

## Article

# A Formation Mechanism of Spatial Distribution Pattern of Industrial Clusters under Flow Space

Yan Shi , Yan Wu, Bingrong Chen \*, Da Wang  and Min Deng

School of Geosciences and Info-Physics, Central South University, Changsha 410083, China;  
csu\_shiy@csu.edu.cn (Y.S.); 205011056@csu.edu.cn (Y.W.); 215001023@csu.edu.cn (D.W.);  
dengmin@csu.edu.cn (M.D.)

\* Correspondence: brchen@csu.edu.cn

**Abstract:** This study focuses on analyzing the spatial distribution pattern and formation mechanisms of urban industrial clusters and aims to address the mismatch between industrial clusters and resource distribution. Firstly, the spatial distribution pattern of industrial clusters is analyzed using the kernel density estimation approach. Subsequently, a multi-layered model of interactive driving factors is constructed to analyze the functional types within the multi-layered network space. Lastly, a spatial weighted regression analysis model, considering the intensity of flow space, is developed to explore the intrinsic formation mechanisms of industrial agglomeration. The experimental results indicate the following: (1) There is a trend of industrial agglomeration in the Yangtze River Delta region, primarily concentrated in cities such as Shanghai, Nanjing, Hefei, Jinhua, and Taizhou. (2) The impact of spatial interaction factors on industrial agglomeration development is significant, and the analysis of interaction networks reflects the strength of interactive influencing factors to a certain extent. (3) The regression analysis model, which incorporates interactive information considering flow space intensity, better aligns with the study of the actual mechanisms behind industrial agglomeration in physical space.

**Keywords:** enterprise space aggregation pattern; spatial element interaction network; spatial interaction regression model; spatial formation mechanism



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## 1. Introduction

In recent years, the number of enterprises has grown massively and become the main driving force of the city's economic development [1,2] and promote the normal operation of cities [3]. Due to economic conditions, geographical factors such as talent, technology, and policy regulations, enterprises gather and form scale effects within a regional scope, and they have positive or negative impacts on the surrounding areas. This spatial pattern phenomenon exhibited in geographical space is called industrial clusters [4].

In industrial cluster development, local and external resources need to be utilized [5]. Studies have shown that industrial clusters are not independent and must cooperate with surrounding areas. The exchange of information includes explicit information, such as technology, talent, capital investment, and energy materials, and implicit information such as the technological innovation capacity brought about by knowledge spillover [6]. Knowledge exchange and industrial complementarity both make industrial clusters achieve higher levels of efficient resource utilization, regional economic efficiency and sustainable development, and improved competitiveness. However, the current spatial layout of industrial clusters has various problems and is not in a “benign interaction” state. The main manifestation is the mismatch between the distribution pattern of industrial clusters and the distribution pattern of resources [7,8], and it is an “extensive” development model that leads to high input, low output, and even resource waste and environmental damage [9]. This has become the main problem for urban industries’ sustainable and healthy development.

The industrial agglomeration areas in cities have great demand for urban resources. The urban resources in some areas can hardly meet local industries' demand, making it difficult for industries to develop with high quality. At the same time, industries in some areas can only partially utilize urban resources, making it impossible for them to be used efficiently. Therefore, in order to achieve both high-quality industrial development and high-efficiency utilization of resources, government policymakers usually adopt the way of resource transportation, i.e., to influence the spatial distribution pattern of local factors in urban space. For example, labor-intensive gathering industrial areas have a great attraction to labor resources in local areas and surrounding areas, and influence the distribution pattern of the urban labor force, and the aggregation state of enterprises may also enable enterprises to achieve joint development, alleviate, or even solve social problems, such as labor industries developed on a large scale provide employment opportunities for the unemployed population in cities, converting urban population pressure into human resource advantages and solving unemployment problems.

Regarding studying the influencing factors and underlying mechanisms of industrial agglomeration, the existing research data are limited and can be broadly classified into two groups: quantitative data [10], which represents the primary influencing factors, and non-quantitative data [11], also known as "latent factors". Researchers who use these two types of data mainly treat regions as independent individuals. However, some scholars have already demonstrated the existence of various connections between industrial agglomeration zones, and they have even proposed concepts such as "borrowed scales", "agglomeration benefits", and "shadow of agglomeration" [12,13] to illustrate the substantial connections between regions. Therefore, analyzing the causal mechanism of industrial agglomeration from the perspective of "flow space" [14–16] is more suitable for the practical situation of industrial agglomeration, this way can help uncover more profound and valuable information.

## 2. Related Works

### 2.1. Spatial Distribution Patterns in Industrial Clustering

Industrial agglomeration refers to the geographical distribution of urban industries. The existing literature on spatial distribution patterns of industrial clustering mainly focuses on two perspectives: the global and local perspectives. The global perspective involves constructing agglomeration coefficients to statistically characterize the degree of industry agglomeration and dispersion in spatial terms. The global method mainly expresses the overall state of industrial clustering in space through attribute values. The main methods are location entropy index [17], spatial dispersion coefficient [18], industrial spatial Gini coefficient [19,20], Hoover industrial index [21], and EG index [22–24]. The local perspective shows the differences in the spatial distribution patterns of industrial clustering, mainly from a geographical perspective, comparing differences in industrial clustering in different physical spaces to express the intensity and direction of industrial clustering. The main methods used include KDE [25], spatial clustering [26–28], and spatial autocorrelation, etc.

### 2.2. Spatial Distribution Patterns in Industrial Clustering

The study of influencing factors is the foundation of the mechanisms of industrial clustering [26,29–31]. With the development of theories such as Industrial Location Theory [32] and New Economic Theory [33,34], the current factors influencing industry aggregation can be mainly divided into three categories: the first consists of static factors within the region such as city technology and human resource levels, etc. These factors serve as decisive factors; the second consists of interactive factors between regions such as knowledge spillovers resulting from high levels of interaction; however, due to data acquisition issues, they are treated as auxiliary decision-making factors in the current research; and the third consists of potential factors such as regional culture, government systems, and legal regulations, etc., which are difficult to quantify and therefore primarily serve as auxiliary decision-making factors [35].

Based on the current research, this paper summarizes the influencing factors of industrial agglomeration distribution patterns (see Table 1). Although there is relatively little research on the interaction factors of urban industrial agglomeration, the regional connection between industrial agglomerations has become an important influencing factor, and they cannot be ignored in the process of industrial agglomeration.

**Table 1.** Summary of factors influencing spatial distribution pattern of industrial agglomeration.

| Category                             | Quantification Method                             | Advantages   | Content Description                                                               |
|--------------------------------------|---------------------------------------------------|--------------|-----------------------------------------------------------------------------------|
| Static influencing factors           | Quantitative expression                           | Determinants | Geographical elements of urban location                                           |
| Interaction Influencing Factors [35] | Descriptive expression or quantitative expression | Cofactors    | Impacts of knowledge spillover based on locational proximity and distance failure |
| Potential Influencing Factors        | Descriptive expressions                           | Cofactors    | Government decisions, cultural systems, laws, and regulations, etc.               |

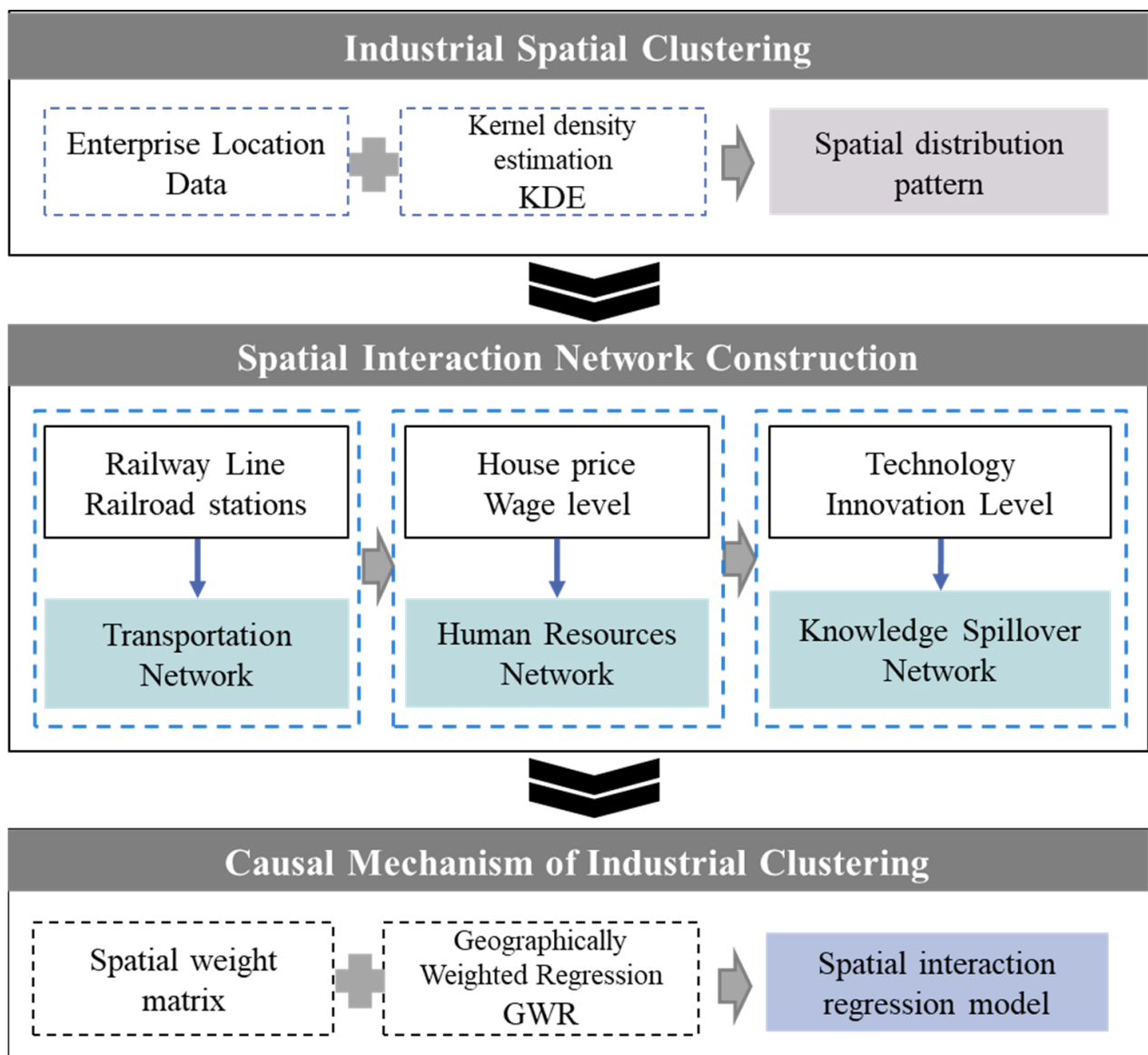
### 2.3. Mechanisms of Industrial Clustering

