Spatial Distribution and Spillover Effect of New Employment in the Strategic Industries: A Case Study in Nine Cities of the Pearl River Delta, China

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Abstract: This study conducted a detailed examination of the spatial distribution of new employment in strategic industries in the nine cities of the Pearl River Delta, using big data on new employment and enterprise data derived from recruitment websites and enterprise search platform. By applying methods such as average nearest neighbor distance and Bivariate Moran's I, the research aims to provide an in-depth understanding of the spatial characteristics and variations in new employment in strategic industries. Results show the following: ① The overall spatial pattern of new employment in strategic industries is characterized by a dual-core structure centered around Guangzhou and Shenzhen, with collaborative development between Guangzhou-Foshan and Shenzhen-Dongguan along the Guangzhou-Shenzhen innovation corridor. ② Different strategic industries displayed distinct spatial patterns of new employment, with the highest concentration observed in the central districts of cities such as Guangzhou, Shenzhen, Foshan, and Dongguan, as well as in high-tech industrial parks. The next-generation Electronics industry's employment demand showed the highest level of spatial agglomeration. ③ The analysis of the spatial correlation between strategic industry enterprises and new employment revealed a spillover effects, which promotes job creation in surrounding areas. By identifying the spatial distribution characteristics of new employment in strategic industries and analyzing the trend of strategic industrial development, this study is expected to provide reasonable and comprehensive guidance for urban planning and cooperation and offer new perspectives for formulating policy implications related to strategic industries and talent employment.

Keywords: strategic Industries; employment dynamics; spatial correlation; spillover effects

1 Introduction

Since the 21st century, the growth of China urban clusters has had an increasingly significant impact on the spatial concentration of population. With the expansion of the urban population, employment pressure has also increased. Employment has always been a major problem for individuals, cities and countries [1]. The rise of unemployment is a pressing issue of Chinese labor market which is a international issue caused by the 2008 financial crisis [2,3]. As a highly populated region in China, the Guangdong-Hong Kong-Macao Greater Bay Area, a national key

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industrial development area, is based on the nine cities of the Pearl River Delta(PRD). How to promote employment demand and decrease unemployment has become more important and prominent [4], which has risen to the national strategy level. Therefore, exploring the spatial differentiation of new employment and the characteristics of industrial development in the Greater Bay Area is of great significance for promoting job creation and inter-city cooperation, and provides important insights into the spatial development patterns and industrial layout of urban clusters.

Previous urban employment research mostly used data from population censuses, national economic censuses, historical data on business establishments, and statistical yearbooks to study the spatial patterns of employment [5,6]. However, such statistical data tends to lag behind and cannot reflect the spatial characterisation of new employment demands. Additionally, panel data in the previous research lack consideration for complex and diverse spatial geographic elements. Compared to statistics based on administrative division, recruitment website data provide real-time information about new employment, focusing on employment dynamics instead of total employment [7].

Innovation and technological progress are regarded as the primary factors of sustained economic growth and urban employment expansion, which has been confirmed in developed and developing regions [8,9]. To deepen the understanding of urban spatial structure and lay the foundation for better urban development planning and policy formulation in the future, the 2010 enterprise registered data from the Beijing Industry and Commerce Bureau was used to study the distribution of urban employment density [10]. The spatial employment structure of the city was explored to demonstrate the role of urban planning in forming an urban spatial structure and provides implications for future planning from the morphological and function dimensions [11]. There are deficiencies in existing studies. Integration of enterprise and new employment data for overlapping analysis has rarely been examined, as well as the regional industrial development and employment trends.

Therefore, this paper attempts to study the spatial distribution and differentiation characteristics of new employment in the Greater Bay Area's strategic industries based on recruitment website data on new employment. Through an assessment of the development trends of strategic industries in the Greater Bay Area and an analysis of the spatial distribution of new employment in strategic industries, the aim is to provide insights for career choices among technology professionals and the rational allocation of talent resources. Additionally, this research intends to serve as a reference for the formulation of science and technology policies in the Greater Bay Area and the restructuring of academic disciplines in universities.

2 Materials and methods

2.1 Study area

The Greater Bay Area (GBA) consists of nine mainland cities, namely Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, Zhaoqing, and the two special administrative regions of Hong Kong and Macao. It covers an area of 56,000 km2 with a total population of about 68 million. As a important growth pole and stimulator in economic and technological innovation, the GBA, based on the Pearl River Delta urban agglomeration and integrated with the advantages of Hong Kong and Macao, has become a new form of mega-city region for China's population and labour force. In 2017, the state Council's Annual Government Work Report first emphasize the development plan for urban agglomerations in the GBA as a national strategy. In 2020, the gross domestic product (GDP) of the GBA reached 11.51 trillion yuan and was top tier in China. The GBA also has a large population and a high level of urbanization. The resident population of the GBA exceeded 86 million people by the end of 2020, with a population density of 1542 people per square kilometer, which was 10 times the average figure of China. [12]. The GBA boasts abundant university resources, strong scientific research capabilities, developed high-tech industries and modern manufacturing, as well as significant advantages in innovation potential [13,14]. The goal is to establish the GBA as an international hub for scientific and technological innovation, with a concentration of technology industries and free flow of innovative elements. Due to variations in data reporting standards, a subset of cities within the Greater Bay Area, excluding Hong Kong and Macau, were selected for analysis. This subset comprises nine cities located in the Pearl River Delta region (Fig. 1): Guangzhou, Shenzhen, Zhuhai, Foshan, Huizhou, Dongguan, Zhongshan, Jiangmen, and Zhaoqing (referred to as the "nine cities of the PRD" hereafter).

