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Comparing the Spatial Distribution of Popular Destinations in the Era of Mobile Internet: Case Studies of 9 Cities in the Pearl River Delta

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Abstract: In the era of mobile Internet, the development of the influencer economy has given rise to emerging consumer spaces and popular destinations, which are new hot topics for urban public space research. Based on TikTok popular destinations check-in data and using statistical analysis, kernel density analysis, and optimized hotspot method, this study quantitatively measures different spatial distributions of popular destinations in the Pearl River Delta and nine cities within it and explores the relationship between spatial structure and built environment and the causes. The results show that the spatial distribution of popular destinations shows an obvious dual structure, and the spatial hotness spreads and decreases from the central cities (Guangzhou and Shenzhen) to the peripheral cities. Meanwhile, the spatial distribution characteristics of popular destinations within different cities have obvious heterogeneity, and the heterogeneity of developed cities is weaker than that of less developed cities.

Keywords: popular destinations, spatial distribution, TikTok, the Pearl River Delta, mobile internet

1. Introduction

The link between time and place has been redefined as a result of a new round of information technology revolution, and the organizational structure and mode of operation of human activities have started to be rebuilt [1]. With the increasing contribution of the influencer economy to regional economies, the study of popular destinations has become a hot research topic [2], the modeling and comparative analysis of the spatial distribution of popular destinations have also become a focus of research [3]. The design of urban leisure and recreation areas, tourism development, transportation, public service facilities, and other urban structures all benefit significantly from studying them [4].

The term "influencer" was originally an abbreviation of "influencer people", but has now evolved into an adjective label, such as "influencer dot", "influencer city", "influencer economy" and so on. As a new phenomenon of spatial pattern, popular destinations have not been strictly defined by the academia, this paper refers to Yang et al., 2022 to define popular destinations as

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some physical places spread over the Internet platform in a short period of time with certain spatial characteristics, and then attract a large number of attractions, resources, and visitors to gather.

This paper uses emerging social media data, TikTok popular destinations check-in data, to examine the spatial distribution of popular destinations. TikTok is a platform for short mobile videos that enables users to make and share videos with the TikTok community. These videos can typically last between 15 and 60 seconds. TikTok has swiftly acquired popularity since its inception in 2017, with 800 million monthly active users and more than 2 billion downloads worldwide [5]. Moreover, TikTok has become a popular social media tool for people to record their daily lives, with 660 million times of usage in 2019 spanning 233 nations and territories. The check-in data of TikTok records the location information, the number of views and the actual number of visitors in popular destinations, and its data volume and data information can greatly improve the accuracy of influencer economy description.

The remainder of the research is structured as follows: The "Related works" covers the many viewpoints and approaches used to research the spatial distribution of well-liked destination, while the section on "Methodology" goes into detail on the data and techniques utilized in this research. And the "Results" section presents the results of the data analysis, visualizing the spatial patterns and hotspots of popular destinations. Finally, the "Discussion" and "Conclusion" sections summarize the full text and discuss the limitations, contributions and future research directions of this area.

2. Related Works

With the development of urban social media and influencer economy, urban popular destinations are becoming more and more diverse and complex. Specifically, accommodation [6], tourism attractions [7], beverage industry [8] or crowd-gathering-oriented retail, all can be considered part of popular destinations, which makes the spatial distribution of popular destinations analysis increasingly significant [9, 10]. The spatial distribution of popular destinations reflects not only the spatial patterns of visitors, but also the connections between tourist spaces, so that popular destinations form a network of relationships with certain structural characteristics [11]. More and more scholars describe and visualize the spatial distribution of popular destinations with the help of spatial data analysis and network analysis to detect hotspot spaces and give spatial planning suggestion [11, 12] .

The spatial distribution of popular destinations has been mostly analyzed using geospatial analysis to reveal the spatial distributions of tourists, the mobility of urban tourism, and the interaction between visitors and popular destinations [13]. Some research have paid attention to the spatio-temporal behavioral patterns of visitors, and they widely recognize punch card data and digital footprint data as more important and credible data in related studies, using hotspot analysis, spatial clustering, and other methods to analyze the spatial patterns [14]. Other scholars focus on the spatial linkage of popular destinations, for example, Ma et al., 2022 used a combination of spatial autocorrelation and geographic probes to identify the tourism distribution patterns of Chinese provinces and analyzed their driving mechanisms, and found that travel space and transportation conditions, socioeconomic physical conditions and development level form a continuous and strong network of interactions. Other scholars have combined social network analysis and traditional quantitative methods to reveal the interaction between visitors and popular destinations, and found that travel distance and attraction popularity have a strong influence on the spatial distribution of popular destinations [4].

It can be seen that the spatial distribution of popular destinations is mainly analyzed by traditional geospatial analysis methods, and most traditional studies on popular destinations are only based on social media platform data to model the spatial pattern of urban tourism [15]. However,

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there is a lack of spatial comparisons between multiple cities, and even fewer studies use the emerging TikTok popular destinations check-in data. Based on this, this paper takes the Pearl River Delta as the case study, the most dynamic city agglomeration in China, as the object of study and compares the spatial distribution of popular destinations among cities and city agglomeration to further compensate for the spatial pattern of the influencer economy. This paper compares and analyzes the spatial distribution of popular destinations of each city and urban agglomeration to further make up for the deficiencies of the spatial pattern of the influencer economy.