There are various mathematical models for researching the correlation between industrial clustering intensity and its influencing factors. Initially, qualitative comparisons were made between the results of industrial clustering at different time panels, and the effects of qualitative factors such as regional policies, local culture, and legal regulations were analyzed. However, these results were subjective and speculative. Subsequently, the researchers quantified the urban geographical elements and integrated them into a data model, such as geographical detectors [36,37], association analysis or grey correlation analysis, correlation analysis [38], regression analysis [39–41], Granger causality analysis [42,43], and the Sharpe value method [44], and the results can accurately quantify the contribution of the influencing factors based on those models. Finally, as existing models could only incorporate quantitative factors, but the driving role of qualitative factors could not be ignored, so a qualitative–quantitative combined approach was employed to construct a comprehensive explanation mechanism for the complete causation of industrial agglomeration [45].

## 3. Materials and Methods

### 3.1. Overview of Study Area and Experiment Data Preprocessing

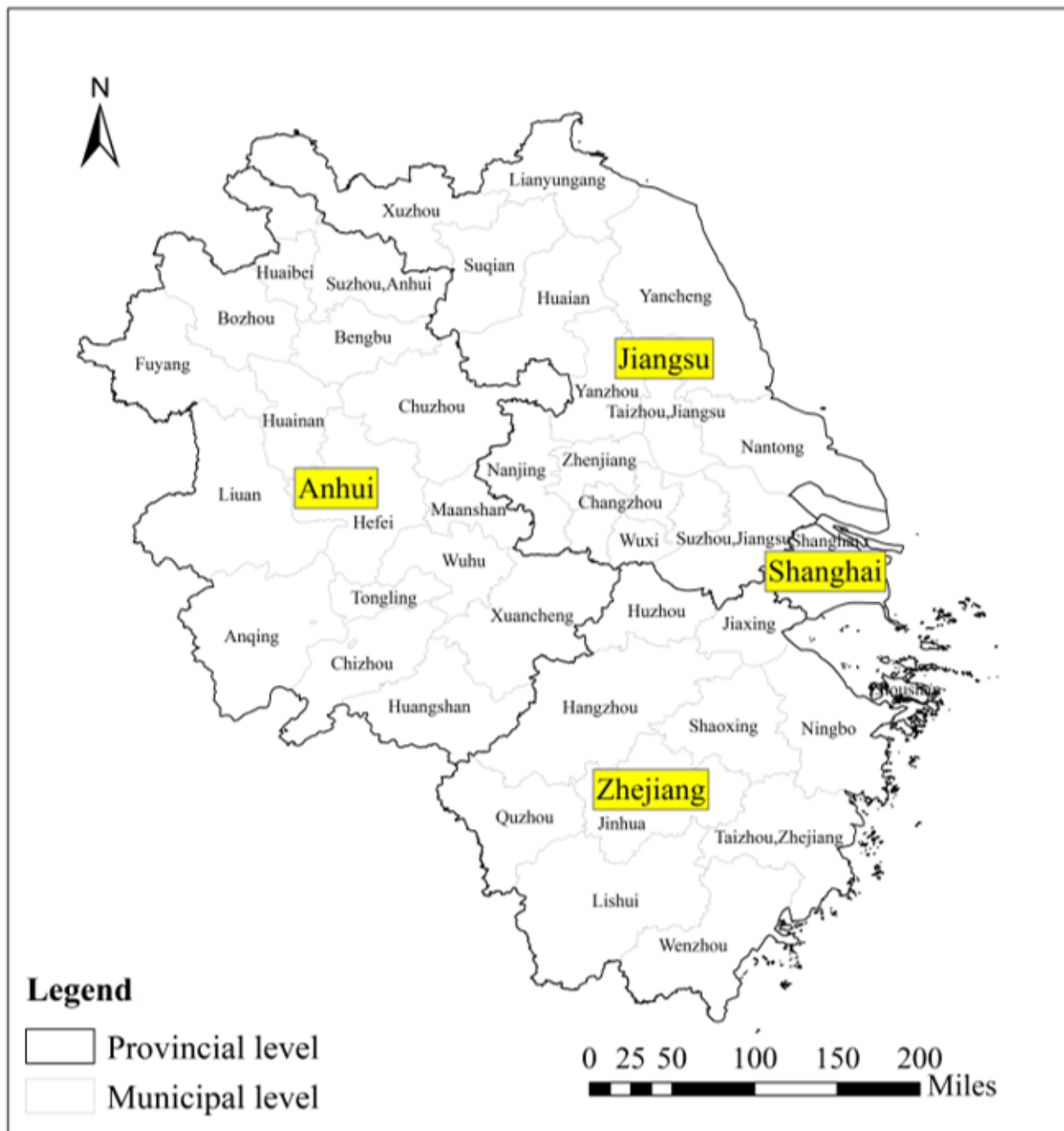
The research framework of this study consists of three parts: cognition of the spatial distribution pattern of industrial agglomeration in the Yangtze River Delta region, construction of spatial interaction networks, and analysis of the urban industrial agglomeration mechanism based on the spatial interaction model. The second part includes three stages: (1) constructing a city-to-city transportation accessibility network based on the railway station and route data; (2) constructing a city-to-city population flow trend network by integrating wage and housing price data based on the transportation accessibility network; and (3) constructing a city-to-city technology innovation flow trend network by integrating urban technology innovation level based on the population flow trend network. The third part consists of two stages: (1) integrating the transportation accessibility network, population flow trend network, and technology flow trend network to construct an interaction weight coefficient matrix for cities; and (2) incorporating the weight coefficient matrix from (1) into the geographically weighted regression model to construct a spatial interaction regression model to study the influencing factors and mechanism of urban industrial agglomeration [46–48]. The framework of this study is shown in Figure 1.



**Figure 1.** Framework of this study.

### 3.1.1. Study Area

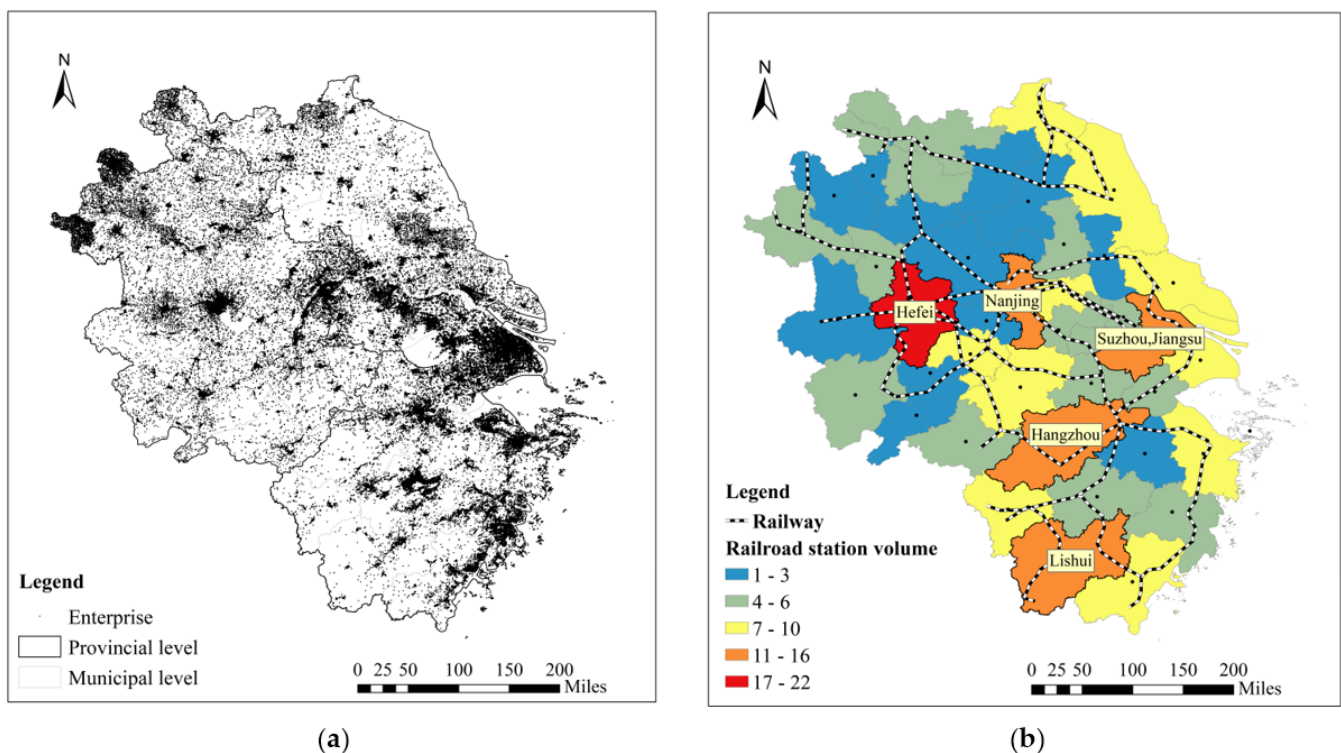
Based on the definition of the Yangtze River Delta Regional (Figure 2) Integrated Development Plan [49] issued in December 2019, this study selects the Yangtze River Delta region (including Shanghai, Jiangsu, Zhejiang, and Anhui provinces) with the largest concentration of foreign population in China as the study area. The Yangtze River Delta region is also located at the intersection of ‘One Belt, One Road’ and the Yangtze River Economic Belt. Therefore, domestic industries and foreign investment are found here in large numbers, and it is one of the regions with rapid economic development in China, and this place plays an important leading role in the development of the Yangtze River Economic Belt.