In this study, considering both the number of samples and the percentage of null-value units across grid scales of 1km, 2km, and 3km, we chose to use the 3km × 3km grid as our research unit. The density of new employment per unit area was calculated by dividing the number of new jobs within each grid by the grid area. The results were then visually observed by employing the natural break method to reclassify the density of new employment grids, providing a more intuitive understanding of the spatial distribution density of new employment opportunities.

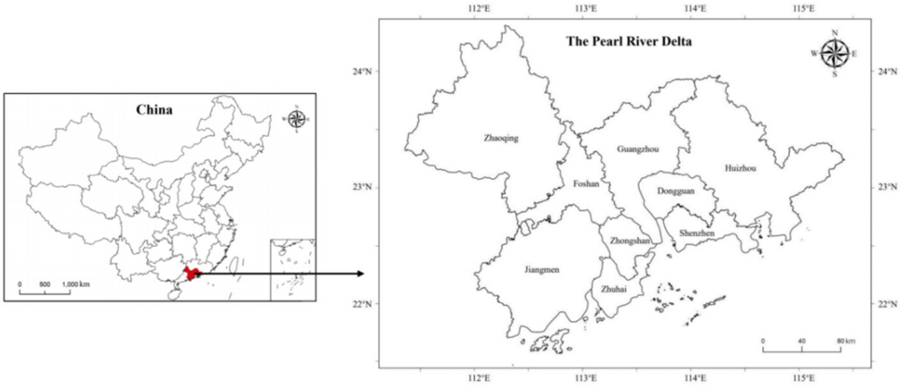

Figure 1. Location of 9 cities in the PRD, China

2.2 Data description

A Web Scraper tool was employed to collect employment demand data from the 51job recruitment website (https://www.51job.com/), specifically targeting postings published from February to April 2023. The data include job titles, salary, company name, nature of the company, workplace, industry classification, education and experienced requirements. Geographical coordinates for each employment demand were obtained using the AMap API interface (https://m.amap.com/). After applying coordinate correction and outlier removal techniques, a total of 2,311,749 valid items were obtained and stored in a database within ArcGIS software.

The Outline Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area (2019) prioritized the establishment of an international science and technology innovation center as a key task for the GBA. Referred to industry subcategories that reflect the innovation capabilities of the GBA and the Guangdong Provincial Government's development plans for the "Ten Strategic Pillar Industries" and "Ten Strategic Emerging Industries" (referred to as the "Double Ten Strategies"), as well as the research on the status and countermeasures of strategic pillar industry clusters in Guangdong Province, six strategic industries were selected based on their economic contributions and technological innovation attributes in this study. The analysis focused on these six strategic industry categories: green petrochemicals, automobiles, software and information services, biomedicine and healthcare, next-generation electronics, and advanced materials. This study examined the spatial distribution characteristics and differences in employment generated by these strategic industries in the nine cities of the PRD, from GBA perspective. The subcategories of the six strategic industries were presented in Table 1. We used this as a basis for filtering the recruitment data to identify six categories of new employment in strategic industries. The Point of Interest data (POI) for strategic industries in the PRD were obtained from a enterprise search platform, Qichacha (https://www.qcc.com/), and filtered enterprises in normal status with more than zero insured personnel to extract data. The data include company name, industry classification, company size and address. A total of 253,246 relevant companies were identified across the nine cities of the PRD.

Table 1. Statistical Caliber of Strategic Industries in the Nine Cities of the PRD.

Major Industry Categories	Subcategories of Industries
Green Petrochemicals	Chemical Fiber Manufacturing Industry; Chemical Raw Materials and Chemical Products Manufacturing Industry; Petroleum, Coal, and Other Fuel Processing Industry; Rubber and Plastic Products Industry
Automobiles,	Automobile Manufacturing Industry
Software and Information Services	Software and Information Technology Services Industry; Internet and Related Services Industry
Biomedicine and Healthcare	Healthcare; Pharmaceutical Manufacturing Industry; Medical Instruments, Equipment, and Apparatus Manufacturing; Medical Services; Health and Wellness
Next-generation Electronics	Computer, Communication, and Other Electronic Equipment Manufacturing Industry
Advanced Materials	Non-Metallic Mineral Products Industry; Smelting and Rolling Processing of Ferrous Metals Industry; Chemical Raw Materials and Chemical Products Manufacturing Industry; Computer, Communication, and Other Electronic Equipment Manufacturing Industry; Metal Products Industry; Rubber and Plastic Products Industry; Smelting and Rolling Processing of Non-Ferrous Metals Industry; Chemical Fiber Manufacturing Industry

Note: The statistical data on strategic industries are published by the Guangdong Provincial Bureau of Statistics and the Department of Industry and Information Technology of Guangdong Province

2.3 Methods

2.3.1 Average nearest neighbor distance method

This study employed the Average Nearest Neighbor Distance (ANN) method to assess the average distance and proximity between new employment points. By comparing the observed nearest neighbor distances with the expected values, the R-value is calculated. The R-value, along with its standard deviation (Z-value) and significance level (P-value), collectively determine the spatial agglomeration of the newly generated employment. A smaller R-value indicates a stronger degree of spatial clustering [15].

