land

MDPI

Article

Researching Tourism Space in China's Great Bay Area: Spatial Pattern, Driving Forces and Its Coupling with Economy and Population

Lingfeng Li [1,2] and Quan Gao [1,2,*]

1 School of Geography and Planning, Sun Yat-sen University, Guangzhou 510006, China; 20192631025@m.scnu.edu.cn
2 Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519082, China
* Correspondence: gaoq59@mail.sysu.edu.cn

Abstract: Analysis of the spatial patterns and dynamics of tourism services and facilities is crucial for tourism and land use planning. However, most studies in the spatial analysis of tourism rely on the city- or regional-level data; limited research has used POI (point of interest) data to accurately uncover the spatial distribution of tourism, especially its interactive and coupling relationship with the local economy and population. Based on POI data, this paper, therefore, investigates the spatial patterns and driving forces of tourism services distribution and how tourism space is coupled with the local economy and population in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) of China. The results show the following: (1) Different categories of tourism services (catering, shopping, scenic spots, leisure, and sports) exhibit diverse spatial patterns and agglomerations, but they tend to align with the variables of economic level and population in a grid of 1 km^2. (2) The spatial econometric models further reveal that population density, transportation, and hospitality facilities are positively correlated with the spatial distribution of tourism services, but GDP in a grid of 1 km^2 shows a weak negative correlation with the POI of tourism services, which may be attributed to the incoordination between GDP and tourism in some areas. (3) The analysis of coupling degree further identifies the areas where tourism services have good interaction/coupling with the local GDP and population density, such that these areas can be viewed as hotspots suitable for tourism promotion. This paper thus offers meaningful policy implications by calling for an optimization of the coupling of tourism services with local social–economic factors in the GBA.

Keywords: tourism space; POI; spatial pattern; coupling degree; Guangdong–Hong Kong–Macao Greater Bay Area

check for updates

Citation: Li, L.; Gao, Q. Researching Tourism Space in China's Great Bay Area: Spatial Pattern, Driving Forces and Its Coupling with Economy and Population. *Land* **2023**, *12*, 1878. https://doi.org/10.3390/land12101878

Academic Editor: Alexandru-Ionuţ Petrişor

Received: 7 September 2023
Revised: 4 October 2023
Accepted: 5 October 2023
Published: 6 October 2023

1. Introduction

Tourism services, facilities, or amenities are playing an increasing role in economic growth and social development in many regions. Tourism and leisure activities are not only a manifestation of urbanism that can improve the happiness of the urban way of life, but are also an important driver of the consumption-oriented economy [1,2].

In the literature of tourism studies, the concept of "space" matters in the understanding of the pattern of tourism resources and its impact on or connection with local society [3]. The notion of "tourism space" was first proposed by Oppermann [4] to discuss the spatial organization of tourism resources and infrastructure in a way that can help facilitate the economic transition of developing countries. In the past two decades or so, scholars in tourism studies and land management have put great emphasis on investigating the spatial layout and patterns of tourism resources and how it can form an essential understanding of the planning of tourism and land use [5]. In particular, recent attention has been paid to the spatial difference and unbalanced development of tourism [6], the impacts of transportation on tourism resource distribution [7], and tourism's spatial coupling with the local economy [8], urbanization level [9], and ecological system [10]. Some other scholars are interested in revealing how the spatial distribution of tourism resources or facilities can optimize tourism's economic impact on local society. For example, Law et al.'s [11] research suggests that the distribution of hotels and travel agencies serves as an important intermediary that provides hospitality and distribution channels to facilitate the development of tourism. Santana-Jiménez et al. [12] use population density to examine whether tourism services and facilities are overcrowded in a tourism area so as to provide a policy reference for reconciling tourism with the population and other supply-side factors. In other words, the distribution of tourism services needs to be consistent with their supporting system, including population, transportation, and hospitality facilities.

Notwithstanding the growing literature exploring the spatial patterns of tourism and its relationship with regional development, there are still two lines of inquiry that warrant further examination. First, the arrival of the era of big data has provided new avenues for the spatial analysis of tourism beyond traditional data sources like statistical yearbooks. In this paper, we use point of interest (POI) data to achieve a more accurate analysis of tourism space by appropriating POI's advantages of comprehensive coverage, high identification accuracy, and easy data accessibility [13]. In this sense, POI data can help us improve the spatial accuracy of spatial econometric models. Compared with most spatial econometric studies of tourism that normally rely on city- or provincial-level panel data, this paper uses panel POI data of a 1 km^2 grid to re-evaluate the influencing factors of tourism space.

Second, less research has paid attention to the coupling relationship of tourism space with local socio-economic indicators such as GDP (gross domestic product) and population density, despite there being some research on tourism's coupling with environmental sustainability [14]. The concept of coupling, originating from physics, refers to the phenomenon in which two or more systems establish a collective relationship through a range of interactions [15]. The degree of coupling serves as an index to investigate the extent of mutual influence and interaction between these systems. When the components of systems are interdependent, coordinated, and mutually promoted, a relationship of coordinated development emerges, indicating a high degree of coupling. The value of coupling directly reflects the level of association/consistency between the two systems. For instance, Gal, Gal, and Hadas [16] delve into the growth of rural tourism in the Israeli agricultural sector, exploring the potential synergies between rural tourism and farming, as well as how tourism may influence the transformation of agricultural processes. Akama [17] identifies that the coordinated development of urbanization and tourism is an important indicator for urban planning in terms of satisfying the economic, social, and cultural needs of local communities. However, one difficulty in examining the coupling of tourism with GDP and population is identifying areas with different types of high coupling degrees, including (1) high–high congregation with high coupling between two variables; (2) low–low congregation with high coupling between two variables. In this paper, we achieve this through combining the degree of coupling with the local Moran's I index to identify the areas where tourism has a good interaction with GDP or population and, thus, can be viewed as suitable for tourism development.