**Figure 2.** Overview of study area.

### 3.1.2. Experimental Data and Sources

We relied on POI (Point of Interest) data in OpenStreetMap to extract the Yangtze River Delta railroad station data, and we use the Baidu (<https://baike.baidu.com/> (accessed on 20 March 2022)) to complement each railroad line and GIS visualization technology to convert point data into line data to show the complete railroad network in the Yangtze River Delta region (Figure 3b). The construction of the inter-city transportation network in the Yangtze River Delta region is based on the data of the railway line. Data on enterprises in the Yangtze River Delta region are obtained based on Gaode Map (<https://www.amap.com/> (accessed on 20 March 2022)), and the results are shown in Figure 3a. In addition, the other data in this paper are shown in Table 2.



**Figure 3.** (a) Data on enterprises in the Yangtze River Delta. (b) Number of urban railroad stations and railway line data.

**Table 2.** The data sources.

| Data Set                    | Data Description    | Data Source                                                                                            |
|-----------------------------|---------------------|--------------------------------------------------------------------------------------------------------|
| The Wage Level              | Urban Scale in 2020 | <a href="https://www.gotohui.com/">https://www.gotohui.com/</a><br>(accessed on 20 March 2022)         |
| The House Price Level       | Urban Scale in 2020 | <a href="https://anjuke.com/">https://anjuke.com/</a><br>(accessed on 20 March 2022)                   |
| Technology Innovation Level | Urban Scale in 2020 | <a href="https://opendata.pku.edu.cn/">https://opendata.pku.edu.cn/</a><br>(accessed on 20 March 2022) |
| Human Resources             | Urban Scale in 2020 | <a href="https://www.gotohui.com/">https://www.gotohui.com/</a><br>(accessed on 20 March 2022)         |
| Economic Development Level  | Urban Scale in 2020 | <a href="https://www.gotohui.com/">https://www.gotohui.com/</a><br>(accessed on 20 March 2022)         |

### 3.2. Formation Mechanism Method of Spatial Distribution Pattern of Industrial Clusters under Flow Space

#### 3.2.1. Cognitive Approach to Spatial Distribution Patterns of Industrial Aggregation

In the physical space, the area where a small number of enterprises gather cannot be designated as an industrial gathering area, so the scope identification of industrial gathering areas needs to exclude the area where a small number of enterprises are distributed. However, the clustering method may misjudge the area where a small number of enterprises are distributed as an industrial agglomeration area, and the misjudgment leads to inaccurate regional identification. At the same time, the aggregation intensity and other related index methods cannot show the spatial distribution pattern of industrial agglomeration. Therefore, this paper selects the kernel density analysis method based on smoothing, which

highlights the regions with high industrial density aggregation and can obtain the local regional industrial aggregation density values as follows:

$$f(s) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right) \quad (1)$$

where  $f(s)$  is the kernel density calculation function at spatial location  $s$ ,  $h$  is the bandwidth,  $n$  is the number of facility points within a path distance less than or equal to  $h$  from location  $s$ ,  $K$  is the spatial location weight function, and  $x_i$  is the grid search center of gravity.

The spatial aggregation results were classified into four classes (high density, medium density, low density, and no significant aggregation) by the natural discontinuity method and were further analyzed.

### 3.2.2. Spatial Interaction Network Inference Methods

- Traffic Interaction Intensity Network Construction;

In geographic space, railway lines connect cities, and the interaction of various elements between cities relies on transportation networks, so the interaction of transportation networks of neighboring and non-areas plays an important role. The traditional method for building inter-regional accessibility is based on the Euclidean distance of railway lines, and it is difficult to express the inter-regional “distance failure” in geographic space. Since the amount of railroad stations is an essential measure of a city’s accessibility intensity, this paper improves the inter-city accessibility measure by using the amount of urban railroad stations:

$$O_{ij} = \max\left(\frac{1}{D_{ij}} * (T_i + T_j)\right) \text{ if (Direct rail line exists between } i \text{ and } j) \quad (2)$$

$$O_{ij} = \frac{1}{\min\left(\frac{1}{O_{ik}} + \frac{1}{O_{km}} + \dots + \frac{1}{O_{mj}}\right)} \text{ if (No direct rail line between } i \text{ and } j) \quad (3)$$

where  $O_{ij}$  represents the interaction strength of the transportation network between city  $i$  and city  $j$ ,  $T_i$  and  $T_j$  represent the number of stations within city  $i$  and the number of stations within city  $j$  on the railway line connecting city  $i$  and city  $j$ , and  $D_{ij}$  represents the shortest Euclidean distance between city  $i$  and city  $j$  based on the railway line.  $k$  and  $m$  represents the cities through which the transportation link between city  $i$  and city  $j$  is to pass.

- Human Resource Mobility Trends Network;

Urban human resource mobility trends are an essential component of industrial agglomeration influencing factors. Since inter-city transportation accessibility is the basic conditions for population mobility trends, and consumption and income levels are the main drivers of human resource mobility, we use urban wage levels to represent basic urban income levels and use house price levels to represent living consumption levels, and construct the inter-city human resource mobility trend network based on transportation accessibility networks:

$$POP_{ij} = \left(\frac{S_j - S_i}{S_i} - \frac{H_j - H_i}{H_j}\right) \times (O_{ij}) \text{ if } \left(\frac{S_j - S_i}{S_i} > \frac{H_j - H_i}{H_j}\right) \quad (4)$$

$$POP_{ji} = \left(\frac{S_i - S_j}{S_j} - \frac{H_i - H_j}{H_i}\right) \times (O_{ij}) \text{ if } \left(\frac{S_i - S_j}{S_j} > \frac{H_i - H_j}{H_i}\right) \quad (5)$$

$$C_{i+}POP = \sum_{j=1}^n POP_{ij} \quad (6)$$

$$C_{i-}POP = \sum_{j=1}^n POP_{ji} \quad (7)$$

where  $POP_{ij}$  is the intensity of the population movement trend from city  $i$  to city  $j$ ,  $S_i$  represents the wage level of city  $i$ ,  $H_i$  represents the house price level of city  $i$ ,  $C_{i+}POP$  represents the integrated human resource outflow trend of city  $i$ , and  $C_{i-}POP$  represents the integrated human resource inflow trend of city  $i$ .

- Technological Innovation Flow Trend Network.

The technology flow trend network is constructed based on the inter-regional human resource flow trend network and the level of technological innovation in the region indicates the intensity and direction of the technology flow trend among cities in the Yangtze River Delta region:

$$TEC_{ij} = POP_{ij} \times \left( \frac{N_i - N_j}{N_j} \right) \quad (8)$$

$$C_{i+}TEC = \sum_{j=1}^n TEC_{ij} \quad (9)$$

$$C_{i-}TEC = \sum_{j=1}^n TEC_{ji} \quad (10)$$

where  $TEC_{ij}$  is the intensity of technological innovation knowledge spillover between city  $i$  and city  $j$ ,  $N_i$  represents the level of comprehensive innovation capability of region  $i$ ,  $C_{i+}TEC$  represents the trend of comprehensive technological innovation outflow from city  $i$  to the surrounding region, and  $C_{i-}TEC$  represents the trend of comprehensive technological innovation inflow from city  $i$  to the surrounding region.