2.3.2 Kernel Density Estimation

Kernel density estimation is a method to explore the density of an area with a number of samples of known points [16]. It can be applied to detect the spatial agglomeration and distribution of new employment in the nine cities of the PRD. It can be expresses as follows:

$$\lambda(s) = \sum_{l=1}^{n} \frac{1}{\pi r^2} \phi(d_{ls}/r) \tag{1}$$

where $\lambda(s)$ is the density location s; r is bandwidth, which is the search radius of the kernel density function; n is the number of sample employment; d_{ls} is the distance between sample employment l and s; ϕ is the weight of the distance.

Kernel density estimation is a widely used technique for identifying clusters of newly generated employment points. However, it does not offer a quantitative measure of the degree of agglomeration. To overcome this limitation, this study incorporates the standard deviation threshold test, a statistical method that assumes a normal distribution and has been widely employed in data analysis [17,18]. The standard deviation ranges, which encompass mean $\pm\sigma$, mean $\pm 2\sigma$ and mean $\pm 3\sigma$, correspond to approximately 68%, 95% and 99% of the total data distribution, respectively. By integrating the principles of kernel density estimation and the normal distribution, this study establishes the distribution boundaries of the new employment points which provides the accurately identified locations of employment agglomeration cores and a quantitative measure of the level of agglomeration.

2.3.3 Spatial correlation test

We utilized bivariate Moran's I to investigate the spatial clustering (positive spatial correlation) and dispersion (negative spatial correlation) between enterprises and new employment in strategic industries. Two types of bivariate Moran's I methods are employed for this purpose: global bivariate Moran's I and local bivariate Moran's I (bivariate LISA). The global bivariate Moran's I examines the presence and extent of spatial correlation between existing enterprises and new employment in strategic industries across the entire study area, while the local bivariate Moran's I reveals the spatial correlation within different spatial units [19]. The formulas used for computation are as follows:

$$I_{B,Global} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(y_j-\bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{2}$$

$$I_{B,Local}(i) = \frac{(x_i-\bar{x}W(i))(y_i-\bar{y}W(i))}{\sum_{j=1}^{n}\omega_{ij}\sum_{j=1}^{n}\omega_{ij}} \tag{3}$$

where $I_{B,Local}$ is the global bivariate Moran's I statistic; n is the number of spatial units; ω_{ij} represents the spatial weight between spatial units i and j; x_i and y_j are the values of the two variables (strategic industry enterprise and new employment) being analyzed for spatial autocorrelation; $\overline{x}$ and $\overline{y}$ are the means of the two variables across all spatial units; $I_{B,Local}(i)$ is the Local bivariate Moran's I statistic for spatial unit i; x_i and y_j are the values of the two variables at spatial unit i; $\overline{x}W(i)$ and $\overline{y}W(i)$ are the weighted means of the two variables for the neighboring spatial units of i; ω_{ij} is spatial weight between spatial units i and j.

The bivariate LISA method enables the visualization of local spatial correlations through the generation of Moran scatter plots, cluster maps and associated significance maps which can illustrate the relationship between the value of new employment at a given location and the average value of enterprises at adjacent locations at a certain significant level. The analysis results can be categorized into five types: high-high agglomeration (H-H), low-low agglomeration (L-L), high-low agglomeration (H-L), low-high agglomeration (L-H) and non-significant.

3 Results

3.1 Comprehensive spatial patterns of new employment in strategic industries

At the scale of nine cities of PRD, the spatial pattern of new employment showed core agglomeration, cluster interconnections, and peripheral dispersion characteristics (Fig. 2). Moreover, the new employment was concentrated primarily in Guangzhou, Shenzhen, Foshan, and Dongguan, forming two major employment clusters, namely the Guangzhou-Foshan cluster and the Shenzhen-Dongguan cluster. In contrast, the peripheral areas showed a more dispersed distribution of employment, mainly concentrated in industrial parks. Notably, Guangzhou and Shenzhen constituted two distinct cores, where the density of new employment was relatively high. Guangzhou, occupying 13.4% of the study area, accounted for 33.9% of the new employment, while Shenzhen, covering 3.6% of the study area, accounted for 36.4% of the new employment.

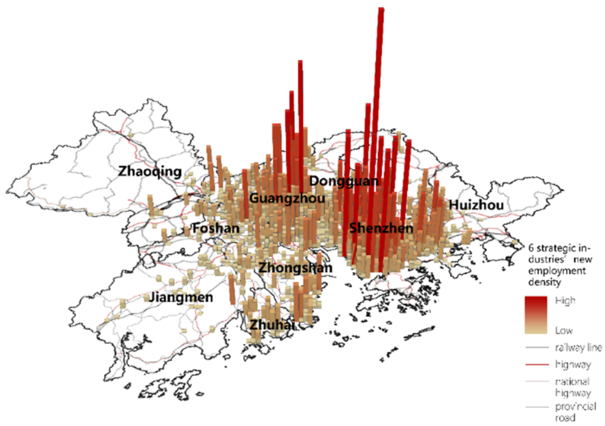

Figure 2. Comprehensive spatial patterns of new employment in strategic industries in nine cities of PRD.

