > L2-L2 > L1-L1 > T2-T2 > T1-T1 > T1-L2 > T1-L1 > T1-T2$ in 2017 indicated that the social connection between the transplanted and the surrounding firms are weaker.

4.3. The Multi-Core Characteristics of Network Systems Are Becoming More and More Obvious. In the three networks in 2009, the degree value of ZB ranked first and was much higher than other nodes, indicating that ZB was the absolute core of the network in the Minquan refrigeration industry network in 2009. In 2013, ZB and XXH ranked first in the technical cooperation network, and the degree value far surpassed other firms. ZB and XXH ranked first and second in the social communication network. The degree value of XXH ranked third, and ZB is in the ninth place in the economic relation network. Therefore, the dominance of the

old local firm ZB has changed after 2013, and the transplanted firms XXH has also become the core node of the network. In 2017, the degree value of XXH ranked the first among the three networks, followed by ZB, HM, BH, and HKPJ alternately, indicating that XXH has replaced ZB as the absolute core of the network in 2017. It is worth noting that, the “rightward inclined long-tailed distributions” of the three network nodes in 2017 is not as obvious as in 2013, indicating that the multi-core characteristics of the Minquan refrigeration industry network are more prominent with the entry of large-scale transplanted firms such as XXH and HM.

4.4. Intermediary Nodes Have Strong Heterogeneity. The importance of a node in network connectivity, that is, its “network power” is not only related to its degree value, but also closely related to its mediating role in the network. Nodes with high betweenness centrality often act as intermediaries on the shortest connection lines of other nodes, and the intermediary becomes the “broker” for other nodes to communicate with each other.

TABLE 4: Intermediary node and its betweenness centrality of refrigeration firms network in Minquan County.

No.	2009 (%)		2013 (%)		2017 (%)	
	Technical cooperation	Social communication	Technical cooperation	Social communication	Technical cooperation	Social communication
1	ZB/24.18	ZB/42.95	XXH/30.64	XXH/27.87	ZB/22.65	XXH/27.38
2	JXPJ/13.19	XP/28.48	ZB23.66	ZB/27.50	XXH/22.52	ZB/11.91
3	JX/7.69	BH/14.10	BH/18.33	BH/13.50	BH/18.08	JXPJ/8.47
4	—	—	HKDQ/8.55	HM/9.23	KMR/10.85	BH/8.42
5	—	—	AJ/8.51	XP/6.71	SC/10.70	HM/8.20
6	—	—	HM/6.47	HKDQ/5.68	JXPJ/9.13	WB/6.31
7	—	—	HKPJ/4.96	WB/4.55	HM/6.65	HKDQ/5.72
8	—	—	AAS/4.86	SB/4.47	AKMDQ/5.54	HKPJ/3.77

TABLE 5: Similarity degree of refrigeration firms network in Minquan County.

	Economic relation-technical cooperation	Social communication-economic relation	Social communication-technical cooperation
2009	23.08	23.08	24.18
2013	11.15	14.23	8.97
2017	13.64	16.91	13.21

Considering that the products in the economic relation network will have a specific flow, two whole machine firms that are in contact with a supporting equipment firm at the same time may rarely have industrial connections, so the following focuses on identifying the intermediary nodes in the technical cooperation network and social communication network. Taking the top 20% nodes of betweenness centrality on three timestamps for analysis (Table 4), it can be found that the intermediary nodes in the Minquan refrigeration industry network have strong heterogeneity, including large-scale whole machine firms, smaller-scale supporting equipment firms, local firms, and newly-settled transplanted firms. These firms either have high degree values or occupy key positions in the network, thus becoming intermediaries for other firms to contact.

It should be noted that the intermediary nodes of the Minquan refrigeration industry network are mainly local firms, and the proportion of transplanted firms are relatively low. For example, in the intermediary nodes of the technical cooperation network and social communication network in 2017, the proportion of transplanted firms were 44.44% and 33.33%, respectively. The research results also show that some leading transplanted firms, such as WB and AKMDQ, which are highly expected by local governments, fail to play the corresponding role of internal leading and external communication.