3. Methodology

3.1. Research Area and Data

This study is an empirical study of the Pearl River Delta mega-city region, one of the three major urban agglomerations in China (Figure 1).

The Guangdong-Hong Kong-Macao Greater Bay Area, which includes the PRD and the two neighboring Special Administrative Regions (Hong Kong and Macau), is located in southern China's Guangdong Province. The PRD, one of China's greatest mega-city zones, has played a significant role in the socioeconomic growth of the nation [16]. With a total population of 78.01 million, the region has a land area of 55,368.7 km2, making it 2.6 times larger than the New York Bay Area, 3.3 times larger than the San Francisco Bay Area, and 4.2 times larger than the Tokyo Bay Area. It also has a population density that is more than 1,200 people/km2, making it significantly denser than the other three Bay Areas [17]. Thus, the PRD region, which accounts for only 0.6% of the national land area, is home to 4.3% of the population and contributes 10.03% of

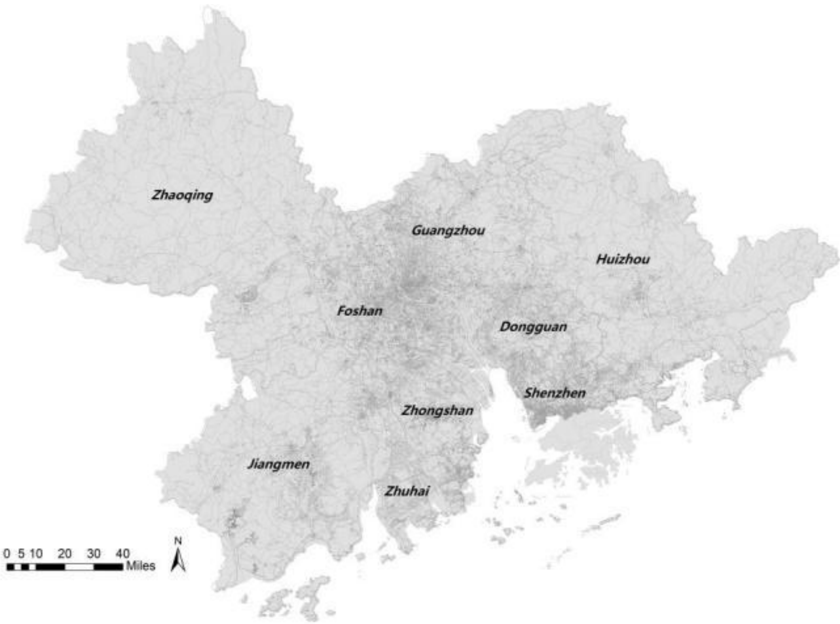

Figure 1: Nine studied cities of the prefecture-level in the PRD region.

the total national GDP [18].

The Pearl River Delta consists of nine cities of the prefecture-level, including Guangzhou, Shenzhen, Foshan, Zhuhai, Zhongshan, Dongguan, Huizhou, Zhaoqing, and Jiangmen. The Pearl River Delta is in a dominant position in China's influencer economy, for example, there are more than ten 5A tourist attractions, and each city has several popular Destinations, and the cities' influencer economy is extremely dynamic. Therefore, the study in this paper takes the Pearl River

Delta as the research object, and through the case study of this mega-city cluster, it helps to refine the understanding of the spatial distribution of popular destinations in Chinese mega-city regions, and potentially provides new ideas for further research on the civic dynamics of urban clusters in the global South.

This study uses social media check-in data from TikTok, the most popular short video production and distribution platform in China, to identify the spatial distribution of popular destinations in the Pearl River Delta. (https://data.new rank.cn/). The data set includes the number of short video plays and the number of check-ins in the physical space from the publication of TikTok to July 18, 2022, where the number of short video plays is used to characterize the virtual hotness of the space and the number of check-ins is used to characterize the actual number of visitors to the corresponding location. According to the needs of this study, the top 500 destinations in each city are regarded as popular destinations, and are classified into four categories according to the types of destinations: shopping district, tourist attractions, food and beverage, and leisure and