3.2 Spatial patterns of new employment in each strategic industry

3.2.1 Spatial identification of new employment in each strategic industry

In order to analyze the spatial distribution characteristics and dominant development trend of 6 strategic industries, the standard deviation value test was chosen to determine the agglomeration core of new employment space for 6 strategic industries (Table 2)(Fig. 3). The green petrochemicals industry exhibited the largest clustering area for new employment, with its 1 standard deviation (1sd) area accounting for 8.78% of the study area and encompassing 94.57% of green petrochemical industry's new employment. The next-generation electronics industry represented the most concentrated spatial core for new employment, with a density of 38.03 jobs per square kilometer within the 1sd standard deviation range. It was followed by the advanced materials and the software and information services industries, with densities of 34.47 and 33.65 jobs per square kilometer respectively.

The spatial distribution of the 6 major strategic industries were different from each other. Four industries, namely software and information services, biomedicine and healthcare, next-generation electronics and advanced materials industries, exhibited Guangzhou and Shenzhen as their primary clustering cores. Dongguan, Foshan, and Zhuhai served as sub core areas, while other cities within the PRD showed dispersed clusters of new employment. On the other hand, the green petrochemicals and automobiles industries demonstrated a "dispersed overall, clustered locally" characteristic. The dispersed high-value areas mainly aligned with GBA's "Guangzhou-Shenzhen" innovation corridor, while the clustering cores consisted of industry clusters, like industrial bases and industrial parks. The software and information services industry's new employment spatially concentrated in Guangzhou and Shenzhen, primarily within the administrative centers of the major cities. The biomedicine and healthcare industry exhibited a core clustering pattern in Guangzhou, with scattered cores in Shenzhen, Zhuhai, Dongguan and Foshan. This pattern aligned with the current distribution of the biomedicine and healthcare industry clusters and the strategic plan outlined in the Development Plan for the Biomedicine and Healthcare Strategic Pillar Industry Cluster in Guangdong Province (2021-2025). The plan aims to take Guangzhou and Shenzhen as main development cities and focus on building key industrial innovation clusters in Zhuhai, Foshan, Huizhou, Dongguan and Zhongshan. The next-generation electronics and advanced materials industries showed similar spatial distribution characteristics for new employment, with Shenzhen serving as the primary area. These industries encompassed Bao'an-Nanshan-Longhua-Futian-Longgang-Pingshan Districts, as well as forming clustering cores in Guangzhou Baiyun Chemical New Materials Base and Dongguan Songshan Lake High-tech Zone. Additionally, all six strategic industries have formed smaller clustering cores in Nansha District, Guangzhou, where the talents demand contributed to the strategic platform of "relying on the Greater Bay Area, collaborating with Hong Kong and Macau, and facing the world."

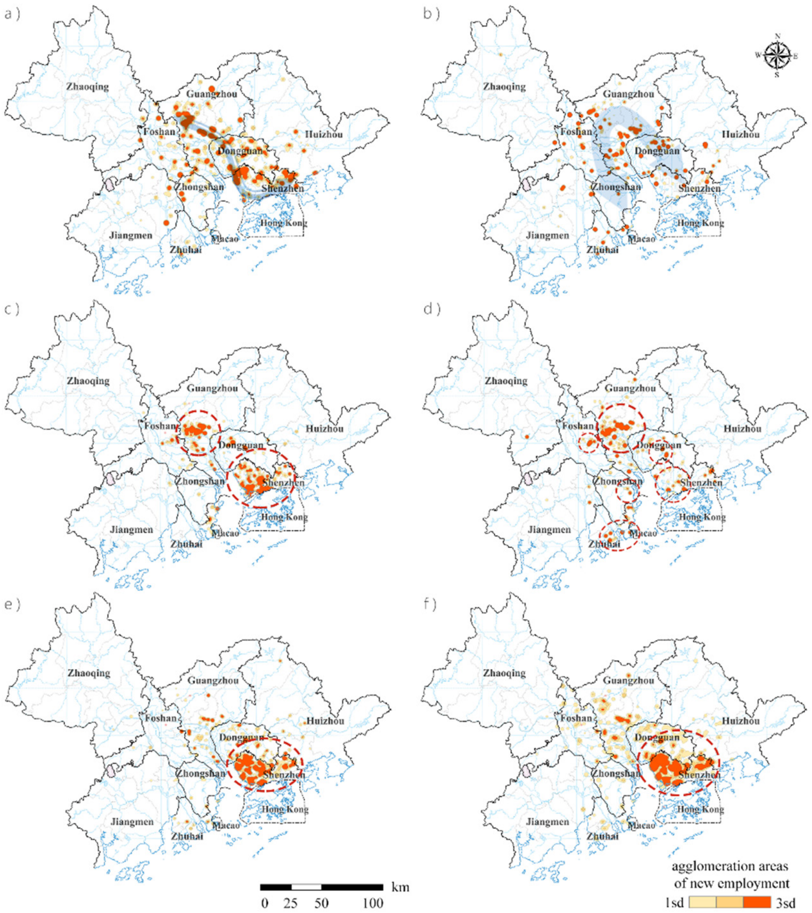

Figure 3. Spatial identification of new employment in each strategic industry in nine cities of PRD. (a.green petrochemicals, b.automobiles, c.software and information services, d.biomedicine and healthcare, e.next-generation electronics, f.advanced materials)

Table 2. Spatial identification of new employment in each strategic industry in nine citied of PRD.