4.5. Economic, Technological, and Social Relational Network Systems Have Similar Structural Characteristics. The formula (1) is employed to calculate the similarity of any two of the three networks at each time section (Table 5). The results show that the similarity of the three networks in 2009 is relatively close, while the similarity between the three networks in 2013 and 2017 is generally expressed as “social communication-technical cooperation similarity > economic relation-technical cooperation

similarity > social communication-economic relation similarity.” It can be seen from Table 1 that the economic relation network and social communication network of the Minquan refrigeration firms have similar densities, which are much higher than the density of technical cooperation network, but the structure of social relation network is the closest to technical cooperation network from the similarity of network structure. The main interview also found that the intra-cluster technology flow mainly occurs between firms with relatively close social relations. This phenomenon just confirms the existing results that social communication is the lubricant of tacit knowledge transmission. In addition, the degree centrality of the social communication network ranks first in the three timestamps, indicating that the construction of the social communication network has a stronger directionality, and the connection of the entire network is more dependent on the core node firms.

5. Conclusions

Based on the perspective of firm network, and putting forward a research framework of “relationship-network-evolution,” this study extracts the economic relation, technical cooperation, and social communication firm network of the refrigeration industrial cluster of Minquan County in 2009, 2013, and 2017. Then, it analyzes the structure and evolution characteristics of the firm network, determines the degree and effect of local embeddedness of transplanted firms, and discusses whether there are also embeddedness difficulties and failures in the process of local embeddedness of domestic transplanted firms. The following conclusions are drawn:

- (1) The local embeddedness of transplanted firms has significantly promoted the development of the Minquan refrigeration industry network. In 2009, only 1 of the 15 firms in the cluster transplanted in. In 2017, a total of 44 major firms included 27

transplanted firms. Transplanted firms not only had an obvious advantage in quantity, but their output value accounted for more than 80% of the total output value of the cluster, and the large-scale, high-efficiency star firms in the cluster basically are all transplanted firms of the whole machine such as AKMDQ, WB, XXH, and ASDDRSQ. It can be said that it is the local embeddedness of the transplanted firms that promotes the development of the firm network within the cluster.

- (2) The “network power” of large-scale transplanted firms in the cluster is increasing day by day, and the network presents a multi-core trend. Before 2009, most of the local firms in the cluster were local firms derived from “Old Ice Bear,” and ZB, the largest whole machine firm, naturally became the core of the network. By 2013, the transplanted firms XXH and HM had a sudden emergence, the absolute core position of the local firm ZB was severely impacted, and the Minquan refrigeration industry network showed a certain multi-core trend. As of 2017, the degree value of transplanted firms XXH ranked the first in the three networks, and the local firm ZB and transplanted firms HM, BH, and HKPJ followed alternately. Moreover, the degree distribution of the three network nodes has the feature of “rightward inclined long-tailed distributions,” which is significantly weaker than that in 2013. It can be seen that its multi-core characteristics are also more obvious during the study period as the network develops.
- (3) Some of the transplanted firms have low local embeddedness, and the overall network connectivity is not strong. Although the cluster has undertaken many transplanted firms since 2010, the regional firm network construction is not perfect, and the overall network connectivity is not ideal. Among them, the technical cooperation network not only has a low level of connectivity, but also tends to become sparse, indicating that a good atmosphere for technical learning and collaborative innovation has not yet been formed within the cluster. The results of centripetal-centrifugal structure analysis show that the degree of local embeddedness of the transplanted firms are not high, and they are mainly distributed in the fringe area of the firm network. There are three main reasons for this phenomenon. First, most of the local firms in the cluster originated from “Old Ice Bear,” and this unique “identity” makes them form relatively close formal and informal connections, but the network performance of some transplanted firms is not ideal due to the lack of such social capital. Second, transplanted firms generally do not agree with the supporting capabilities and business models of local firms. Large-scale whole machine firms such as WB and AKMDQ seek farther, and even purchase spare parts from the original place. Third, when some whole machine firms moved to Minquan, they also brought some original

supporting firms, which formed a closer connection between them and showed a strong “personal club” feature.