### 3.2.3. Spatial Interaction Regression Model

Previous studies have mostly used multivariate linear or nonlinear regression models that do not consider the influence of geographic location or geographically weighted regressions, which means they fully comply with the first law of geography—distance decay effect [50,51]. However, relevant basic research shows that the influencing factors of industrial agglomeration include the urban geographic factors within the region and the influencing factors outside the region. Since the transportation accessibility network, human resource flow trend network, and technology flow trend network are the main influencing factors of inter-city interaction, and their values express the intensity of inter-regional influence, we construct a three-dimensional vector based on the above three types of interaction influencing factors and represent the intensity of inter-regional influence using the modal length of the vector:

$$w_{ij} = \text{pow} \left( (O_{ji})^2 + (POP_{ji})^2 + (TEC_{ji})^2, 0.5 \right) \quad (11)$$

$$w_i = (w_{i1}, w_{i2}, w_{i3}, \dots, w_{in}) \quad (12)$$

$$w_{ii} = 1 \text{ if } (i \in n) \quad (13)$$

$$w = (w_1, w_2, w_3, \dots, w_{n-1}, w_n) \quad (14)$$

where  $n$  denotes the number of cities,  $w_{ij}$  denotes the combined influence weight of city  $j$  on city  $i$  in terms of traffic link strength, population inflow trend, and technology inflow trend, and  $w_i$  denotes the weight matrix of the influence of  $n$  cities on city  $i$ , which is mapped

to geographic space to denote the magnitude of the influence weight of city  $k$  on city  $i$ .  $w$  denotes the weight coefficient matrix composed for each city  $i$ .

The intensity of industrial agglomeration is the dependent variable on the research of the formation mechanism of urban industrial agglomeration. Industrial agglomeration area refers to the scope of high density industrial agglomeration area and low density industrial agglomeration area. Therefore, for each city, this paper takes the area of industrial agglomeration area as the weight to solve the urban industrial agglomeration intensity:

$$den_i = \sum_1^s \frac{Area_{ik}}{Sum\_Area_i} \times den_{ik} \quad (15)$$

$$Sum\_Area_i = \sum_1^s Area_{ik} \quad (16)$$

$$den_{ik} = \frac{High\_Density_{ik} + Medium\_Density_{ik}}{Area_{ik}}$$

where  $den_i$  denotes the industrial agglomeration intensity of city  $i$ ,  $den_{ik}$  denotes the average agglomeration density of the  $k$ th industrial agglomeration in city  $i$ ,  $Area_{ik}$  denotes the area of the  $k$ th industrial agglomeration in city  $i$ ,  $sum\_area_i$  denotes the total area of industrial agglomeration in city  $i$ ,  $s$  denotes the number of industrial agglomerations in city  $i$ .  $High\_Density_{ik}$  denotes the product of the area of high-density aggregation and the value of high-density aggregation of industrial agglomeration area  $k$ , and  $Medium\_Density_{ik}$  denotes the product of the area of medium-density aggregation and the value of medium-density aggregation of industrial agglomeration area  $k$ .

Since the traditional geographically weighted regression model adopts the weight coefficient that follows the laws of geography, it is difficult to consider the “distance failure” in the physical space. Therefore, in this paper, we take the average intensity of urban industrial agglomeration  $den_i$  as the dependent variable  $Y$ , the level of economic foundation, the level of human resources and the ability of innovative technology as the dependent variable  $X$  and take the three network values as the spatial influence weight. Finally, we further construct a weighted regression model considering the intensity of flow space:

$$Y = (Y_1, Y_2, Y_3, \dots, Y_i, \dots, Y_{n-1}, Y_n) \quad (17)$$

$$X = (X_1, X_2, X_3, \dots, X_i, \dots, X_{n-1}, X_n) \quad (18)$$

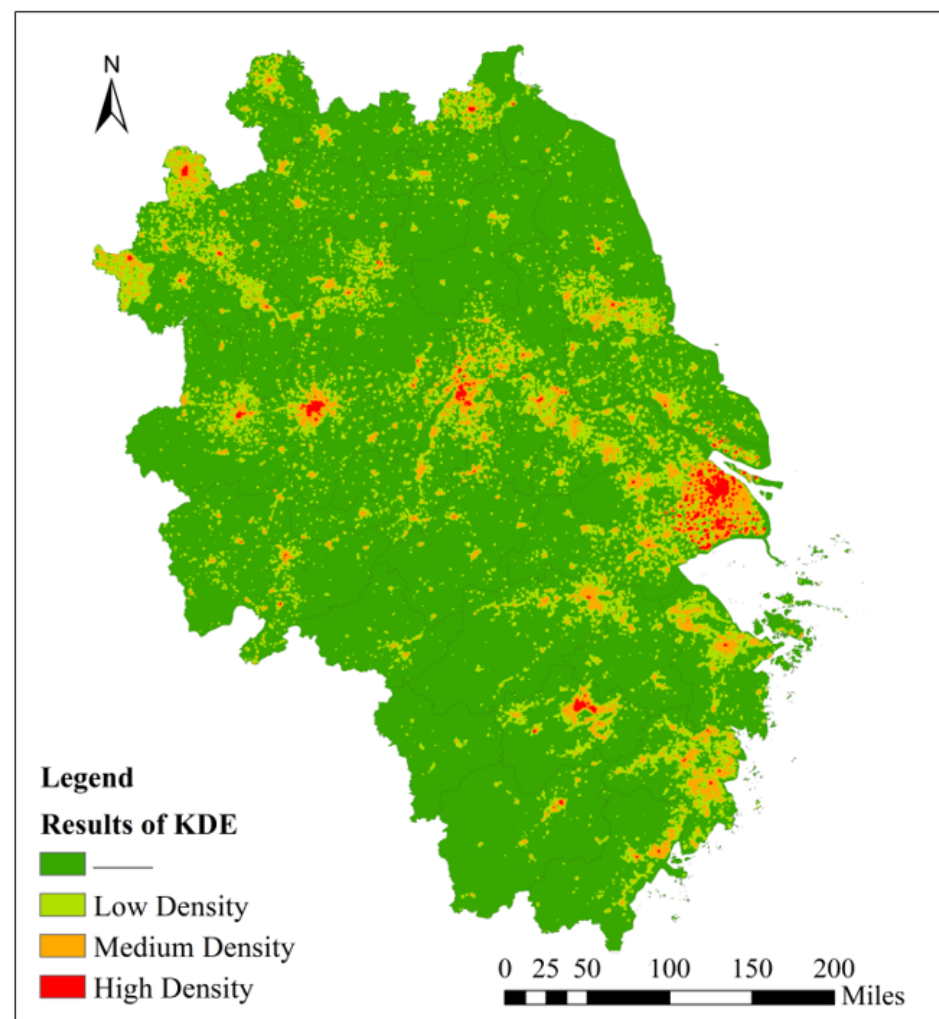
$$Y_i = \sum_1^p A_i w_i X_i + b_i \quad (19)$$

where  $b_i$  is a constant term,  $A_i$  denotes the coefficient matrix obtained for city  $i$ ,  $X_i$  denotes the influence factor matrix extracted for city  $i$ , and  $p$  denotes the total number of influence factors participating in the model.

## 4. Analysis of Experiment Results

### 4.1. Perception of Spatial Distribution Pattern of Industrial Aggregation

Figure 4 shows the results of enterprise location data visualization in the Yangtze River Delta region. In the Yangtze River Delta region, industries are mainly distributed in the eastern, central, and northwestern parts of the region, that is, in the whole Shanghai area, Jiaxing, Hangzhou, Jinhua, and Taizhou in Zhejiang Province, Hefei, Fuyang, and Bozhou in Anhui Province, and Nanjing, Suzhou, and Zhenjiang in Jiangsu Province. According to the administrative divisions, the industrial distribution is also not spread throughout the region; there is a spatial aggregation of industrial distribution, that is, there is a key development orientation within the city. Table 3 shows the results.



**Figure 4.** Results of nuclear density analysis in the Yangtze River Delta.

**Table 3.** Key development cities and directions.

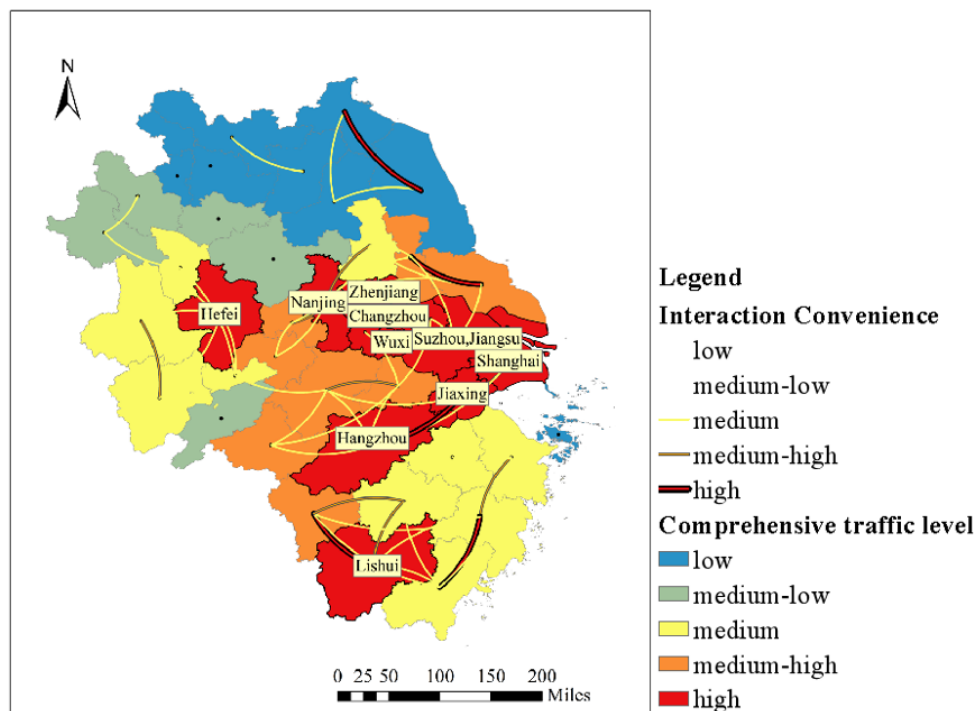
| Province          | City (District)                        |
|-------------------|----------------------------------------|
| Shanghai          | Shanghai (almost the entire region)    |
| Anhui Province    | Hefei City (Central)                   |
|                   | Bozhou City (West and Northwest)       |
|                   | Fuyang City (Central and West)         |
|                   | Lu'an City (West)                      |
|                   | Chuzhou City (Southeast and Northwest) |
| Jiangsu Province  | Huainan City (Northwest)               |
|                   | Nanjing City (Central)                 |
|                   | Lianyungang City (Midwest)             |
|                   | Suzhou City (Central and East)         |
|                   | Taizhou City (North)                   |
|                   | Yancheng City (South)                  |
|                   | Nantong City (Southwest)               |
|                   | Zhenjiang City (Central)               |
| Zhejiang Province | Changzhou City (Central)               |
|                   | Wuxi City (East)                       |
|                   | Jinhua City (Central and Northeast)    |
|                   | Taizhou City (Central and East)        |
|                   | Ningbo City (Northwest and Central)    |
|                   | Hangzhou City (Northeast)              |
|                   | Jiaxing City (Central and North)       |
|                   | Wenzhou City (East)                    |