Types of strategic industries	1sd standard deviation surface area/ km²	Area ratio/%	Number of new jobs/unit	Percentage of new jobs in industry/%	Density of new employment/(units/km²)
Green Petrochemicals	4883.54	8.78	39606	94.57	8.11
Automobiles	2080.56	3.74	13658	98.56	6.56
Software and Information Services	2168.32	3.90	72954	95.97	33.65
Biomedicine and Healthcare	1916.04	3.44	36744	96.17	19.18
Next-generation Electronics	2707.14	4.87	102958	95.05	38.03
Advanced Materials	4496.82	8.08	155022	89.26	34.47

3.2.2 Spatial quantification of new employment in each strategic industry

There were variations in the number and density of new employment among different types of strategic industries. The advanced materials industry emerged as the largest contributor, accounting for 7.51% of the total new employment demand. Following were the next-generation electronics and the software and information services industries, accounting for 4.69% and 3.29% each. The biomedicine and healthcare, green petrochemicals, and automobiles industries ranked subsequently in terms of their contribution to new employment.

The distribution of new employment provided by each strategic industry was significantly polarized, with Guangzhou and Shenzhen obviously forming two agglomeration centers. The study included grid density analysis (Fig. 4) employing natural breaks classification for density values and nearest neighbor analysis (Table 3) to examine the clustering of new employment distribution. Among the strategic industries, the next-generation electronics industry displayed the highest level of clustering, with an R-value of 0.00081 and an expected mean distance of 318.76 meters. It showed apparent agglomeration characteristics, particularly in Shenzhen, where multiple high-value clusters were widely distributed, reflecting the city's leadership in technological innovation and innovation ecosystem [20]. The automobiles and the advanced materials industries also displayed relatively high levels of clustering in their new employment distribution, with R-values of 0.00113 and 0.00200, respectively. The former showed clusters in other 7 cities except Guangzhou and Shenzhen, such as Foshan, Dongguan, and the Zhuhai High-tech Zone. The latter exhibited a relatively broader distribution. The distribution of new employment in the biomedicine and healthcare industry and the software and information services industry presented clear "core-periphery" spatial characteristics, primarily concentrating in the core areas of Guangzhou and Shenzhen. The green petrochemicals industry, with an R-value of 0.00282 and an expected mean distance greater than 500 meters, demonstrated a lower level of agglomeration compared to other industries.

Table 3. Spatial characteristics of new employment in each strategic industries.

Types of strategic industries	Number of new employment/unit	proportions/%	expected mean distance	P-Value	R-Value	Spatial distribution
Next-generation Electronics	108319	4.69%	318.76	0.00	0.00081	high agglomeration
Automobiles	13858	0.60%	907.50	0.00	0.00113	comparative agglomeration
Advanced Materials	173678	7.51%	269.08	0.00	0.00200	comparative agglomeration
Biomedicine and Healthcare	38208	1.65%	436.63	0.00	0.00239	General agglomeration
Software and Information Services	76016	3.29%	287.88	0.00	0.00252	General agglomeration
Green Petrochemicals	41879	1.81%	534.69	0.00	0.00282	General agglomeration