- (4) The network intermediary nodes have strong heterogeneity, and the intermediary role of some large transplanted firms need to be improved. The measurement results show that the intermediary role of some large-scale transplanted firms is not prominent, which is quite different from common sense. In general, leading transplanted firms tend to have stronger capital and technological advantages, as well as greater “network power,” and the location of network “structural holes” makes it easier for them to become the absolute intermediary of global-local production network connection. In the technical cooperation network, similar firms are used to be called “technological gatekeeper.” In the Minquan cases, the intermediary role of some large-scale transplanted firms is weak. The reasons are as follows. First, the local embeddedness of the relevant firms is not high. For example, the local procurement ratio of AKMDQ is very low, and its technology research and development activities are all located in the Qingdao headquarters. Middle and senior management personnel return to Qingdao to rest on weekends. Second, the Minquan refrigeration industry cluster is still a regional “Marshallian industrial district,” and the degree of strategic coupling with the global production network is relatively low.
- (5) The three networks have similar structural characteristics, and social capital plays an important role in network development. This paper quantitatively measures the similarity between any two networks in the same year by building a model. The results show that the social communication network and technical cooperation network have the highest similarity, and the social communication network is more dependent on core nodes. Looking back on the history of the Minquan refrigeration industry, it can be seen that the “Old Ice Bear” collapsed and gave birth to more small- and medium-sized firms. At the same time, as a relationship link, it also attracted many transplanted firms to move in. This phenomenon is vividly called “an ice bear fell down, and thousands of bear soldiers stand up.” As an important virtual asset or social capital, the identity of “Old Ice Bear” plays an important role in the development of the Minquan refrigeration industry network. The implicit relationship network formed based on this identity has become the background of the Minquan refrigeration industry network to a certain extent. Furthermore, it has a subtle influence on the economic connection and technical cooperation between firms, especially the transmission of tacit knowledge.
- (6) Compared with international transplanted firms, interregional transplanted firms are more adaptable in terms of local embeddedness. It can be seen that,

domestic transplanted firms are less likely to encounter structural dislocation, cognitive dislocation, and other embeddedness obstacles under the comprehensive effect of institutional environment adaptation, local cultural identity, and social capital lubrication, and there are fewer difficulties and failures in local embeddedness compared with global transplanted firms. Based on the above findings, it is necessary to strengthen research in two aspects in the future. One is the mechanism of cultural identity and social capital in the local embeddedness of transplanted firms, and the other is the deep impact of social exchanges between firms on economic relations and technical cooperation.

The innovation of this paper is that it studies the local embeddedness of transplanted firms from the perspective of “firm network,” and the theoretical framework constructed with “relationship-network-evolution” as the main line can clearly study and judge the process, mechanism, and effect of local embeddedness of transplanted firms. Combined with the empirical research of the Minquan refrigeration industry cluster, it was found that the transplanted firms strengthen their local embeddedness by establishing economic, technological, and social connections with local firms, and affect the evolution and upgrading of local industrial cluster. In addition, the domestic transplanted firms are less likely to encounter embedded obstacles such as structural dislocation and cognitive dislocation, and have stronger adaptability than global transplanted firms. The abovementioned research framework construction and empirical analysis provide a new path and paradigm for the existing industrial transfer research. The disadvantage of the research is that some small-scale firms are omitted in the research process, resulting in a small number of samples, and the extracted firm network can only approximate the actual situation of the Minquan refrigeration industry to the greatest extent. The firm connection relationship is binarized to construct an undirected and weightless relationship network, which cannot reflect the strength difference and directionality of the connection and will affect the accuracy of structural analysis to a certain extent. In addition, the local embeddedness and de-embeddedness of transplanted firms often have a long time period, and short-term observation and research may not be able to form accurate conclusions. In the future, it is necessary to observe and analyze the network construction and interaction coupling through a longer research period, and further explore the network evolution mechanism of the cluster firms under the influence of the local embeddedness of the transplanted firms.

Data Availability

Data used for this work are available upon request from the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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