In order to facilitate understanding, we summarize the results of the industrial agglomeration distribution in the Yangtze River Delta region based on the results in Figure 4, as shown in Table 3, which gives the reader a preliminary understanding of the industrial agglomeration distribution pattern in the Yangtze River Delta region, such as the industrial agglomeration areas in Shanghai are distributed in almost the whole Shanghai area; in Anhui province, the main industrial agglomeration areas are in the central part of Hefei city, the west and northwest of Bozhou city, the central and west of Fuyang city, the western part, southeastern and northwestern part of Chuzhou city, and northwestern part of Huainan city. Other regions are similar in interpretation.

#### 4.2. Interaction Network Inference Results

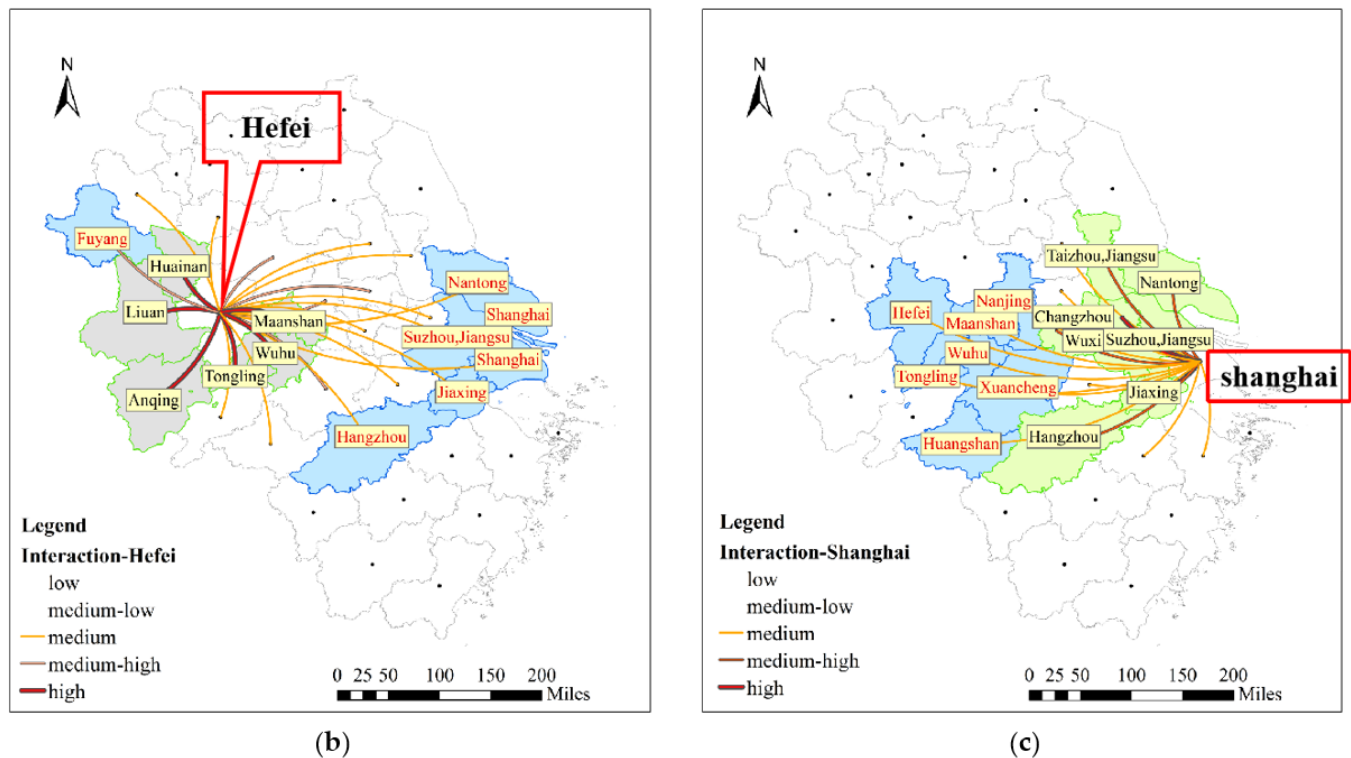
##### 4.2.1. Traffic Interaction Intensity Network Results and Analysis

Figure 5a shows that the cities with a strong level of comprehensive traffic interaction are divided into two main lines: one is Shanghai–Suzhou–Wuxi–Changzhou–Zhenjiang–Nanjing and the other is Shanghai–Jiaxing–Hangzhou. Among the inland cities, Hefei has the strongest comprehensive traffic interaction level capability. In terms of the traffic interaction level between Hefei and the surrounding cities, Figure 5b shows that the traffic accessibility level between Hefei and the neighboring regional cities, such as Huainan, Liuan, Anqing, Tongling, Wuhu, and Maanshan, is relatively high. The connection is also strong between Hefei and distant regions, such as Shanghai, Hangzhou, Nantong, and Jiaxing etc., and these cities are mainly located in the eastern region. The close connection between Shanghai and its surrounding areas and Hefei City provides the basis for other information interactions. Among the eastern cities, Shanghai’s leading position cannot be ignored (Figure 5c). The results show that Shanghai not only has strong traffic connection levels with neighboring regional cities, such as Suzhou, Jiaxing, and Huzhou, but the convenience of the railway line also makes it possible for Shanghai to have relatively convenient traffic interactions with distant cities, such as Xuancheng, Huangshan, Hangzhou, and Hefei, etc. Due to its relative location and the fact that the railway line is not directly planned, Nantong does not have the strongest level of transportation links with Shanghai.



(a)

Figure 5. Cont.

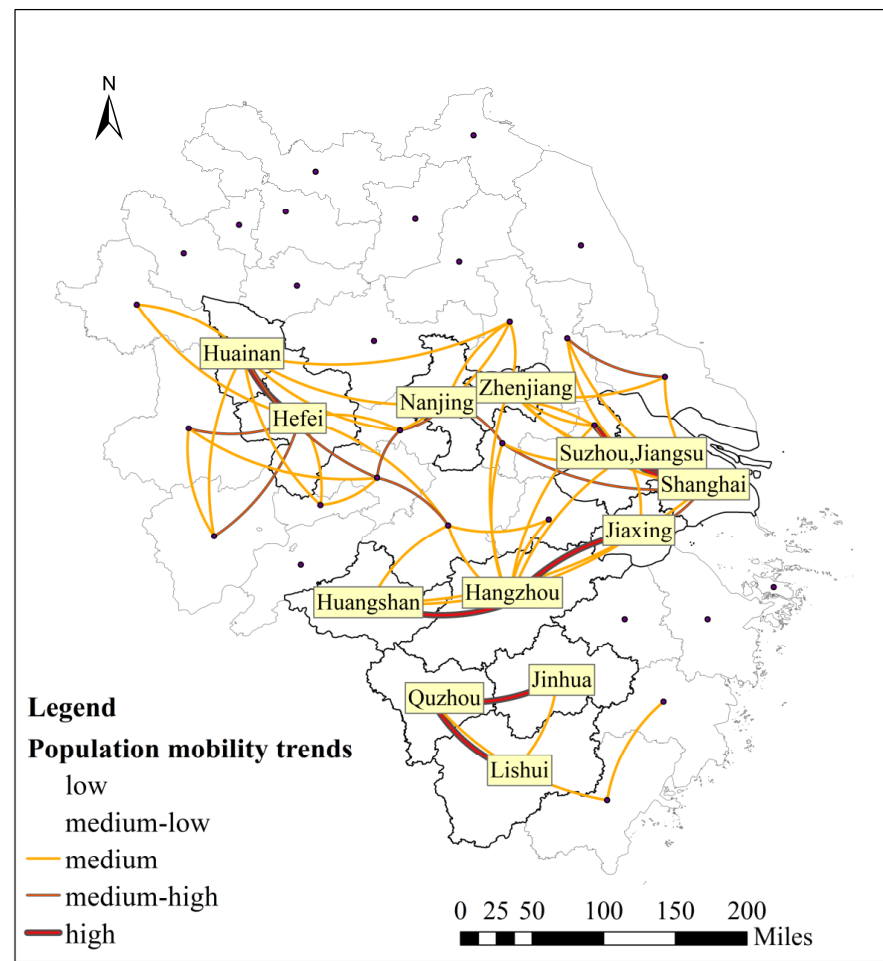


**Figure 5.** Traffic interaction intensity network results: (a) Urban rail accessibility network strength; (b) Intensity of transportation links between Hefei and various other cities; (c) Intensity of transportation links between Shanghai and various other cities.