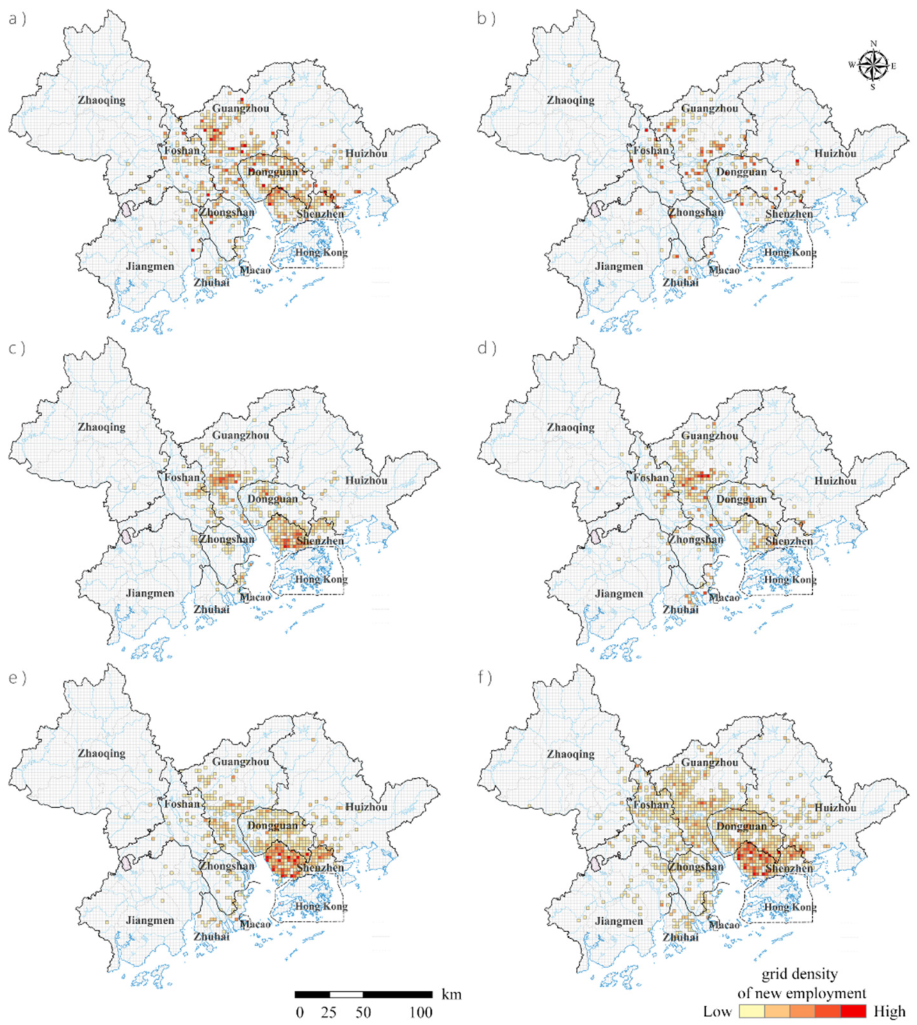

Figure 4. Spatial patterns of new employment in each strategic industry in nine cities of PRD. (a.green petrochemicals, b.automobiles, c.software and information services, d.biomedicine and healthcare, e.next-generation electronics, f.advanced materials)

3.3 Spatial correlations between strategic industry enterprises and new employment

The results from the global bivariate Moran's I displayed significantly positive spatial correlation between strategic industry enterprises and new employment (all Moran's I values >0 and p-values <0.05). This meant that strategic industry enterprises promoted new employment demand. The bivariate LISA map showed four types of spatial correlations between strategic industry enterprises and new employment (Fig. 5). Focusing on high-high and low-high clustering areas, this study aimed to identify the hotspots and potential areas for new employment in the 6 strategic industries. Hotspots refer to regions with high values for both the number of enterprises and new employment, indicating areas where new employment clusters emerge due to the concentration of enterprises. Potential areas, on the other hand, have a low number of enterprises but a high level of new employment, indicating regions where enterprise development apparently generates new employment demand.

We observed significant disparities in the spatial distributions of new employment hotspots. The green petrochemicals industry predominantly concentrated in the urban border areas of the GBA's "Guangzhou-Shenzhen" innovation corridor, particularly in the Baiyun District of Guangzhou, the Binhai-Songshan Lake High-tech Zone in Dongguan, and the adjacent region of Bao'an District in Shenzhen. The automobiles industry exhibited a more dispersed pattern, with smaller hotspots located outside of Guangzhou and Shenzhen, such as Sihui District in Zhaoqing, Xiegang District in Dongguan and Nanhai District in Foshan. The remaining four strategic industries showed similar hotspot patterns. These industries formed contiguous clusters in the traditional city centers of Guangzhou and Shenzhen, including Liwan, Yuexiu, Tianhe, Haizhu, Nanshan, Futian and Luohu Districts. The software and information services industry concentrated a dual-core in the urban center of Guangzhou and Shenzhen, with a sub core in the urban center of Dongguan. The biomedicine and healthcare industry concentrated a single core in Guangzhou, while the advanced materials and next-generation electronics industries concentrated single cores in Shenzhen, particularly in the Bao'an-Longhua-Nanshan-Futian-Luohu-Longgang Districts, primarily concentrated in the western part of Shenzhen.

The phenomenon of hotspot-potential areas reflects the spatial spillover of new employment resulting from corresponding strategic industry enterprises clustering. We also examined the directional nature of this spillover effect, where areas with fewer enterprises on the periphery of the core experienced higher new employment demand. The hotspot-potential areas formed at the junction of Baiyun District in Guangzhou and Nanhai District in Foshan in the automobiles industry reflected synchronized expansion of new employment between the two cities. The software and information services and the biomedicine and healthcare industries demonstrated intra-city diffusion patterns, with potential areas for new employment emerging within Guangzhou and Shenzhen urban center instead of moving in outer suburban areas. The next-generation electronics and advanced materials industries exhibited apparent diffusion of potential areas surrounding hotspots, filling the gaps between hotspots within Shenzhen and forming significantly contiguous hotspot-potential areas. The results indicated that the spatial spillover effect of new employment in the software and information services, biomedicine and healthcare, next-generation electronics, and advanced materials industries tended to be oriented towards the city centers. We also found that some independent contiguous potential areas were located within industrial parks. For example, the green petrochemicals industry relied on the Guangzhou Petrochemical Base, the Daya Bay Petrochemical Base in Huizhou and downstream processing industries developed in Shenzhen, Foshan, Dongguan, and other cities, forming a complete petrochemical industry chain. This resulted in contiguous potential areas within the Guangzhou Petrochemical Base. The software and information services industry has established a complete industry chain between the urban center of Dongguan and Shenzhen, leading to the formation of smaller potential areas within the Songshan Lake High-tech Zone of Dongguan. These results are consistent with the conclusion of research [21]. Li found that Shenzhen, Dongguan and Huizhou had built up a systematic production network that was globally competitive in computer, communication and other electronic equipment manufacturing.