This paper therefore advances existing research on the spatial analysis of tourism by looking at the tourism space in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA), one of the most dynamic and economically powerful regions in China. In recent years, tourism planning has been a crucial aspect to facilitate the integration of GBA development. Therefore, researching the spatial patterns and driving factors of tourism space and its coupling with the regional economy and population can provide useful policy insights for tourism planning in the GBA. By using the advantages of POI data, this paper focuses on three research questions related to the tourism space of the GBA: (1) How do we describe the spatial patterns of tourism services in the GBA through POI data? (2) What are the driving forces that are associated with the spatial distribution of tourism services in the GBA? (3) How do we identity the specific areas that are suitable for tourism development by examining the index of the coupling degree? In other words, how can we measure the extent to which tourism services are coupled with other socio-economic factors of development such as GDP and population?

2. Materials

2.1. Overview of the Study Area

The Guangdong–Hong Kong–Macao Greater Bay Area (GBA) is situated in the Pearl River Delta, within the southeast coastal region of China (Figure 1). It encompasses nine cities within the Pearl River Delta urban agglomeration, namely Guangzhou, Shenzhen, Foshan, Dongguan, Huizhou, Zhongshan, Zhuhai, Zhaoqing, and Jiangmen, along with the two special administrative regions of Hong Kong and Macao. Covering a total area of 56,000 km^2, the GBA accommodates a population of over 86.0 million people engaged in various livelihoods and economic activities, and it contributed more than USD 166.68 billion to the GDP in 2020 (https://www.bayarea.gov.hk/ (accessed on 7 August 2023)). Functioning as a pivotal economic engine, the GBA, despite occupying only 5.8% of China's land area, constitutes a significant share of the nation's gross domestic product, accounting for 11.4% (https://www.ndrc.gov.cn/ (accessed on 7 August 2023)). Recognizing the strategic importance of regional tourism cooperation, a key current objective is to develop the GBA into an internationally recognized premier bay area destination for tourism [18]. Based on official documents, the GBA is envisioned as a high-quality living, employment, and tourism hub. Its thriving tourism sector is vital for promoting overall economic transformation, enhancing comprehensive competitiveness, and establishing a strong brand image for the GBA city cluster (https://www.gov.cn/ (accessed on 7 August 2023)). As a distinctive regional economy, the bay area's economy holds immense significance and exhibits substantial development potential [18].

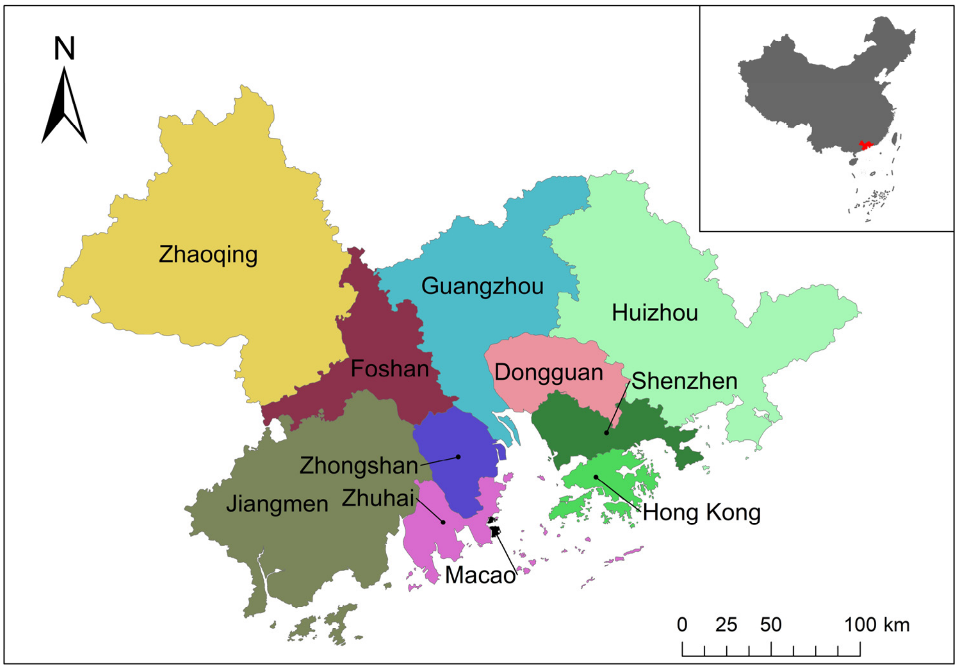


Figure 1. The location and administrative borders of the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) and its constituent cities.

2.2. Sources of Data

Point of interest (POI) data possess a rich volume of accurate geographic information. Essentially, they consist of point data that represent actual geographic locations, including information such as latitude and longitude coordinates, the corresponding area, name, and type. POIs play a crucial role in enhancing the precision of the distribution characteristics and spatial structures of urban tourism [19]. The POI data used in this study were obtained from the Gaode network map service platform (https://lbs.amap.com/ (accessed on 7 August 2023)). It encompasses 23 major categories, including finance and insurance, accommodation, transportation facilities, science, education and culture, food and beverages, shopping and lodging, etc. Each major category further contains medium and small subcategories, contributing to a dataset comprising over 5.1 million points of data per year. For analysis purposes, the POIs were classified based on four fundamental elements of urban tourism: catering services, scenic spots, shopping services, and sports and leisure facilities (See Table 1). Subsequently, an attribute table was opened in ArcGIS, and data were exported as new layers, organized according to the four categories of different land types. Blank values, abnormal entries, and duplicate points were removed, followed by unifying and projecting the data into a standardized coordinate system. Furthermore, the study incorporated the 2019 WorldPop population dataset (https://hub.worldpop.org/project/categories?id=18 (accessed on 7 August 2023)), with a spatial resolution of 1000 m, and China's GDP spatial distribution kilometer grid dataset [20] for spatial econometrics analysis.

