OPEN ACCESS Freely available online

IJESP
International Journal of Environmental Sustainability and Protection

ISSN 2737-5447
Volume 2, Issue 1
https://www.iikii.com.sg/journal/IJESP
International Journal of Environmental Sustainability and Protection

Article

Spatial Differentiation of Regional Innovation Capacity in Jiangsu, China

Fan Wu [1], Haiying Xu [2,*], and Xinyi Lu [2]

[1] Business School, Hohai University, Nanjing 211100, China; 191313070041@hhu.edu.cn
[2] School of Urban and Environmental Science, Huaiyin Normal University, China
No. 111, Chang Jang W. Road, Huai'an City, Jiangsu Province, 223300, China
* Correspondence: sqxhy@126.com; Tel.: +86-15052645869

Received: Dec 3, 2021; **Accepted:** Jan 3, 2022; **Published:** Mar 30, 2022

Abstract: This article addresses regional innovation capacity as an important driver of regional economic growth and a way to achieve coordinated regional development. With the number of patents as the index of innovation capacity measurement and the data from the Statistical Yearbooks from 2008 to 2017, we explore the spatial differentiation of innovation capacity in Jiangsu, China. Spatial clustering analysis and spatial autocorrelation analysis are used for this research. The result shows that the innovation capacity of 13 cities in Jiangsu is categorized into four levels. The gradient innovation capacity is weakened significantly from the south to the north in space. Jiangsu province has the distribution of regional innovation capacity level as the characteristics of spatial agglomeration. However, the province also has the characteristics of stage evolution, which shows the trend of aggregation, dispersion, and reagglomeration. The research results have important implications for optimizing the regional innovation system in Jiangsu Province.

Keywords: Regional Innovation Capacity, Temporal and Spatial Differentiation, Jiangsu Province, China

1. Introduction

Driving regional economic growth with science and technology innovation has become an important strategy of Jiangsu Province. With the implementation of this strategy, Jiangsu's regional innovation capacity has been significantly improved. At present, the overall innovation capacity of the province ranks the top in China, but there are obvious spatial differences within the region. Thus, it is important to explore the spatial differences and influencing factors of innovation capacity at the provincial level for coordinated development. In this researc2h, 13 prefecture-level cities in Jiangsu Province, China, are taken as the research objects. Through cluster and spatial autocorrelation analysis, the spatial differentiation and mechanism of the regional innovation capacity in Jiangsu province are explored. The analyzed data were obtained from the China Jiangsu Statistical Yearbook and the China City Statistical Yearbook from 2008 to 2017.

2. Literature Review

It is believed that regional innovation capability is a manifestation of the comprehensive capability of the regional innovation system. In innovation, "collective learning" is the key to the enhancement of regional innovation capacity. A better collective environment can be created when firms and institutions become interactive in the economy and society. In a regional innovation system, the key factors of regional innovation capacity include knowledge sharing and flow, regional accumulation habits, and absorption and reconstruction of new knowledge [1]. Regional innovation capacity consists of the "ability of government departments and public institutions to create and provide collective competitive products" and the "ability to stimulate and stabilize communication and cooperation among enterprises, institutions, technical institutions, R&D institutions, and administrative agencies in the region " [2]. According to the China Regional Innovation Capacity Report, the innovation capacity of a region is the ability to transform knowledge into new products, technologies, and services [3,4]. Innovation is the primary driver of development and is the essence of green, healthy, and sustainable economic development [5]. Regional innovation capacity focuses on practical results and the ability to commercialize knowledge [6,7]. Regional innovation capacity is locally rooted to achieve sustainable regional development mainly by building innovation exchange networks and optimizing resource allocation [8].

In terms of empirical studies, most scholars carry out quantitative analyses of the articles to define the indicators of innovation capacity. However, the articles do not effectively translate the capacity into economic benefits [9,10]. Therefore, it is necessary to measure innovation capacity with filed patents that are more reliable for the related research. In addition, the patent data is easily accessible, universal, and consistent. In addition, several patents have high technological and commercial values than utility patents and design patents [11,12]. Thus, patents are appropriate as an indicator of innovation capability. Based on various considerations, such as the relatively fewer number of patents in Jiangsu Province, the availability of data, and the comparability of a model, we choose patents as the key indicator to analyze the spatial differentiation of innovation capacity.