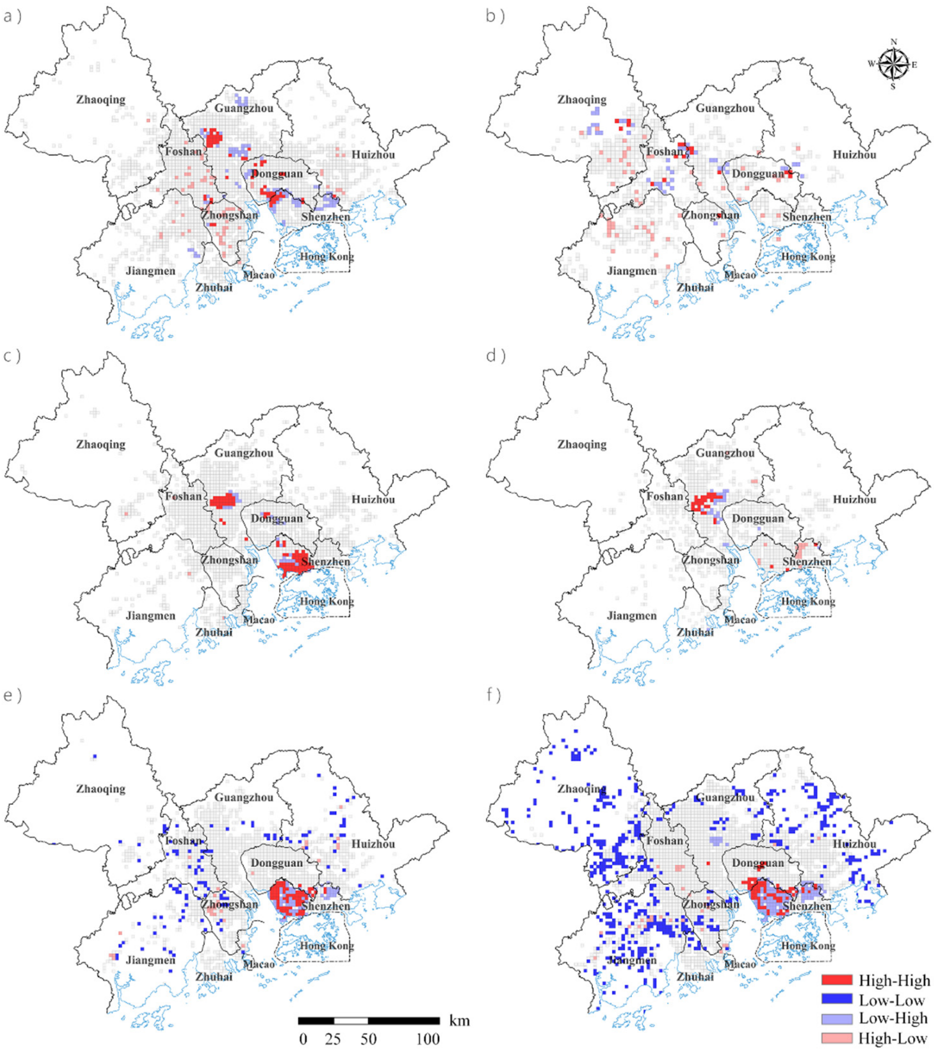

Figure 5. LISA cluster maps between individual strategic industry enterprises and new employment. (a.green petrochemicals, b.automobiles, c.software and information services, d.biomedicine and healthcare, e.next-generation electronics, f.advanced materials)

4 Discussion

4.1 Implication of spatial relationship between strategic industry enterprises and new employment

Against the backdrop of stock planning, studying urban employment from an strategic industry demand perspective offers new insights for formulating strategic industry-related policies and improving talent-occupation matching. The findings aim to provide targeted recommendations for the absorption of strategic industry talents in the PRD.

First, this study identified four types of cluster patterns (i.e., HH, LL, LH, HL) between strategic industry enterprises and corresponding new employment, aiming to establish a consistent relationship between strategic industry policies and cluster patterns in specific regions. Hotspot areas with a high concentration of strategic industry enterprises and significant new employment growth were typically found in urban core areas or well-established industrial parks, aligning with the traditional Monocentric City model in the tradition of economic geography [10,22]. These hotspot areas were characterized by a developed service sector, abundant cultural, recreational spaces and the ability to meet the knowledge acquisition and social needs of innovative individuals, thus attracting the clustering of innovative companies [23]. The presence of related industrial foundations also played a crucial role in promoting strategic industry agglomeration. To facilitate job relocation and transfer, governments can implement preferential policies such as streamlined approval processes and rental incentives. Furthermore, efforts should be made to enhance environmental development, increase financial subsidies and invest in universities and research institutions in and around hotspots. Conversely, potential areas with a low concentration of strategic industry enterprises but high new employment growth could serve as sub centers for urban employment structure under the context of stock planning. The Polycentric City model is considered a more compact urban form that is conducive to more effective urban space organization [24]. These potential areas were typically industrial parks and science parks located on the outskirts of urban centers, facing challenges such as single industrial function and inadequate living services. To attract talents and industries, policy interventions can focus on providing cultural and recreational spaces, improving supporting services and enhancing infrastructure. Governments can incorporate the construction layout and subsequent operation of high-tech industry innovation zones and future industrial agglomeration areas into top-level planning, increase support for leading industry enterprises and foster the development of upstream and downstream industrial ecological chains. Additionally, it is worth noting that certain high-tech industry innovation zones within strategic industry plans may not exhibit significant employment population agglomeration effects. Therefore, future efforts should be tailored to local conditions and continue to strengthen the transformation of urban employment spatial structure toward a Polycentric City model.