A spatial grid was adopted as the analysis unit, taking into account the impact of the variables in different geographical cells on urban tourism. Utilizing the Fishnet tool within the ArcGIS 10.2 software [21], a square grid covering the GBA, with each side measuring 1 km, was constructed. By employing spatial correlation and other methods, this grid serves as a statistical unit for calculating various indicators, including catering services, to effectively capture the region's heterogeneity. Moreover, this approach facilitates data processing and variable aggregation within the area.

Table 1. The quantity and proportion of various types of POI data in the Guangdong–Hong Kong–Macao Greater Bay Area in 2019.

Category	Basic Carrier	Category Features	Quantity	Proportion (%)
Catering services	Cafes, bars, fast food, restaurants, etc.	Restaurant-related spaces	690,878	31.3
Shopping service	Supermarkets, stores, convenience stores, marketplaces, and other shopping places.	Space related to shopping	1,410,609	63.9
Scenic spots	Tourist attractions, city squares, scenic spots, parks, etc.	Provide space for sightseeing and cultural experiences	27,613	1.3
Sports and leisure services	Entertainment, vacation, sports complexes, fitness centers, etc.	A space that benefits the body and mind and relaxes stress	76,821	3.5

3. Methodology

This paper used a variety of methods to systematically analyze the spatial dynamics of urban tourism in the GBA of China. First, a series of methods including average nearest neighbor, standard deviation ellipse, the imbalance index, the geographical concentration index, Kernel density estimation, and the bivariate local Moran's I to comprehensively map out the spatial distribution characteristics of tourism services. Then, we utilized different models of regression, including the ordinary least squares model (OLS), spatial lag model (SLM), and spatial error model (SEM), to discern what influences the spatial patterns of tourism services. Finally, we used the coupling degree to identify the areas in which the distribution of tourism services was coupled with the local economy and population.

3.1. Average Nearest Neighbor (ANN)

The average nearest neighbor (ANN) method involves calculating the average distances between the centers of elements and the center positions of neighboring elements. The average nearest neighbor index represents the ratio of the average observed distance to the expected distance and can be addressed in the following form:

The average nearest neighbor ratio is calculated as:

$$ANN = \frac{\overline{D}_O}{\overline{D}_E} \quad (1)$$

where the distance between $\overline{D}_O$ and its closest point of mass is the average of the actual measured elements:

$$\overline{D}_O = \frac{\sum_{i=1}^{n} d_i}{n} \quad (2)$$

$\overline{D}_E$ is the average distance of the random distribution of the elements:

$$\overline{D}_E = \frac{0.5}{\sqrt{\frac{n}{A}}} \quad (3)$$

In the above equation, d_i is the distance between element i and its nearest neighboring elements, n is the number of elements in the region, and A is the area of all element envelopes.

If the ANN < 1, the distribution is agglomerative; if the ANN > 1, the overall distribution is random.

3.2. Standard Deviation Ellipse (SDE)

The standard deviation ellipse (SDE) was proposed by WertilyFifer in 1926 [22], and the spatial distribution characteristics of POI elements are measured by four parameters: the long axis, short axis, rotation angle, and area. The long axis of the ellipse indicates the spatial distribution direction of the traffic facility point data, and the short axis indicates the spatial distribution range of the traffic facility point data:

$$S_X = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i - \overline{X}\right)^2}{n}};\ S_Y = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \overline{Y}\right)^2}{n}};\ tan\theta = \frac{A+B}{C} \quad (4)$$

$$A = \left(\sum_{i=1}^{n}\tilde{x}_i^2 - \sum_{i=1}^{n}\tilde{y}_i^2\right);\ B = \sqrt{\left(\sum_{i=1}^{n}\tilde{x}_i^2 - \sum_{i=1}^{n}\tilde{y}_i^2\right)^2 + 4\left(\sum_{i=1}^{n}\tilde{x}_i^2\tilde{y}_i^2\right)^2};\ C = 2\sum_{i=1}^{n}\tilde{x}_i^2\tilde{y}_i^2 \quad (5)$$

$$\sigma_x = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}\left(\tilde{x}_i^2\cos\theta - \tilde{y}_i^2\sin\theta\right)^2}{n}} \quad (6)$$

$$\sigma_y = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}\left(\tilde{x}_i^2\sin\theta + \tilde{y}_i^2\cos\theta\right)^2}{n}} \quad (7)$$

where x_i and y_i are the coordinates of the traffic facility point elements; S_X and S_Y denote the calculated ellipse centers; n is the number of all traffic facility point elements in the study area; $\overline{X}$ and denotes $\overline{Y}$ the mean center position of the traffic facility point elements; σ_x, σ_y denote the standard deviation of the long and short axes of the ellipse respectively; and θ is the azimuth of the ellipse.

3.3. Imbalance Index (S)

The imbalance index (S) can reflect the balanced distribution of POI points [23] in each city of the GBA, calculated by the formula:

$$S = \frac{\sum_{i=1}^{n} Yi - 50(n+1)}{100n - 50(n+1)} \quad (8)$$

where n denotes the total number of POIs of each type, and Yi denotes the cumulative percentage of the number of POIs of each prefecture-level city to the i-th position of the total number of POIs of the GBA in descending order.