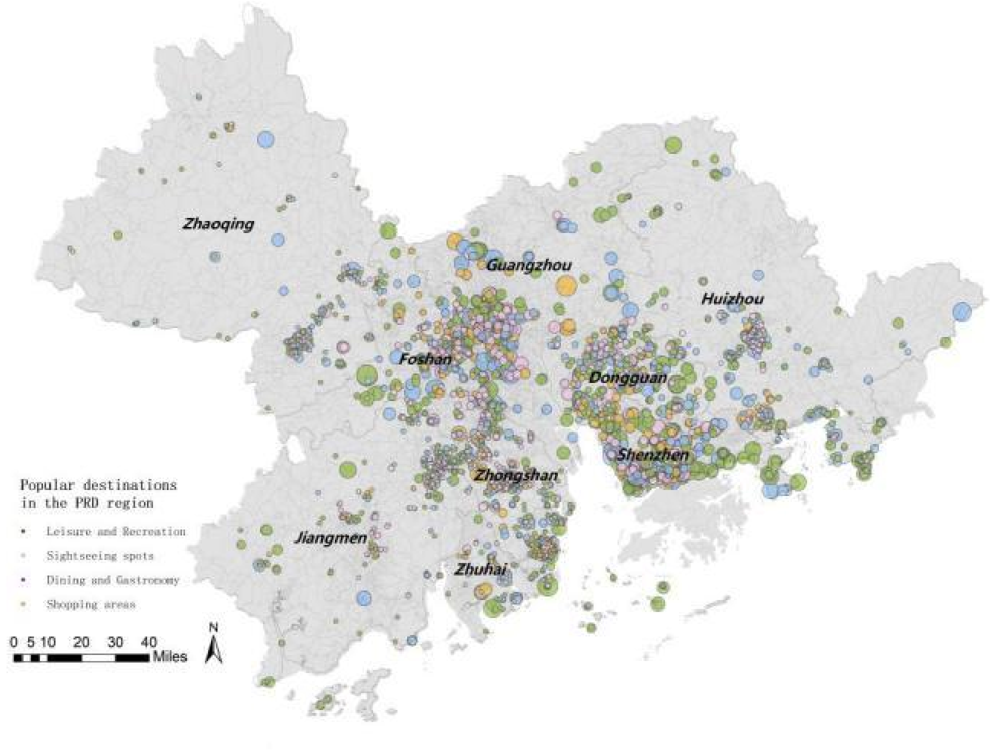

Figure 2: Four types of popular destination in the PRD region (weighted by the actual visitors).

entertainment.

To ensure statistical accuracy, this study further cleansed the data in the study area by combining field research and short video data from platforms. According to the nature of the space, we excluded locations that did not match the real and imaginary hotness and did not match the definition of " popularity destinations" in this study, and screened out non-commercial entertainment places such as companies, business and residents, as well as locations that did not aim at offline traffic gathering such as wholesale markets, professional markets and e-commerce live bases. After data cleaning and integration, a total of 4474 popular destinations were finally screened out, among which the number of shopping districts, tourist attractions, restaurants and food, and leisure and entertainment were 637, 1349, 1515 and 937 respectively (Figure 2), and the highest short video playback of these popular destinations times up to 18 hundred billion, and the highest number of check-ins up to 30 million.

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3.2. Regression Analysis

As a tool for processing data, regression analysis is frequently used to examine the relationship, scope, and impact of one variable on another. The data are typically used to create models, calculate correlation coefficients, and create correlation graphs in order to examine model fit and check for covariance issues. High correlation is indicated by a correlation coefficient with an absolute value more than 0.8, positive correlation is shown by a correlation coefficient greater than 0, and negative correlation is indicated by a correlation coefficient less than 0. In this investigation, the association between the quantity of popular destination video plays and the quantity of physical space check-ins was ascertained using linear regression analysis.

3.3. Kernel Density Estimation Analysis

The kernel density estimation method is used to measure and present the aggregated distribution characteristics of popular destinations, which is calculated as follows:

$$KDE(x) = \frac{1}{N}\sum_{k=1}^{N}\frac{1}{h}K\binom{n}{k} \#(1)$$

Where: $\mathrm{KDE}(x)$ is the kernel density function, $\mathrm{K}(x)$ is the kernel function, h is the bandwidth (i.e., search radius), and let there be a total of N observation points, each of which has a continuous effect on the density and its effect diminishes as the distance increases. The bandwidth h determines the range of observation points selected in estimating the density. The kernel density measure helps to clearly understand the clustering characteristics of the geographical distribution of elements. In this study, the kernel density analysis is mainly performed on the heat distribution of popular destinations, and the bandwidth is determined by the "rule of thumb" to ensure the accuracy of measurement [1].

3.4. Optimized Hotspot Analysis

Optimized hotspot analysis is used to filter the hotness distribution characteristics of popular destinations. Optimized hotspot analysis is a tool that uses parameters derived from input data features to optimize hotspot analysis (Getis-Ord Gi*) to create maps of hot and cold spots with statistical significance. Getis-Ord Gi* creates a map of hotspots and cold spots by calculating the sum of the hotspots of an element and the local sum of its neighboring elements within a given distance compared to the sum of all elements, which is used to analyze the degree of clustering of attribute values at the local spatial level, with the following expressions:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij}(d)X_j}{\sum_{j=1}^{n} X_j} \#(2)$$

Where: X_j is the coordinate of the j-th data point, n is the total number of data points, and W_{ij} is the spatial weight matrix. If the distance between the i-th and j-th spatial cells lies within the given critical distance d, they are considered adjacent and the corresponding element in the spatial weight matrix is 1, otherwise it is 0.