Second, the results showed the significant role played by spillover effects in the relationship between strategic industry enterprises and corresponding new employment growth, which suggested that the development activities in a particular location can have an impact on the new employment opportunities in surrounding areas for strategic industries. In addition to opting for enterprise clusters in urban core areas, relevant talents also have the option to choose peripheral industrial parks and the surrounding areas of hotspots, which offer promising employment demand potential. Currently, Guangzhou and Shenzhen remain the preferred destinations for strategic industry talent employment. Furthermore, high-tech zones and incubation bases in key cities such as Foshan, Dongguan and Zhuhai are also identified as potential areas for new employment in strategic industries. Strategic industry talents are advised to broaden their job search scope to include the PRD, aiming to find the most suitable locations for optimal job matching.

4.2 Advances and limitations of the applied method

This study was conducted at a finer scale compared to previous work [11,25]. We implemented the analysis of strategic industry enterprises and new employment's spatial patterns and spatial relationship on grid level, which can generate results with high spatial resolution. Compared to conventional approaches that rely on national population censuses, economic surveys, statistical yearbook data and historical statistics of enterprise units, the use of precise point data from recruitment website provides more accurate and real-time information, allowing for a market-oriented understanding of resource allocation patterns. The spatial patterns depicted by precise point data contributed to the fine-grained analysis of employment dynamics, enabling a detailed examination of micro-scale spatial units such as industrial parks. This approach offered crucial technical support for accurately capturing the development direction of urban employment spatial patterns. Additionally, this study examined the spatial autocorrelation between strategic industry enterprises and the associated new employment, which has received limited attention in existing literature. The results of global bivariate Moran's I demonstrated spillover effects and interactions between these two variables, while bivariate LISA analysis was employed to visualize clustering patterns between the two variables at each location. If the data used in this study can be collected in other regions or replaced with regional data from other areas, our approach can be applied to evaluate the relationship between strategic industry enterprises and new employment and conduct spatial analysis of the interaction between these two systems. In such cases, we consider that the results obtained from our method are reliable and significant.

However, there are still some limitations in this research. Firstly, limitations arose from the quantity and characteristics of online recruitment data, as certain recruitment information from government agencies, public institutions and individual businesses is inaccessible. Moreover, the acquired new employment data had not been filtered according to job titles, leading to the inclusion of low-skilled workers. These factors may result in erroneous spatial distribution patterns. Secondly, the issue of scale effect is acknowledged. Scale effect is a common phenomenon in spatial analysis, referring to the fact that outcomes may differ when the spatial units or extents used for analysis are altered [26]. In this study, a 3km × 3km grid was employed as the spatial unit, encompassing nine cities with varying administrative areas. Analyzing data at a single scale may capture, miss or distort the real interactions between the two variables [27].

5 Conclusions

This study utilized data from enterprise database and recruitment website, employing methods such as kernel density estimation, standard deviation test, and spatial correlation, to characterize the spatial patterns of strategic industry enterprises and new employment in the nine cities of the PRD. It aimed to provide insights for the rational allocation of talent resources from the perspective of employment growth. The conclusions are following: ①On the whole, the 6 strategic industries' new employment concentrated around the core cities of the PRD, with dual cores in Guangzhou and Shenzhen. A collaborative development along the Guangzhou-Foshan and Shenzhen-Dongguan axis was driven by the Guangzhou-Shenzhen innovation corridor. ②The primary core cluster areas were the central districts of Guangzhou (Tianhe, Yuexiu, Haizhu, Liwan Districts), Nansha Mingzhu Bay and the central-western region of Shenzhen. The sub core areas included Dongguan (Guancheng, Dongcheng, Nancheng, Songshan Lake High-tech Districts), Foshan (Chancheng, Nanhai Districts) and Zhuhai (Xiangzhou District), while the remaining cities exhibited dispersed clusters. Typically, the core agglomerations were located in central urban areas or near industrial clusters, industrial bases and industrial parks. Notably, the biomedical and healthcare industry demonstrated the most prominent agglomeration effects in Guangzhou, while the next-generation electronics, advanced materials, software, and software and information services industries exhibited significant agglomeration effects in the Guangzhou-Shenzhen region. ③Regions with a high proportion of hotspots indicated that industry agglomeration could generate more employment opportunities. Specifically, the green petrochemicals and automobiles industries showed a trend of employment spillover effects across cities. On the other hand, the software and information services, biomedical and healthcare, next-generation electronics and advanced materials industries demonstrated a diffusion of new employment within nine cities of the PRD. Independent clusters of new employment potential were primarily located within the vicinity of relevant industrial parks.

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