3.4. Geographical Concentration Index (G)

The geographical concentration index (G) is mainly used to measure the concentration of the spatial distribution of geographical elements and is a common indicator in geographic studies [23]. It indicates the degree of concentration of the studied elements in the regional space, and the smaller the value, the lower the concentration, and vice versa. Its value is between 0 and 1. The higher its value, the higher the degree of geographical concentration of the industry.

$$G = 100\sqrt{\sum_{i=1}^{n}\left(\frac{X_i}{T}\right)^2} \quad (9)$$

where the larger the value of G, the higher the degree of concentration, assuming the average distribution of POIs is $G = G0$; if $G > G0$, it means that the traditional villages are concentrated, and vice versa, they are scattered.

3.5. Kernel Density Estimation (KDE) Method

The kernel density estimation (KDE) method is employed to estimate the density of traffic facility point elements by using moving cells [24]. Its basic principles include defining a circular domain with a fixed search radius, ensuring that the circle domain encompasses each traffic facility point; determining the size of the output raster based on the required density accuracy; and calculating the density contribution of traffic facility points to each raster within the circle domain. The density contribution of each traffic facility point to every raster within the circle domain is accumulated, and the density value of each raster is assigned to output the density value of each raster.

Kernel density analysis enables the derivation of the distribution pattern of tourism spaces in the Guangdong–Hong Kong–Macao Bay Area, as represented by the following formula:

$$f(x,y) = \frac{1}{nh^2}\sum_{i=1}^{n} k\left(\frac{dist[(x,y),(x_i,y_i)]}{h}\right) \quad (10)$$

where h is the bandwidth; n is the number of point-like elements of traffic facilities in the study area; $k\left(\frac{dist[(x,y),(x_i,y_i)]}{h}\right)$ is called the kernel function; and $dist[(x,y),(x_i,y_i)]$ denotes the distance from the estimated point of traffic facilities to the sample (x_i,y_i).

3.6. Bivariate Local Moran's I

The concept of bivariate spatial correlation is complex and often misinterpreted. It is commonly perceived as the correlation between one variable and the spatial lag of another variable, as originally implemented in the precursor of GeoDa [25]. However, this approach fails to consider the inherent correlation between the two variables. More precisely, the bivariate spatial correlation is between xi and $\sum_j w_{ij}y_j$, but does not take into account the correlation between x_i and y_i, i.e., between the two variables at the same location.

As a result, this statistic is often interpreted incorrectly, as it may overestimate the spatial aspect of the correlation, which could actually be primarily attributed to the in-place correlation. Essentially, this notion of bivariate spatial correlation measures the degree to which the value for a given variable at a specific location is correlated with its neighbors for a different variable.

As in the univariate Moran scatter plot, the interest is in the slope of the linear fit. This yields a Moran's I-like statistic as:

$$Moran's\ I_B = \frac{\sum_i\left(\sum_j w_{ij}y_j \times x_i\right)}{\sum_i x_i^2} \quad (11)$$

where w_{ij} is the element of the spatial weight matrix showing the proximity of the ith region and the jth region, and x_i, y_i are the two variables studied.

The Moran scatter plot classifies spatial associations into four categories, corresponding to the location of the points in the four quadrants of the plot. These categories are known as high–high, low–low, low–high, and high–low, relative to the mean, which is positioned at the center of the graph. The Moran scatter diagram provides a visual representation of spatial associations, grouping them into these four categories based on the positions of the points within the quadrants. This distribution pattern can be displayed on a graph, also referred to as a bivariate Lisa clustering map.

3.7. Ordinary Least Squares Model (OLS), Spatial Lag Model (SLM), and Spatial Error Model (SEM)

Considering the heterogeneity and agglomeration in the spatial distribution of service industries, such as the restaurant industry, a spatial regression model was selected for the analysis to account for the spatial distribution of variables and disturbance terms [26]. In this paper, we employed the OLS model, spatial lag model, and spatial error model to analyze the factors influencing the spatially differentiated agglomeration of service industries, particularly the catering industry.

1. The OLS model is a linear regression model. This model is the most basic and commonly used regression model to determine the closeness to the dependent variable by establishing a numerical model or fitting means to correlate two or more variables, generally in the form of:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{12}$$

where y is the explained variable; x is the explanatory variable; β_0 is the intercept parameter; β_1 is the slope parameter; and ε is the random error vector.

2. The spatial lag model (*SLM*): This model describes the spatial correlation between the dependent variables, i.e., whether the neighboring explanatory variables affect the local explanatory variables through a spatial transmission mechanism, and mainly explores whether the variables have spillover effects in a region, in the general form of

$$y = \rho W_y + x\beta + \varepsilon \tag{13}$$

where y is the explained variable; ρ is the spatial regression coefficient; W is the $n \times n$ spatial weight matrix; W_y is the spatial lagged explained variable of the spatial weight matrix W; x is the $n \times k$ exogenous explanatory variable matrix; β reflects the effect of the explanatory variable on the explained variable; and ε is the random error vector.