After getting the results of the hotspot analysis, the optimized hotspot analysis tool queries the data to get the settings that produce the best hotspot results. For example, if the input element dataset contains event point data, the tool aggregates the event points into weighted elements. By using the distribution of the weighted elements, this tool determines the appropriate range of

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analysis. The statistical significance reported in the output elements is automatically corrected for multiple testing and spatial dependence using the False Discovery Rate correction method.

4. Results and Discussions

4.1. Basic Statistical Analysis

So as to get a preliminary understanding of the main popular destinations in visitors' minds, the number of Shake Shack short video plays and physical space check-ins in popular destinations in each city were quantified, and the rankings of the nine cities are shown in Figure 4. With the same number of popular destinations, Shenzhen and Guangzhou have a much higher share than other cities in terms of both the number of short video plays and physical space check-ins, and they have the strongest tourism attraction for tourists. In contrast, Jiangmen, Zhaoqing, Zhongshan and Zhuhai have significantly less tourist attraction. In contrast, Jiangmen, Zhaoqing, Zhongshan and Zhuhai have significantly less tourist attraction.

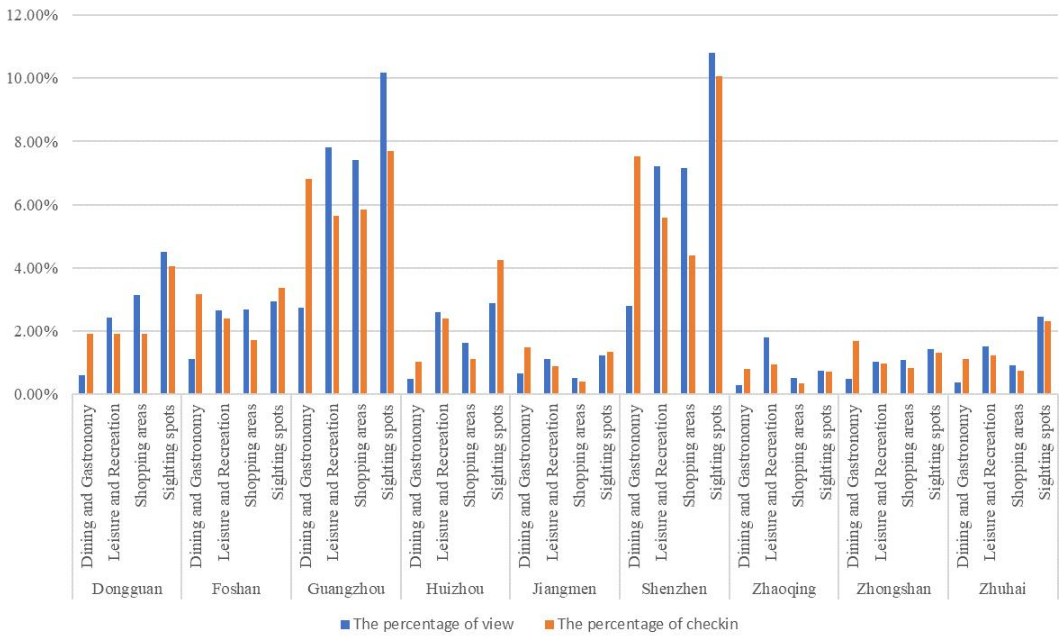

Figure 3: The percentage of view and check-in for four types of popular destinations in the PRD.

Table 1: The regression result of the PRD and cities with it.

Pairs	Correlation
PRD_view & PRD_checkin	.827
Guangzhou_view & Guangzhou_checkin	.857
Shenzhen_view & Shenzhen_checkin	.749
Zhuhai_view & Zhuhai_checkin	.820
Foshan_view & Foshan_checkin	.796
Dongguan_view & Dongguan_checkin	.758
Zhongshan_view & Zhongshan_checkin	.833
Zhaoqing_view & Zhaoqing_checkin	.892
Huizhou_view & Huizhou_checkin	.713
Jiangmen_view & Jiangmen_checkin	.744

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Moreover, the overall linear correlation between the percentage of view and the percentage of checkin is strong (table1), suggesting that the number of views on the web largely determines the number of visitors to physical destinations as well as their degree of fame. In particular, this correlation is significantly negative in the dining and gastronomy category, while a strong positive correlation exists in the other categories, showing that the promotion of popular destinations in the dining category relies not only on online social media, but mainly on a large offline customer base.

4.2. Spatial Patterns of Popular Destinations

Looking at the spatial patterns of popular destinations from the whole PRD (Fig 4), the calculation results of Kernel density estimation show obvious characteristics of a double-core structure, forming a double-center distribution pattern of two central cities, Guangzhou and Shenzhen, gradually spreading to the peripheral urban areas, showing a contiguous spatial pattern of spreading, driving the surrounding cities to all Each forms a relatively low-density center, but its overall heat is not high and fails to form a strong net economic effect in the whole PRD.