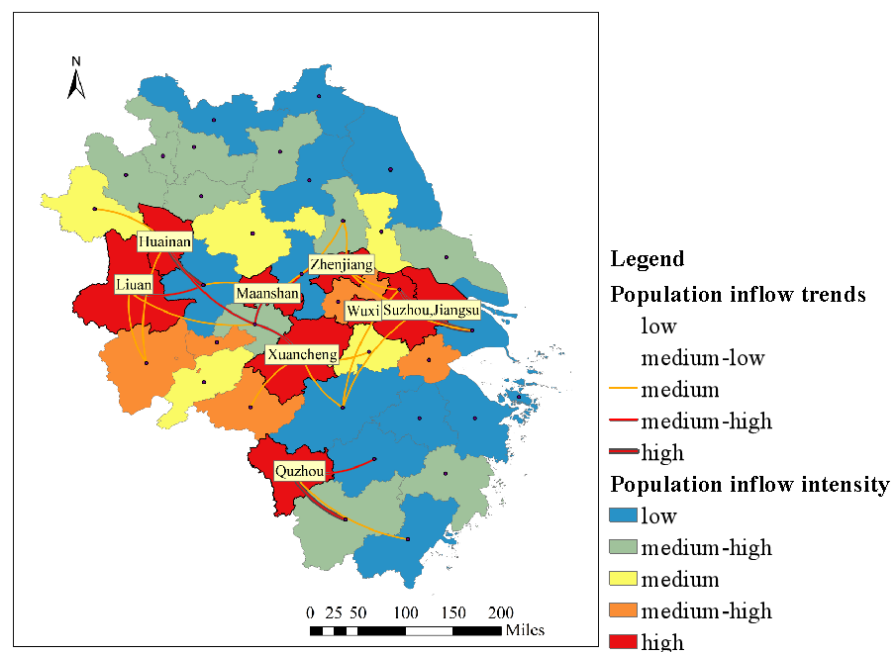
#### 4.2.2. Results and Analysis of the Network of Inter-City Population Movement Trends

Figure 6a shows the network of population mobility trends. The study shows that the population mobility trends mainly form two routes: one is Shanghai–Suzhou–Wuxi–Zhenjiang–Nanjing–Hefei–Huainan and the other is Shanghai–Jiaxing–Hangzhou–Huangshan, and there are some cities around the routes that are connected to the cities on the routes. Therefore, there is complexity in the trend of human resource flow in the Yangtze River Delta region. In addition, in the southwest of the Yangtze River Delta, Quzhou, Jinhua, and Lishui in Zhejiang Province have a strong interaction trend of the population. However, the comprehensive population flow trend in the northern part of the Yangtze River Delta is relatively weak, indicating that the inter-regional exchange is relatively weak and mainly concentrated within cities. In terms of the network of population flow trends, the analysis summarizes the important population flow nodes with four points, they are Shanghai and Suzhou, Nanjing, Hefei and Huainan, and Hangzhou, as the main centers.

The study shows that cities have both population inflow and outflow trends; therefore, in this article, the results are split as shown in Figure 6b,c. In terms of comprehensive population outflow trends, four major cities, namely Shanghai, Nanjing, Hangzhou, and Hefei, have prominent outflow trends: Shanghai mainly flows to Suzhou, Jiaxing, Wuxi, and Changzhou; Hangzhou mainly flows to Jiaxing and Huangshan; Nanjing mainly flows to Zhenjiang, Changzhou, and Maanshan; and Hefei mainly flows to Huainan, Liuan, Anqing. In terms of the comprehensive population inflow trends, Suzhou, Wuxi, Quzhou, Xuancheng, Liuan, Huainan, Zhenjiang, and Maanshan have the largest relative inflow trend, and these cities are mainly located around the cities with large outflow trends.

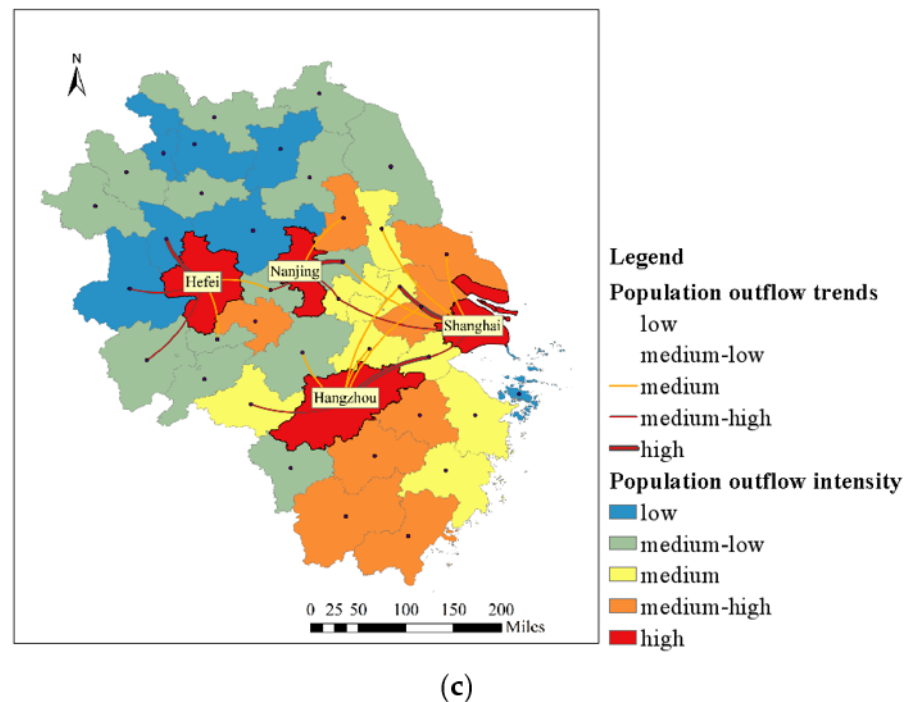


(a)



(b)

Figure 6. Cont.

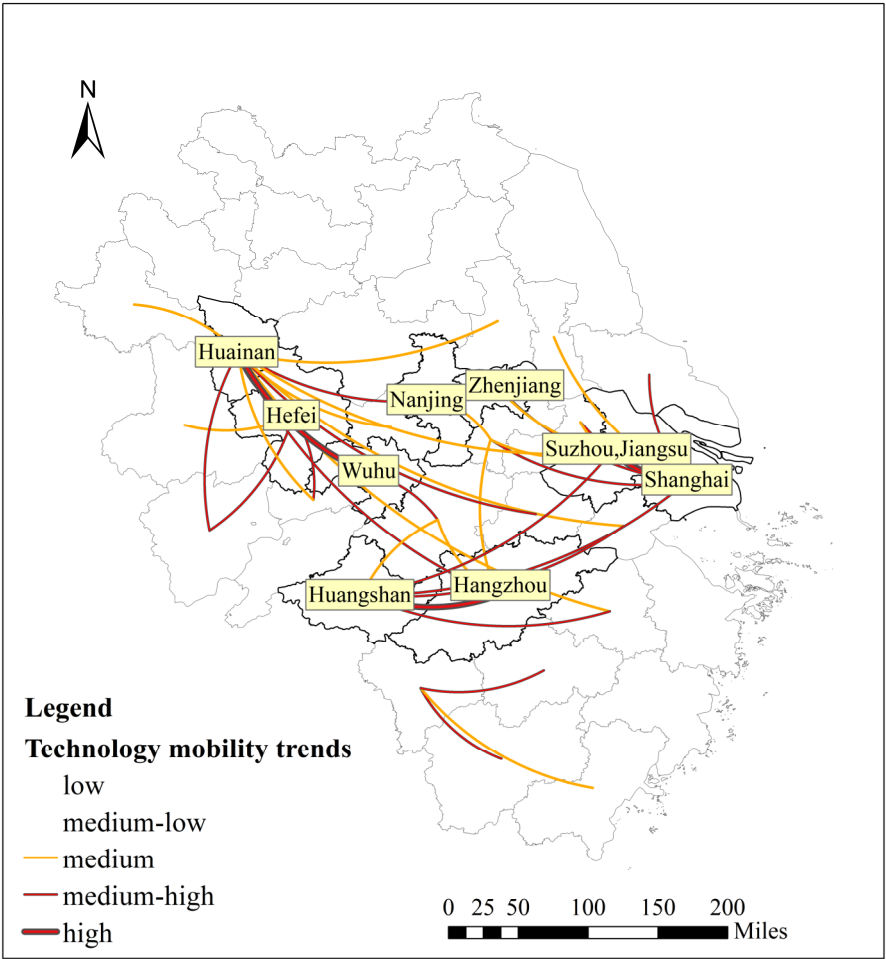


**Figure 6.** Results and analysis of the network of inter-city population movement trends: (a) Trend intensity of integrated population movement; (b) Trend of population outflow; (c) Trend of population inflow.