3. The spatial error model (*SEM*): This model is a regression model that sets a spatial autocorrelation term on the error term in the model, i.e., whether the neighboring error term affects the local explanatory variables through a spatial transmission mechanism, and is applicable to the case where the interaction between regions differs depending on the relative locations in which they are located, and the general form of the model is:

$$y = x\beta + \varepsilon \tag{14}$$

$$\varepsilon = \lambda W \varepsilon + \mu \tag{15}$$

where y is the explanatory variable; x is the $n \times k$ matrix of exogenous explanatory variables; β reflects the coefficient of the degree of influence of the explanatory variable y on the explanatory variable x; ε is the random error vector; λ is the spatial error coefficient of the vector of explanatory variables; W is the $n \times n$ spatial weight matrix; μ is the random error vector of normal distribution.

3.8. Coupling Degree and Coupling Coordination Analysis

Coupling degree is a physical concept utilized to describe the extent of mutual influence and interrelation between systems or elements [27]. On the other hand, the degree of coordination is employed to depict the extent of favorable interaction and coordinated development between systems or elements, thereby reflecting the sustainability of benign interaction and correlation. The concept of coupling coordination degree is built upon both ideas and serves to characterize the degree of mutual influence and coordination between systems or elements. It not only indicates the strength of interconnectedness between systems but also reflects the level of coordination, whether it is favorable or unfavorable, among these systems [28]. The specific formula for calculating the coupling coordination degree is shown as follows:

1. The data normalization process was completed in the previous section, so it is not repeated here.
2. Calculate the weight of the value of the jth indicator for the ith sample:

$$Y_{ij} = X_{ij} / \sum_{i=1}^{m} X_{ij} \tag{16}$$

3. Calculate the information entropy of the indicators:

$$e_j = -k \sum_{i=1}^{m} \left(Y_{ij} \times \ln Y_{ij} \right) \tag{17}$$

$$k = \frac{1}{\ln m} \tag{18}$$

$$\text{If } Y_{ij} = 0, \text{then } Y_{ij} \times \ln Y_{ij} = 0$$

4. Calculate the information entropy redundancy:

$$d_j = 1 - e_j \tag{19}$$

5. Determine the indicator weights:

$$\omega_j = d_j / \sum_{i=1}^{n} d_j \tag{20}$$

6. Calculate the combined score of each system:

$$F_i = \sum_{i=1}^{n} \omega_i X_{ij}, \sum_{i=1}^{n} w_j = 1 \tag{21}$$

7. Calculate the coupling degree and coupling coordination:

$$C = \frac{2\sqrt{F_1 F_2}}{F_1 + F_2} \tag{22}$$

where m is the number of evaluation samples, n is the number of indicators, and α, β is generally taken as 0.5.

3.9. Variable Selection for the Regression Model

The spatial distribution pattern of urban tourism may be affected by multiscale and multidimensional factors. Combining the existing theories and research results, the influencing factors were divided into four categories: demographic factors, economic factors, transportation factors, and facilities of hospitality.

1. Demographic factors: As the population size of an area grows, the level of consumption demand and diversification of tourism also increases. Residential areas are positively correlated with tourism density [29], and the distribution of tourism services often changes in accordance with the spatial changes in population distribution. Small-scale tourism tends to be located in densely populated areas, residential areas, and areas which travelers can conveniently access.
2. Economic factors: Areas with a higher level of regional economic development have better facilities; intensive economic activities; a spatial convergence of human, logistic,

and information flows; and, thus, higher tourism density. However, this conventional idea needs to be re-examined through micro-scale data. In this sense, this paper adopts one-square-kilometer GDP as the spatial unit of panel data, while most of the literature adopts city- and district-level data of GDP [30].

3. Transportation factors: An improvement in public transportation capacity can bring a higher level of convenience to travelers and greater foot traffic and consumption to the area [31]. Thus, the distribution of tourism services tends to be in areas with better transportation accessibility. In this paper, three variables, namely, parking lots, subway stations, and bus stops, were selected to analyze the impact of different levels of transportation accessibility on the distribution of tourism.
4. Facilities of hospitality: Accommodation services and travel agencies can provide convenient conditions for the tourism industry, and the higher the abundance of both, the greater the diversity of choices for tourists, forming a positive driver for the concentration of foot traffic [32]. The variables and specific index design are shown in Table 2.

Table 2. Regression model variable design.

Variable Plates (VP)		Variable Settings (VS)	Indicator Settings
Dependent variable	Tourism service density	Tourism service density (Y_{tour}) Catering service density (Y_C) Scenic spot density (Y_{sc}) Shopping service density (Y_{sh}) Sports and leisure service density (Y_{sp})	Number and density of tourism services (pieces) Number of catering services (pieces) Number of scenic spots (pieces) Number of shopping services (pieces) Number of sports and leisure services (pieces)
Independent variable		Economic vitality (X_{eco}) Population size (X_{pop})	Gross GDP (CNY, millions) Spatial distribution of the population (persons)
		Travel agencies (X_t)	Number of travel agencies (pcs)
		Transportation environment Parking (X_{pa}) Public transport stations (X_{pu}) Subway stations (X_s)	Number of parking lots (pcs) Number of bus stations (pcs) Number of subway stations (pcs)
		Accommodation services (X_a)	Number of accommodation services (pcs)

Note: dependent and independent variables are examined in a spatial grid of 1 km^2.

4. Results

4.1. Descriptive Analysis of the Spatial Distribution of Tourism in the GBA

The results obtained from the average nearest neighbor index indicate that all four types of tourism services exhibit nearest neighbor ratios lower than 1, demonstrating clustering characteristics supported by Z and p values. This paper, therefore, categorizes the 2019 POIs into three levels: catering services and shopping services represent the most aggregated spaces, followed by sports and leisure services distributing in a more clustered tier. The scenic spots, in contrast to the other three types, display the lowest degree of clustering. These findings are presented in the ANN table (Table 3).