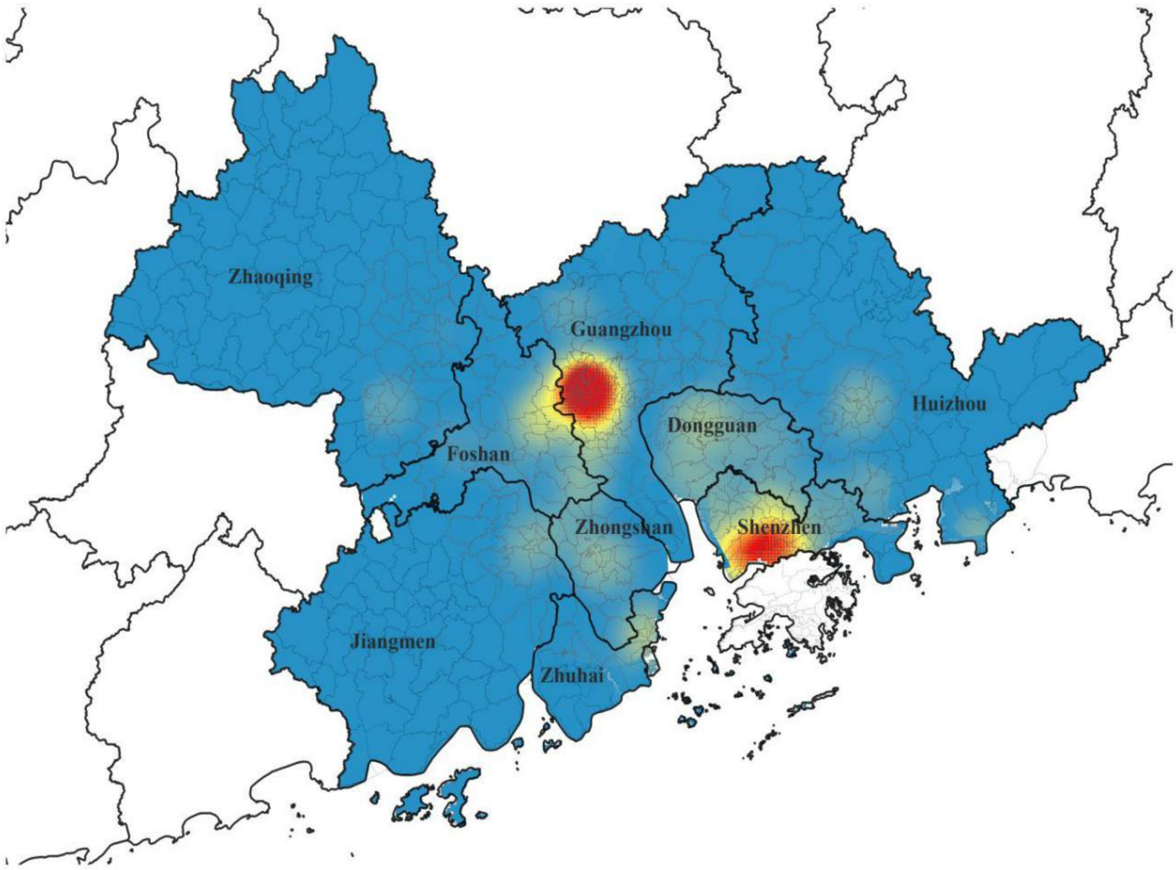

Figure 4: The result of Kernel density estimation in the PRD.

The following internal spatial patterns for each city in the PRD (Fig 5) are used to further analyze the spatial structure, locational characteristics, and business composition of popular destinations:

Guangzhou, one of the density cores, shows a clear monocentric structure in general, with most of the popular destinations gathered in the central city (i.e. Tianhe District, Yuexiu District and Liwan District). Tianhe District is the location of Guangzhou's central business district (CBD), which brings together large shopping districts such as Tianhe City, Tianhuan, and Zhengjia Plaza, as well as retail businesses such as Liuyun Shopping Street and Fashion Tianhe Underground Street, whose main consumer group is young people who are highly influenced by the influencer economy. Yuexiu District and Liwan District are old urban areas, but they are well developed with various retail businesses, especially the tourist and cultural attraction "Beijing Road" in Yuexiu District and the famous European-style attraction "Sha Mian" in Liwan District, which have been gradually transformed in recent years under the impact of the influencer economy, so many tourists are