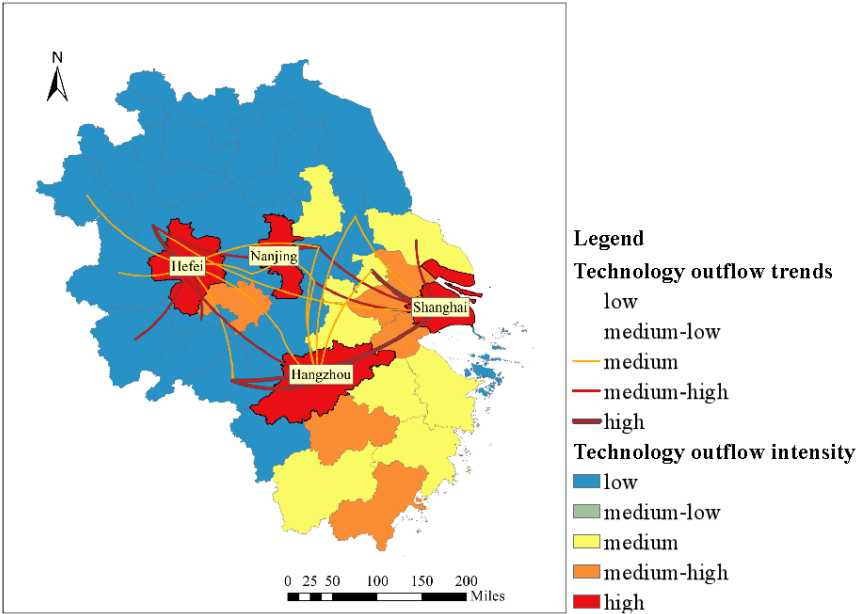
#### 4.2.3. Results and Analysis of the Inter-City Technology Flow Trend Network

Figure 7a shows the urban technology innovation flow trend network. In addition, the figure shows that high-level technology innovation flow is mainly located in the neighboring regions of provincial capital cities, such as Shanghai–Suzhou, Nanjing–Zhenjiang, Hangzhou–Huangshan, and Huainan–Hefei–Wuhu.

The study shows both technology innovation inflow and outflow trends in cities; therefore, the results are split in this article, as shown in Figure 7b,c. Shanghai, Hefei, Nanjing, and Hangzhou have the strongest integrated outflow trends and mainly flow to neighboring cities, with Shanghai mainly flowing to Jiaxing, Suzhou, Wuxi, Zhenjiang, Changzhou, and Huangshan; Nanjing mainly flowing to Zhenjiang, Hangzhou mainly flowing to Huangshan; Hefei mainly flowing to Anqing and Huainan; and Hangzhou mainly flowing to Huangshan. The four major cities have a strong driving effect on the surrounding areas; for example, Shanghai, which plays the leading role, has the widest radius range. In terms of the comprehensive inflow trend of technological innovation, Zhenjiang, Huainan, Huangshan, and Xuancheng cities have the strongest comprehensive inflow trend; the input source of Huainan is mainly Hefei, the input source of Zhenjiang is mainly Nanjing and Shanghai, the main input source of Huangshan are Shanghai and Hangzhou, and the main input city of Xuancheng is Hangzhou. Each city has an important technological input to Xuancheng; however, the difference in intensity is not obvious.

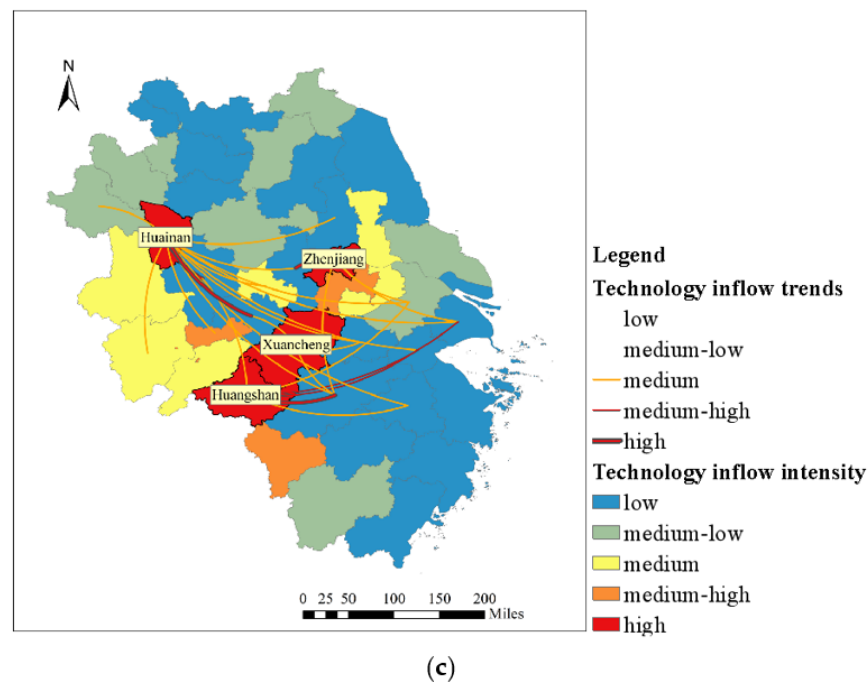


(a)



(b)

Figure 7. Cont.



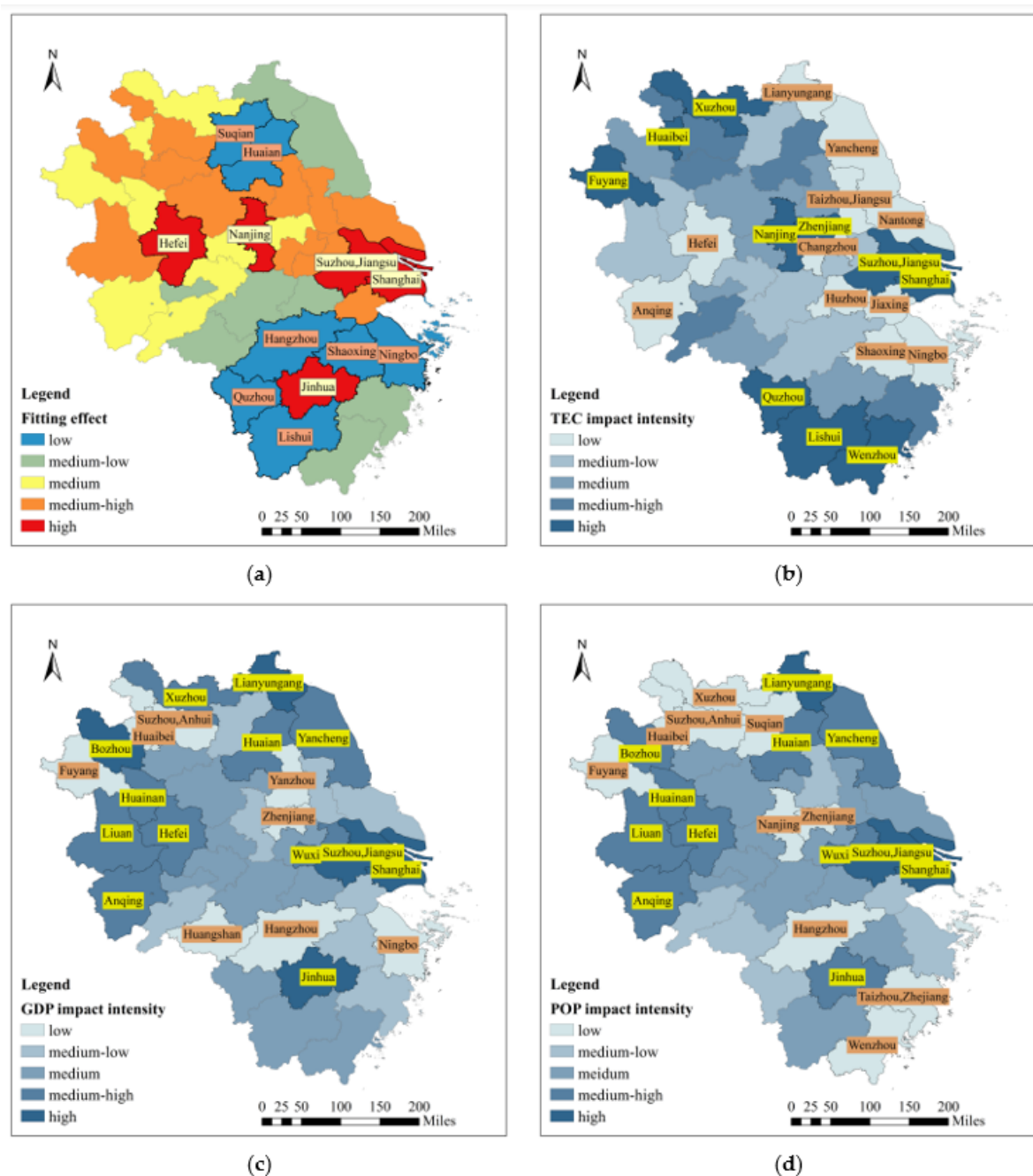
**Figure 7.** Results and analysis of the inter-city technology flow trend network: (a) Trend intensity of integrated technology mobility; (b) Trend of technology outflow; (c) Trend of technology inflow.

#### 4.3. Results of the Causal Mechanism of Industrial Aggregation

In this paper, the interaction relationship between city-scale industrial agglomeration intensity and influence factors is analyzed taking into account the interaction network of those influence factors. Figure 8a shows the results. The models of Hefei, Nanjing, Suzhou, Shanghai, and Jinhua have the highest goodness of fit, and the models of Hangzhou, Lishui, Shaoxing, Ningbo, Quzhou, Suqian, and Huai'an have the lowest goodness of fit; however, the lowest goodness of fit is also greater than 0.7, indicating that the regression relationship between the current industrial agglomeration and the impact factor can explain the variation of the dependent variable to some extent, that means the measure is relatively accurate, and the regression  $p$ -values are all close to 0, indicating that the multivariate linear equation is significant and credible in physical space.