3. Method and Data

Cluster analysis is a multivariate statistical technique. It has two different clustering methods: hierarchical and iterative clustering. Cluster analysis or point cluster analysis is a multivariate statistical method for classification. In this paper, we use satistical product and service solutions (SPSS) to cluster the patents that are filed in 13 prefecture-level cities.

Along with cluster analysis, we use spatial autocorrelation analysis to determine whether a variable is spatially correlated. The spatial autocorrelation coefficient is usually used to quantitatively describe the spatial dependence of the object. Spatial autocorrelation analysis includes global autocorrelation analysis and local autocorrelation analysis. The definition of global autocorrelation Moran's I index is as follows.

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x)(x_j - x)}{s^2\sum_{i=1}^{n}\sum_{j\neq 1}^{n} w_{ij}} \tag{1}$$

where n refers to the number of observed values, Xi and X_j refer to the observed values of spatial positions, i, j, and W_{ij} refers to the proximity of spatial positions. The value range of the global Moran index I is [-1,1]. When space is negatively correlated, the range of Moran index I is [-1,0]. The value 0 means being spatially irrelevant. When the range of Moran index I is [0, 1], the space is autocorrelated.

Local spatial autocorrelation analysis is introduced to measure the spatial correlation degree of patent output in the region and make up for the deficiency of global autocorrelation. Local indicators of spatial association (LISA) and the significance level are analyzed and measured in local Spatial autocorrelation analysis. The results of Local Moran's I can be drawn from a LISA Spatial cluster map to analyze the differences and spatial patterns between individual regions and surrounding regions. Four types of patterns include H-H high-high cluster, L-H low-high cluster, H-L high-low cluster, and L-L low-low cluster on the LISA cluster map.

We use ArcGIS Desktop as hardware. It consists of three user desktop components: ArcMap, ArcCatalog, and ArcToolbox. ArcMap is a user desktop component with powerful map making, spatial analysis, spatial data building and other functions. We use Arcmap software to map the results of the cluster analysis in order to analyze the spatial differences in the innovation capacity of 13 prefecture-level cities. Data used for the quantitative analysis in this study are obtained in the 'Statistical Yearbook of Jiangsu, China' and 'Statistical Yearbook of Chinese Cities' from 2008 to 2017.

4. Temporal and Spatial Characteristics of Regional Innovation Capacity

4.1. Spatial distribution characteristics

In the paper, ArcGIS is used for cluster analysis of the number of filed patents from 13 cities of Jiangsu, China in 2016. We adopt the ‘natural breakpoint method’ for the natural grouping of data. The natural breakpoint method is for grading and classifying the data according to the statistical distribution of values to maximize the differences between classes. There are natural turning points and characteristic points in any statistical series. With the point, the objects are divided into groups with similar properties to find the boundaries of the breakpoints for grading. The result of this research presents 4 levels, and Arcmap software is used to map their spatial characteristics (Fig. 1).

Figure 1 shows the highly uneven distribution of innovation capacity among 13 cities in Jiangsu. The southern part of Jiangsu Province has more filed patents. A clear trend is observed as the number decreases from the south to the north.

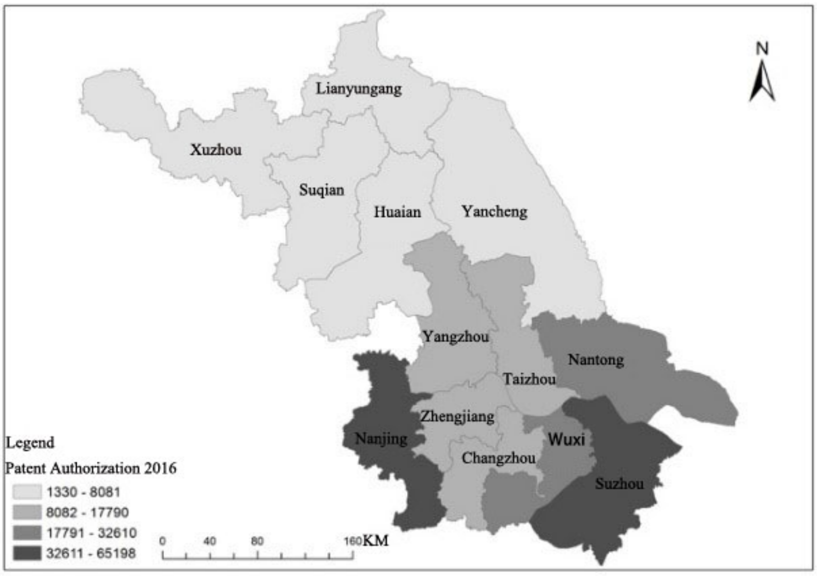

Figure 1. Spatial distribution pattern of patents granted from 13 cities in Jiangsu, China in 2016.