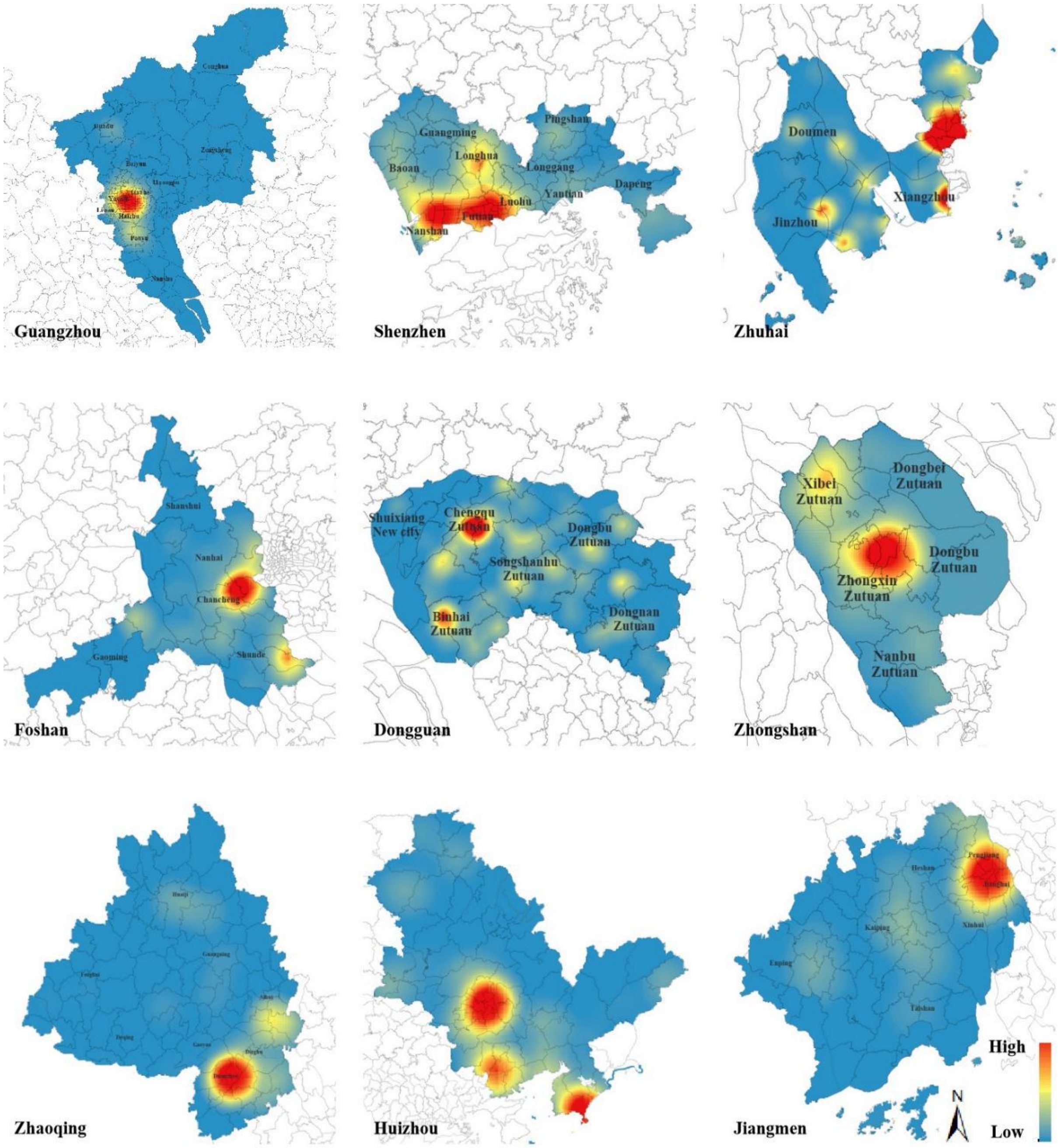

Figure 5: The result of Kernel density estimation in each city of the PRD.

attracted to come here.

Another density core, Shenzhen, overall shows a dual-center structure of mutual checks and balances, with most of the popular destinations gathered in Futian and Nanshan District in the coastal area, and a local gathering effect also formed in Longhua District. Futian District is the

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central city of Shenzhen, is also the location of the Shenzhen CBD, similar to the Guangzhou CBD, the area gathered a large number of high-tech industrial parks, Cocopark and other large shopping areas, so the number of popular destinations is large, the number of people playing cards. Nanshan District is the center of scientific research, education and sports in Shenzhen, and is the location of Shenzhen University, Southern University of Science and Technology and other universities, and is rich in tourism resources, with the famous Happy Valley, Window of the World and other attractions, so the consumer groups favoring the influencer economy are large, which has greatly contributed to the development of popular destinations in Nanshan District.

The spatial patterns of popular destinations in other cities can be divided into two main categories: monocentric and polycentric, with Foshan, Zhaoqing, Jiangmen and Zhongshan all showing a significant agglomeration of cores in the city center. This is due to the fact that most of the cities' central urban areas are more well developed and concentrated in terms of residential population, which allows popular destinations to develop. In contrast, Dongguan, Huizhou and Zhuhai show a spatial structure of multiple small cores because these areas are typical of cities with insufficient central urban areas, and therefore fail to form a significant aggregation effect of influencer economy in the central area, but rather gather in multiple areas of the city in a small scale.