In this paper, we analyze in detail three factors that have a greater degree of influence on industrial agglomeration. These factors are the economic and technological level, technological innovation ability, and human resource level.

- (1) Figure 8c shows that the economic development level has a greater influence on the industrial agglomeration intensity of Jinhua, Shanghai, Suzhou, Wuxi, Bozhou, Huainan, and Lianyungang cities. When such cities want to develop local industries vigorously or introduce other industries, increasing local economic investment is a relatively direct way. However, the economic development level has a relatively weak influence for Fuyang, Hangzhou, Huangshan, and Zhenjiang. This means that the intensity of industrial agglomeration in these cities is relatively insensitive to the level of economic development, and it is inferred that the current level of economic input is relatively saturated, and continued input will result in market economy redundancy and a waste of resources. Therefore, these cities should find a breakthrough to strengthen industrial agglomeration from other perspectives;



**Figure 8.** Results of the causal mechanism of industrial aggregation: (a) Fitting effect; (b) Sensitivity to the level of technological innovation; (c) Sensitivity to the level of economic development; (d) Sensitivity to the level of human resource.

- (2) Figure 8b shows that the level of technological development has a greater impact on the industrial gathering intensity of Shanghai, Suzhou, Quzhou, Lishui, Wenzhou, and Nanjing, indicating that there is a technological deficiency in industries in these cities, and the appropriate introduction of high technology can influence industrial gathering. Therefore, we can summarize that technological innovation development is an important influencing factor in the development of industrial gathering in these cities;
- (3) Figure 8d shows that the cities with great influence of human resources on industrial agglomeration intensity are mainly Shanghai, Suzhou, Hefei, Yancheng, Jinhua, Lu'an and Anqing. Therefore, there has been a huge demand for a labor force in these cities, and a possible reason is the lack of local labor resources. These cities can attract and

concentrate a large number of human resources through government decision-making and the migration of labor resources is realized by means of inter-city communication. The effect of ‘borrowing’ can help realize the vigorous development of the labor force industry. However, the level of human resources has relatively less influence on industrial gathering in Nanjing, Hangzhou, Suzhou, and Fuyang.

In this study, the sensitivity of cities to three types of influencing factors is summarized. Table 4 summarizes the typical characteristics of the industrial agglomeration development of cities in the Yangtze River Delta region and provides suggestions for such development on a city scale.

**Table 4.** Sensitivity of factors influencing the development of urban industrial agglomeration.

| Economic Development | Technology Innovation | Human Resources | Typical Cities                   |
|----------------------|-----------------------|-----------------|----------------------------------|
| S                    | S                     | S               | Shanghai, Suzhou                 |
| S                    | S                     | INS             | Xuzhou                           |
| S                    | INS                   | INS             | ----                             |
| S                    | INS                   | S               | Jinhua, Wuxi, Hefei, Lianyungang |
| INS                  | S                     | S               | Huangshan                        |
| INS                  | INS                   | S               | Nantong City, Taizhou            |
| INS                  | INS                   | INS             | Ningbo City                      |
| INS                  | S                     | INS             | Nanjing, Hangzhou, Zhenjiang     |

S = sensitive, INS = insensitive.

- Shanghai’s industrial agglomeration intensity is relatively sensitive to the level of human resources, economic development, and technological innovation, indicating that the regulation of Shanghai’s industrial agglomeration intensity can be directly regulated from several angles, and because of the interconnection and influence of urban elements, the effect of the regulation influence will be continuously expanded to all kinds of urban geographical elements. In addition, as the ‘leading city’ in the Yangtze River Delta region, Shanghai’s industrial agglomeration intensity and its sensitivity to the influencing factors indicate that the city also has great development potential, industrial development vitality, great absorption, and integration of the three main influencing factors, etc. Shanghai’s absorption power is strong because the large-scale agglomeration industries can provide a lot of employment opportunities. Meanwhile, due to its relatively high cost of consumption and relatively low cost of livability, Shanghai’s overall human resource mobility is relatively high. Therefore, given today’s shortage of talent resources, retaining highly skilled personnel and basic labor force is an issue that the Shanghai government and related departments need to focus on;
- The intensity of industrial agglomeration in Hangzhou is relatively insensitive to the level of economic development and human resources, and relatively sensitive to the level of technological innovation. Such cities have sufficient market labor and economic base investment. However, their industrial technology is relatively backward and the demand for technology is strong. In terms of the technology innovation flow trend network, Hangzhou has a relatively high level of technology innovation compared with the surrounding cities, but its technology innovation development level hinders the city’s industrial agglomeration. Therefore, it needs to invest heavily in technology innovation and attract high-quality talents in order to develop the agglomeration industry.
- Nanjing and Hangzhou are similar, but Nanjing shows more obvious sensitivity to the influencing factors. Therefore, Nanjing has a more significant effect when regulating the influencing factors of industrial agglomeration intensity;

- Hefei is not sensitive to the level of technological innovation and is relatively sensitive to the level of economic development and human resources, indicating that in the western region of the Yangtze River Delta, the development of industrial technological innovation is not a major concern, or that the current level of urban technology is sufficient to support the needs of intra-city industrial development. The biggest obstacle to the development of intra-city industrial agglomeration is the severe shortage of labor, so the level of human resources is an important factor in determining industrial agglomeration. Thus, it is inferred that labor-intensive industries are mainly distributed in the western part of the Yangtze River Delta;
- Nantong, Taizhou, and Huangshan are relatively sensitive to the level of human resources, indicating a shortage of labor force, and that vigorously introducing labor force is a key measure to promote industrial agglomeration. However, the high demand for technology in Huangshan shows that the level of technological innovation within the city can no longer meet the demand for industrial development. Based on the technology flow trend network, it was found that Shanghai has a high intensity of knowledge spillover, and a large amount of technology development level is imported into Nantong and Taizhou. This drives the rapid development of technological innovation in Nantong and Taizhou, which can meet the needs of industrial development within the cities. Therefore, the demand for technological innovation is not large for Nantong and Taizhou;
- In addition, for Ningbo, industrial agglomeration is relatively insensitive to all three types of influencing factors, which are analyzed as the following two situations: first, there are almost no industries with large aggregation within the city, and second, we do not use the key factors of industrial agglomeration in this paper; therefore, the three types of influencing factors are insensitive. However, the industrial agglomeration distribution pattern shows that there is large aggregation in Ningbo. Therefore, it is inferred that the key influencing factors affecting industrial aggregation in Ningbo may not be among the influencing factors selected for this study, which is consistent with the result that the goodness-of-fit of Ningbo is in the lowest range. However, since the lowest value of the goodness-of-fit is also greater than 0.7, it is inferred that these three categories of factors have an interactive relationship with other key factors.

In summary, the responsiveness of industrial agglomeration intensity to influencing factors varies across different cities. Therefore, targeted measures should be formulated according to the actual situation when regulating industrial agglomeration in cities. In addition, it is necessary to further explore the influencing factors of industrial agglomeration in some cities.

## 5. Conclusions

With the rapid development of China's economic level, the massive increase in the number of enterprises, the influence of urban geographic location elements, the role of government decision-making, and the spatial polarization effect of industrial agglomeration development, industrial agglomeration areas are gradually emerging within the geographic space. The study of the spatial distribution pattern of urban industrial agglomeration and the mechanism of the causes of industrial agglomeration has become an important part of geography research. However, the current research on the formation mechanism of industrial agglomeration mostly analyzes the formation mechanism of industrial agglomeration from a static perspective, but with a lack quantitative consideration of the impact of surrounding regions.

Based on the above problem, this study first visualizes the spatial distribution pattern of urban industrial agglomeration and analyzes it, and we construct an inter-city traffic interaction network that further infers population flow trend and technology innovation flow trend network. Finally, based on the regression analysis model considering the intensity of flow space, this paper studies the specific relationship between industrial agglomeration and influencing factors, and puts forward effective suggestions for the

high-quality development of urban industrial agglomeration and the efficient utilization of urban resources. However, the relevant findings we expressed are only based on the experimental results of this paper; the article does not contain any discussion of the results, theoretical review, nor previous studies.

The research work in this paper is still inadequate and needs to be further explored:

- (1) In the process of spatial distribution pattern analysis of industrial agglomeration, we used the traditional GIS visualization results for analysis, but this way is subjective. This is due to the different selection of threshold values, resulting in different visualization results, so the results are subjective. Therefore, how to express the spatial orientation of urban industrial agglomeration more accurately and objectively is a question worth considering;
- (2) In the paper, we constructed three major networks of cities, but their accuracy needs to be further verified in physical space. Although this paper has been optimized in the construction of multi-layer networks, the differences with the actual state of the physical space are not mentioned in this paper. Meanwhile, the inter-city interaction network is a relatively complex process, and there may be problems of incomplete consideration of influencing factors of network construction process in this paper.
- (3) Urban location elements in studies are not comprehensively considered, and many potential elements that are difficult to measure cannot be incorporated into the model, such as customs and culture, legal system, and policy guarantee; therefore, this study has some limitations. In addition, the reasonableness of the current research results and the match of physical space need to be proved by actual data. Therefore, further studies are necessary.

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