4.2. Evolutionary characteristics

4.2.1.Global Moran's I analysis

The value of Moran's I is used for testing the spatial autocorrelation analysis of 13 cities in Jiangsu, China. The analysis result is shown in Table 1 and Fig. 2. The innovation capacity of 13 cities in Jiangsu shows a spatial clustering from 2007 to 2016 (Table 1). Figure 2 presents that Moran's I value is the largest in 2010 and indicates that the 13 cities in Jiangsu have cooperated closely and exchanged innovation knowledge frequently. From 2012 to 2013, Moran's I value dropped sharply and rose steadily after 2014, indicating that the innovation links among cities has been stable after 2014.

Table 1. Moran's statistics of urban patent innovation activities in Jiangsu, China (2007-2016)

Year	Moran's I
2007	0.048968
2008	0.118341
2009	0.310743
2010	0.393973
2011	0.266331
2012	0.296986
2013	0.090345
2014	0.090345
2015	0.128229
2016	0.120787

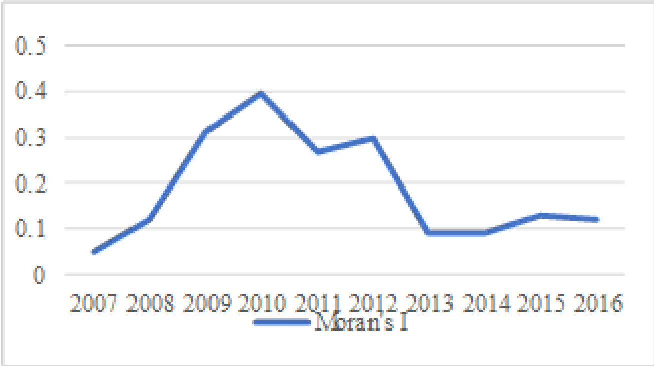

Figure 2. Moran's I statistics of patent innovation activities in 13 cities of Jiangsu, China from 2007 to 2016

4.2.2. Local Moran's I analysis

The global Moran's I shows the analysis result of the overall spatial correlation degree of the region, while the LISA index of local Moran's I is used for reflecting the correlation degree of the innovation capacity of each city more clearly. The distribution map of innovative LISA clusters in Jiangsu in 2007 and 2016 with ArcGIS (Figs. 3 and 4). H-H regions are mainly concentrated in southern Jiangsu, while L-L regions are located in northern Jiangsu during the decade.

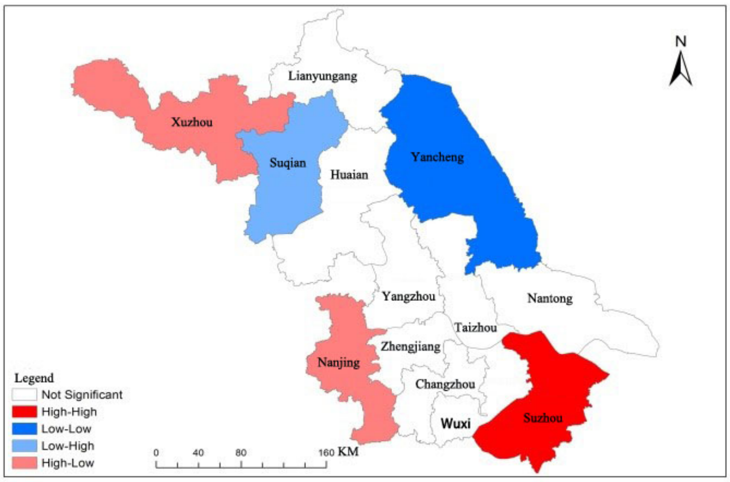

Figure 3. LISA cluster distribution map of innovation capacity in 13 cities of Jiangsu, China in 2007.