4.3. Hot Spots of Popular Destinations

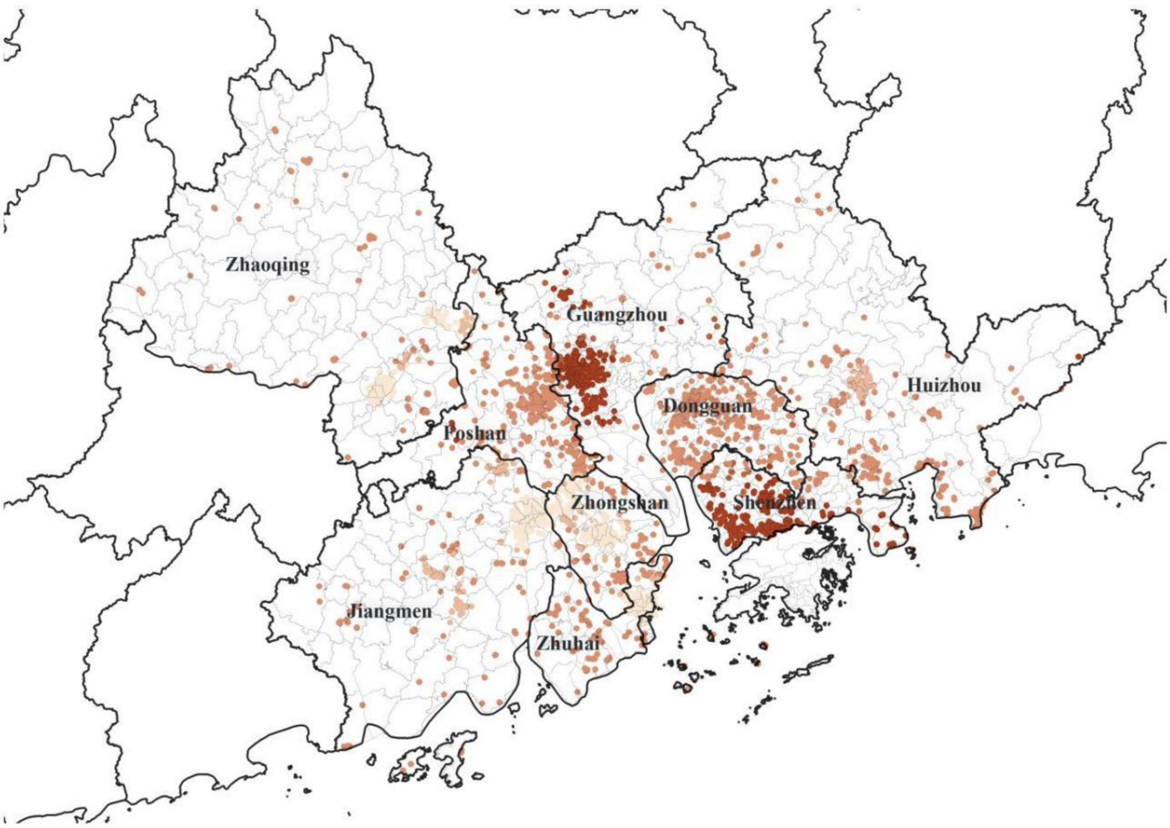

Figure 6: The result of optimized hotspot analysis in the PRD.

Looking at the hot spots of popular destinations from the whole PRD (Fig 6), the optimized hot spot analysis mainly reflects the hitting hotness of each popular destinations, forming a bicenter structure similar to the Kernel density estimation, with the high hotness mostly gathered in Guangzhou and Shenzhen, and the medium hotness of popular destinations are mainly distributed in Dongguan and the urban fringe of other cities, while the central area of each city gathers more popular destinations, but the overall hotness is low.

The following internal hot spots of each city in the PRD (Fig 7) are used to further analyze the dynamic heat of popular destinations:

Density core Guangzhou and Shenzhen, although the heat value of each popular destination is relatively high, but the overall show a relatively even heat distribution, not reflecting the main heat center, which indicates that the development of popular destinations in each district in developed cities are more balanced and form a cooperative competition between each other.

Similarly, in less developed cities such as Zhaoqing, Huizhou and Jiangmen, popular destinations are more loosely distributed across districts, with tourism resources being the main focus, so many are located on the fringes of the city, but because the city has a small population and is less attractive to foreign populations, it has failed to develop a high level of heat overall, or a significantly high level of heat in popular destinations.

However, in the sub-developed cities such as Zhuhai, Foshan, Dongguan and Zhongshan, popular destinations have obvious high and low value areas, perhaps because the overall city has an unbalanced regional development and a mismatched industrial layout, so that popular destinations also have a more obvious difference in visitor flows.

4.4. Discussion

The emergence of popular destinations is an inevitable product of the influencer economy, which has a great influence on urban public space and urgently requires research in urban and rural planning, social sciences, geography, and other related disciplines to support better planning and policy responses. This study discusses and compares the spatial patterns of popular destinations in the PRD as a whole and in nine cities within the PRD, and describes the spatial characteristics of the influencer economy, which is beneficial to government planning, corporate positioning and retail siting, and other related practices to provide new analytical perspectives and decision support.

However, this study only initially presents the spatial patterns of popular destinations and provides a qualitative structural interpretation based on the existing built-up environment of the city. Due to the lack of data volume and data accuracy, it is not possible to discuss more about the specific spatial and temporal evolution of popular destinations, the changes in pedestrian flow and the causes of formation, which can be the direction of further research in the future.