Furthermore, by combining the outcomes of the standard deviation ellipse analysis (Figure 2, Tables 4 and 5), the following becomes evident:

The center of the standard deviation ellipse for tourism in the Guangdong–Hong Kong–Macao Greater Bay Area primarily lies to the right of the Nansha Wetland in Guangzhou, exhibiting a noticeable trend of southeastward distribution. The aggregation area follows a rough “southeast-northwest” orientation, covering most regions within Guangdong, Dongguan, Foshan, Shenzhen, Zhuhai, Hong Kong, and Macao.

The overall spatial distribution pattern of tourism services in the GBA is characterized by a denser concentration within the ellipse and sparser distribution outside the ellipse. Furthermore, the calculation of the imbalance index S reveals that the data of various POIs are unevenly distributed within the GBA. Meanwhile, the geographical concentration index G and G0, derived from the above equation, demonstrates that each G is greater than G0, indicating a high level of POI data concentration, corroborating the results of the analysis of nearest neighbor ratio.

Table 3. Spatial clustering analysis of GBA tourism in 2019.

Category	Average Observation Distance [m]	Expected Average Distance [m]	Nearest Neighbor Ratio	Z-Score (-)	*p*-Value	Characteristics
Catering services	24.093	199.224	0.121	1397.823	<0.01	clustered
Shopping services	16.753	138.437	0.121	1997.180	<0.01	clustered
Scenic spot services	294.201	998.299	0.295	224.213	<0.01	clustered
Sports and leisure services	143.882	588.596	0.244	400.621	<0.01	clustered

Table 4. Standard ellipse difference data for each category in 2019.

Category	CenterX	CenterY	XStdDist	YStdDist	Rotation	Oblateness
Catering services	113.601	22.862	0.717	0.420	104.212	0.414
Shopping services	113.557	22.887	0.732	0.420	101.439	0.427
Scenic spot services	113.550	22.841	0.787	0.466	109.551	0.408
Sports and leisure services	113.619	22.846	0.710	0.442	106.674	0.377

Table 5. Imbalance index and geographic concentration index in 2019.

Category	S	G	G0
Catering services	0.494	39.196	30.151
Shopping services	0.479	38.349	
Scenic spot services	0.451	38.032	
Sports and leisure services	0.481	39.056	

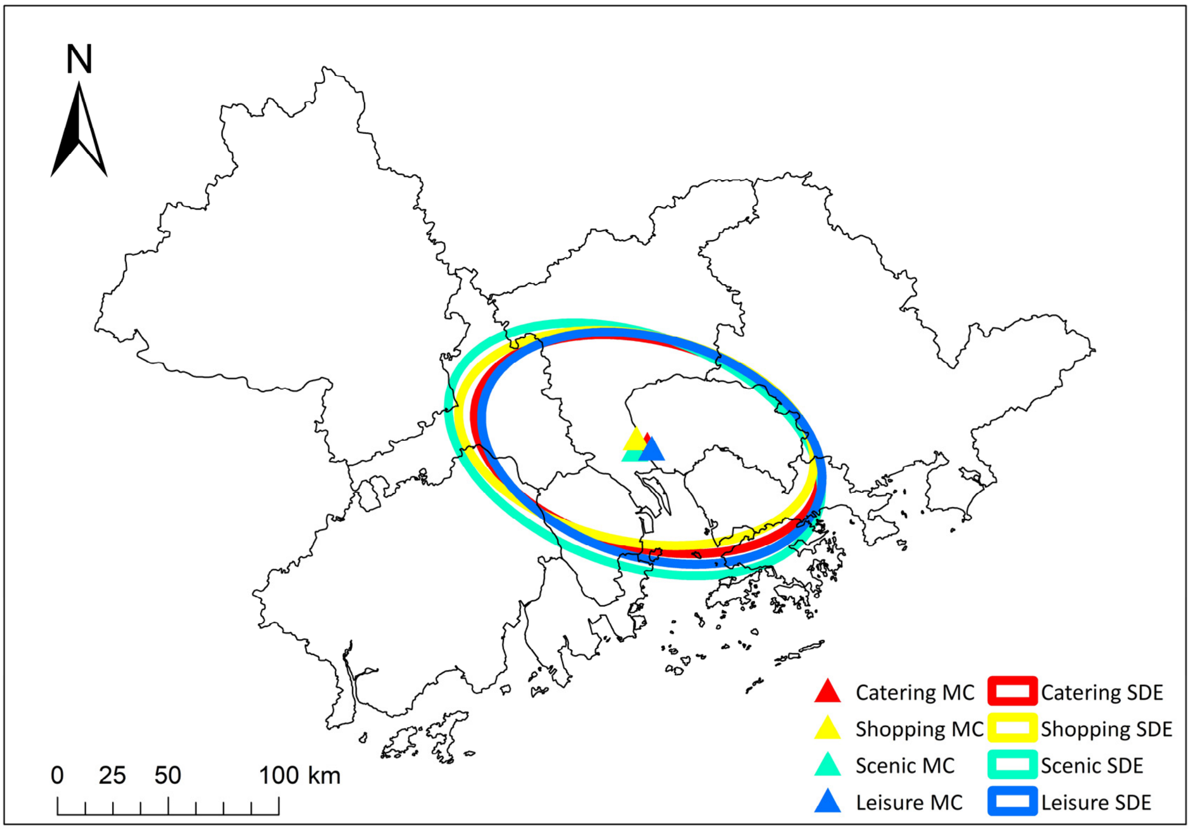
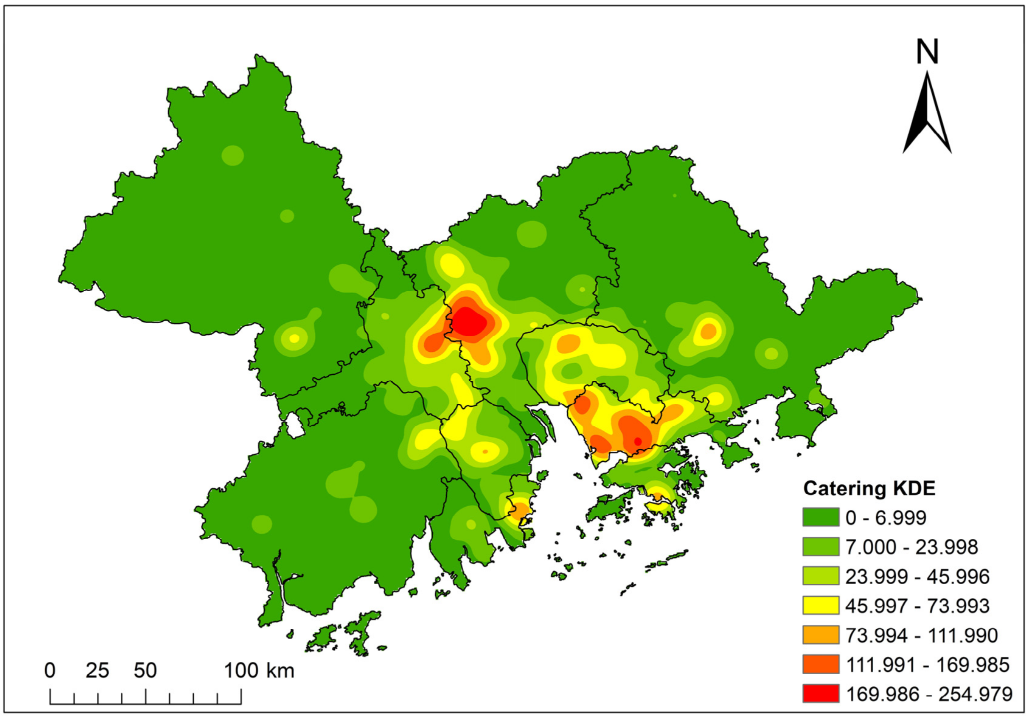