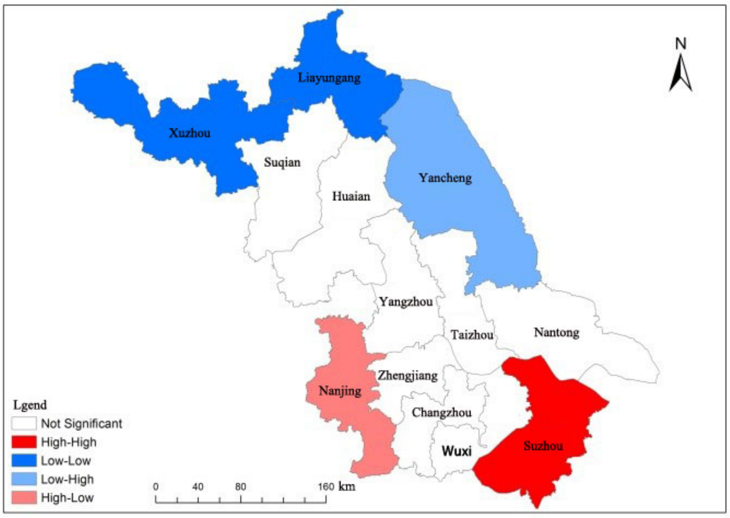

Figure 4. LISA cluster distribution map of innovation capacity in 13 cities of Jiangsu, China in 2016.

The result of the analysis is as follows.

(1) H-H area (high-high agglomeration area) refers to a city with strong innovation capacity and strong radiation of innovation capacity to surrounding cities. Suzhou has been in the H-H region from 2007 to 2016. Suzhou has a strong innovation capacity and developed economy in Jiangsu, China.

(2) H-L area (high low agglomeration area) has a strong innovation capacity of the cities, but that of the surrounding cities is weak. Xuzhou and Nanjing in the region were changed into Nanjing from 2007 to 2016.

(3) L-H area (low high agglomeration area) has a weak innovation capacity of the cities but that of the surrounding cities is strong. The region is in the vicinity of regions with the fast growth of innovation capacity and experiences the transition from the rapid improvement of innovation capacity to slow improvement. Suqian was included in the L-H area in 2007. Yancheng belonged to the L-H in 2016 because of the continuous development of the city and surrounding cities with high innovation capacity.

(4) L-L area (low-low agglomeration area) shows weak innovation capacity in general. Even though the city in the L-L area was changed from Yancheng to Xuzhou and Lianyungang from 2007 to 2016, the cities of the area were mainly concentrated in northern Jiangsu, China.

5. Conclusions

Through cluster analysis and spatial autocorrelation analysis, we quantitatively analyze the pattern change of innovation capacity differences of 13 cities in Jiangsu Province. The results showed that the development of innovation capacity was uneven among the 13 cities. From the perspective of spatial agglomeration distribution, the regions with strong innovation capacity are mainly concentrated in the south of Jiangsu Province, while the weaker regions are distributed in the north of Jiangsu Province. The primary cities include Suzhou and Nanjing, and the secondary cities include Wuxi and Nantong, which are adjacent to Suzhou. Southern Jiangsu is the most innovative region in Jiangsu Province, China. There are many universities and research institutes in the region, the foreign trade turnover is high, and high-tech industries are gathered together. Nanjing is the capital of Jiangsu Province, China. There are many development opportunities, while Suzhou is adjacent to Shanghai. It has more trade opportunities, which is influenced by the Shanghai megalopolis, so it has a strong natural innovation capacity. Wuxi and Nantong are adjacent to Suzhou, which is radiated by the innovative influence of Suzhou. It has a strong innovation capacity.

The result of this research lacks an explanation of the driving mechanism of innovation capacity differences, and the quantitative analysis is mainly conducted on the number of patents. Therefore, more quantitative analysis is necessary for the future, which leads to the result of output for an innovative environment.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Author Contributions: conceptualization, F.W.; methodology, H.X.; software, F.W; validation, X.L.; formal analysis, H.X.; investigation, F.W.; resources, F.W.; data curation, X.L.; writing—original draft preparation, H.X.; writing—review and editing, H.X.; visualization, F.W.; supervision, X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive external funding.

Acknowledgments: We would like to thank anonymous reviewers for their valuable comments and suggestions for improving this paper

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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