5. Conclusions

Based on TikTok popular locations check-in data, this study analyzes the PRD and the spatial distribution of popular destinations in nine cities in detail, and finds that social media has greatly impacted people's daily travel choices, and public spaces with high traffic flow tend to have high hotness, so the hotness of cyberspace and physical space shows an obvious positive correlation. In terms of spatial structure, the development of popular destinations still follows the development status of cities, although each city has its own "influencer center". But for the overall PRD, the highest popularity is still gathered in the developed cities of Guangzhou and Shenzhen, and these cities have formed a more balanced development. For the less developed prefecture-level cities in the PRD, due to the differences in public demand, functionality and marketing intensity, the popular destinations in different regions show a more obvious heterogeneity. These findings, which can reflect the different characteristics and development trend of the spatial distribution of highly hot and popular areas in cities in the era of mobile Internet, can assist us to further describe the urban public activity space and then provide planning reference for urban spatial planning and industrial layout.

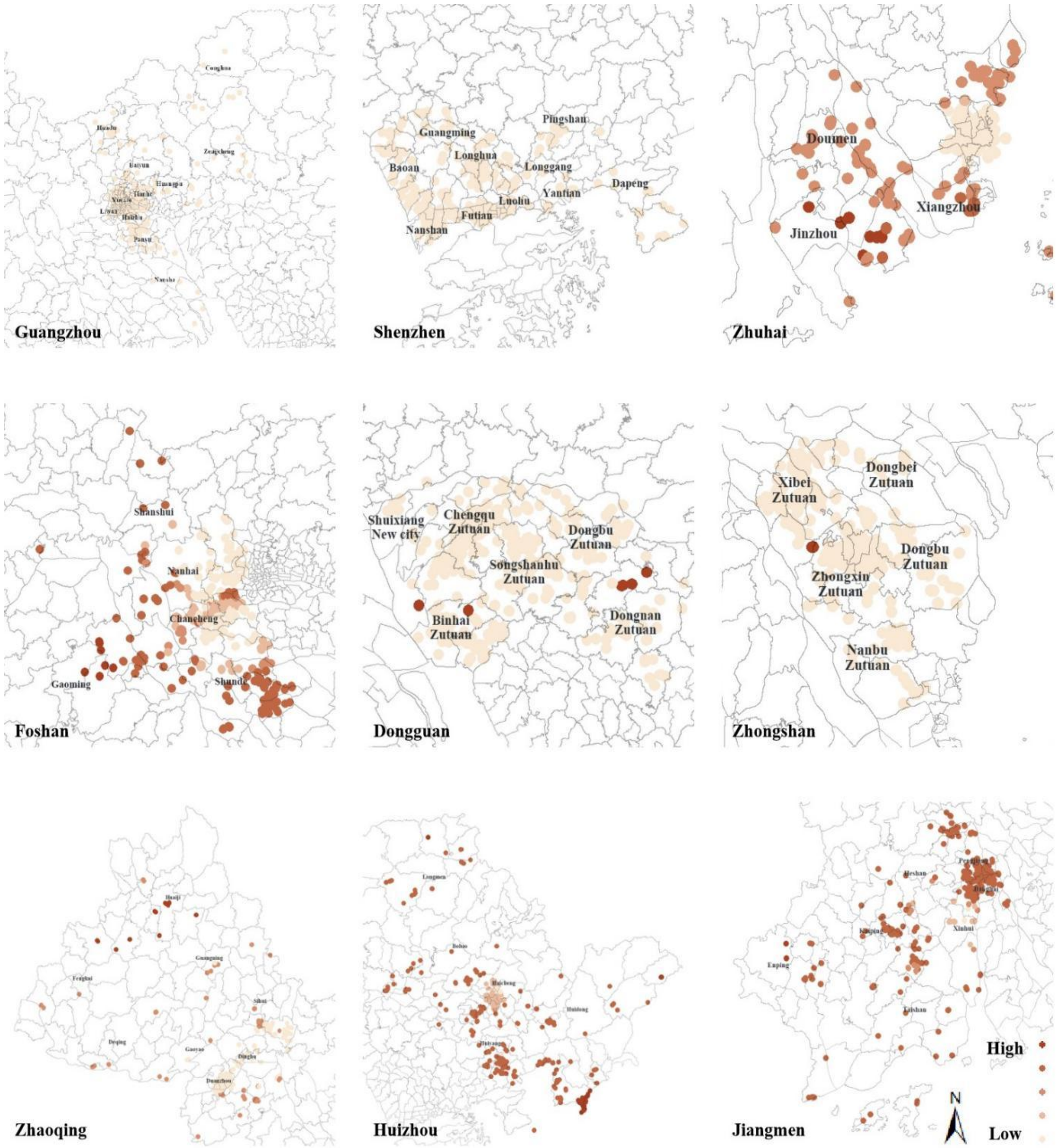

Figure 7: The result of optimized hotspot analysis in each city the PRD.

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