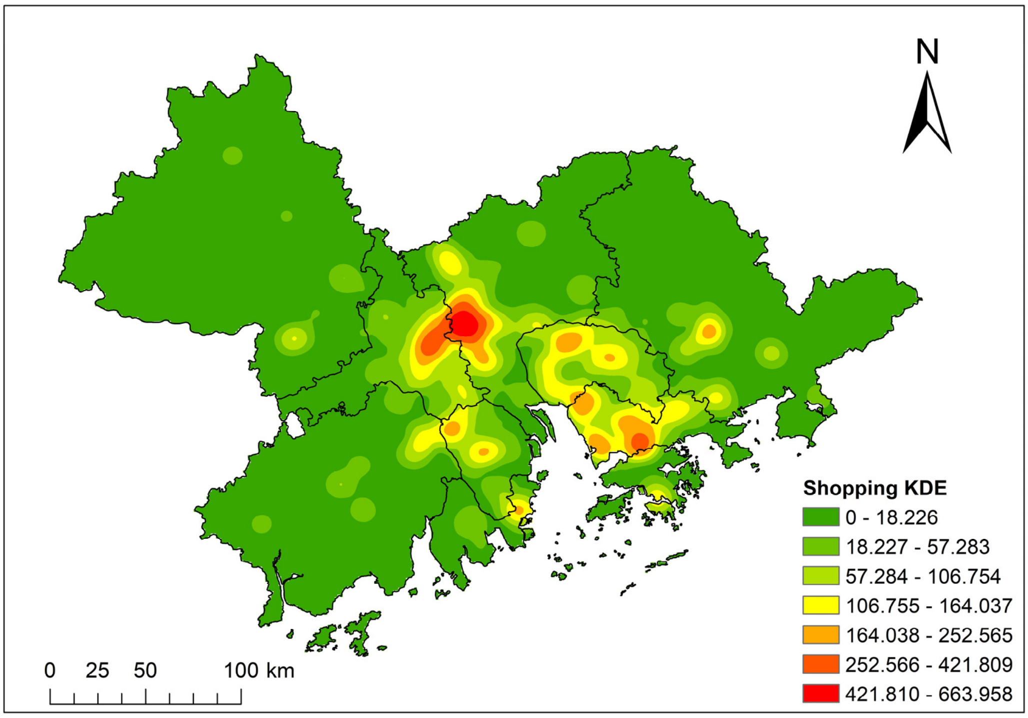
Figure 2. The standard deviation ellipse of different tourism services.

4.2. Kernel Density Analysis of Tourism Service in the GBA

In order to identify the specific area of agglomeration of tourism services in the GBA, the degree of spatial agglomeration of different types of tourism POI was examined using kernel density analysis (see Figure 3).

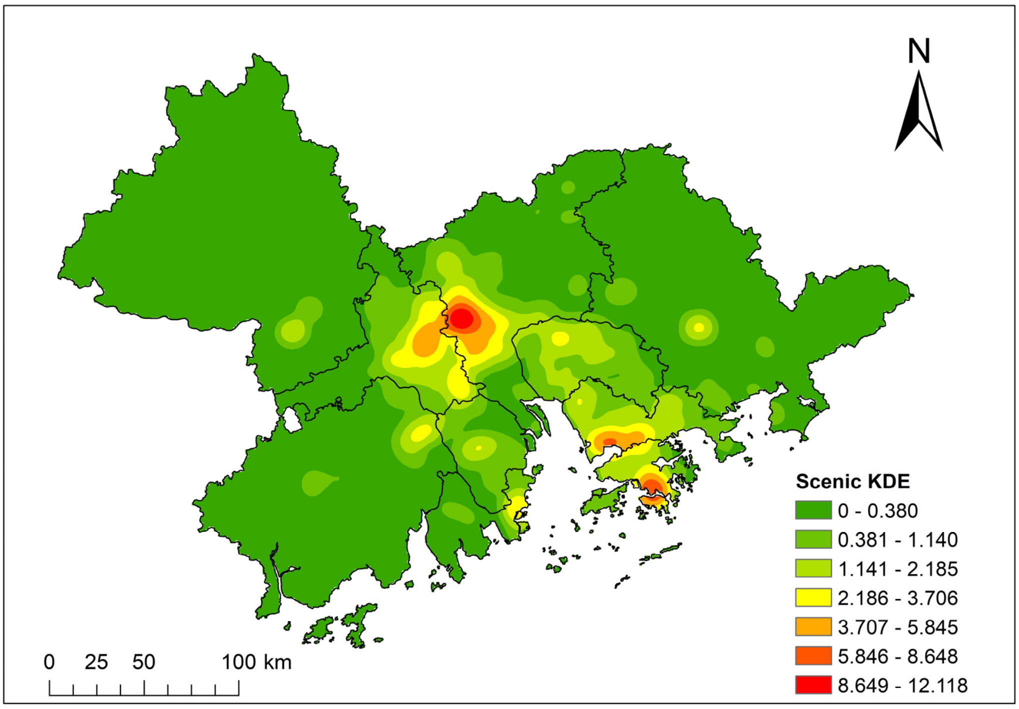


(**a**)

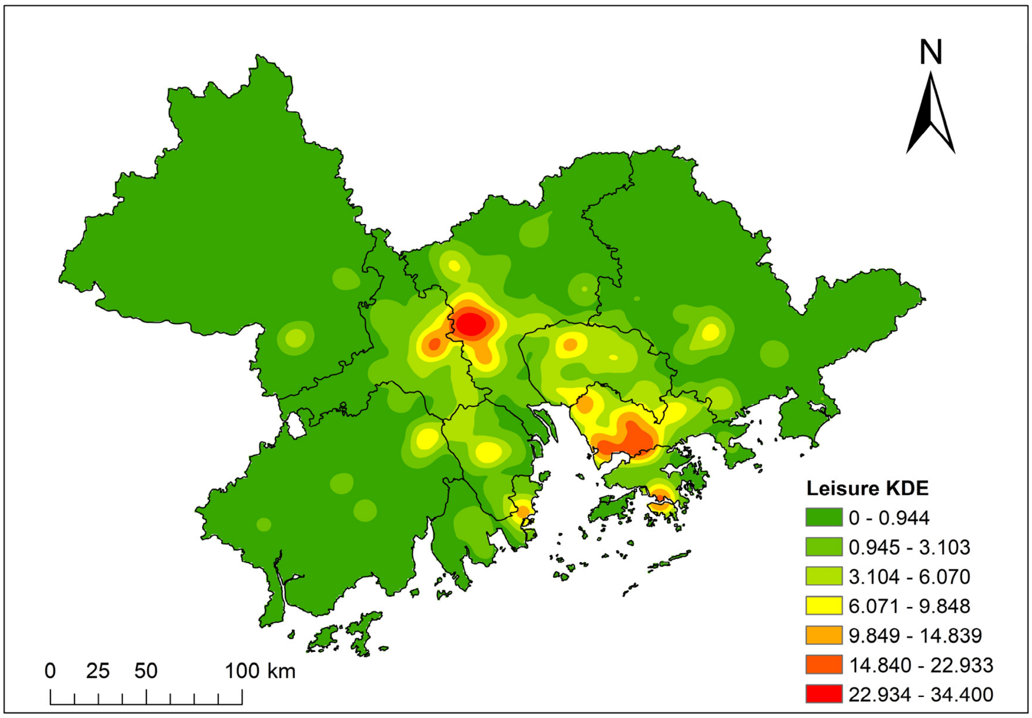


(**b**)

Figure 3. *Cont.*



(**c**)



(**d**)

Figure 3. The 2019 kernel density estimation diagrams consist of four categories: (**a**) catering kernel density estimation, (**b**) shopping kernel density estimation, (**c**) scenic spot kernel density estimation, and (**d**) sports and leisure kernel density estimation.

Catering and shopping services show a similar pattern of large-scale and highly concentrated clustering within the downtown areas of the cities in the GBA. Specifically, there are three main cores of tourism services: (1) Guangzhou's downtown areas of Tianhe, Yuexiu, and Liwan; (2) the eastern part of Zhuhai–Macao clustering; (3) Shenzhen and Hong Kong clustering. The peripheral areas between these cores display a discrete distribution of tourism services. Additionally, non-core regions like the downtown area of Huizhou are anticipated to emerge as a new core area.

As for sports and leisure services, they are currently clustered at low density in Guangzhou City's Huangpu and Nansha Districts, as well as in Foshan City's Shunde District. A continuous development trend is expected in Guangzhou's Tianhe and Huangpu Districts, along with Shunde District, in the future. Scenic services generally cluster in bands, forming several medium- and high-density centers in Guangzhou, Shenzhen, and Hong Kong. Compared with other tourism categories, scenic spots highly aggregate within the downtown areas of Guangzhou, Shenzhen, and Hong Kong.

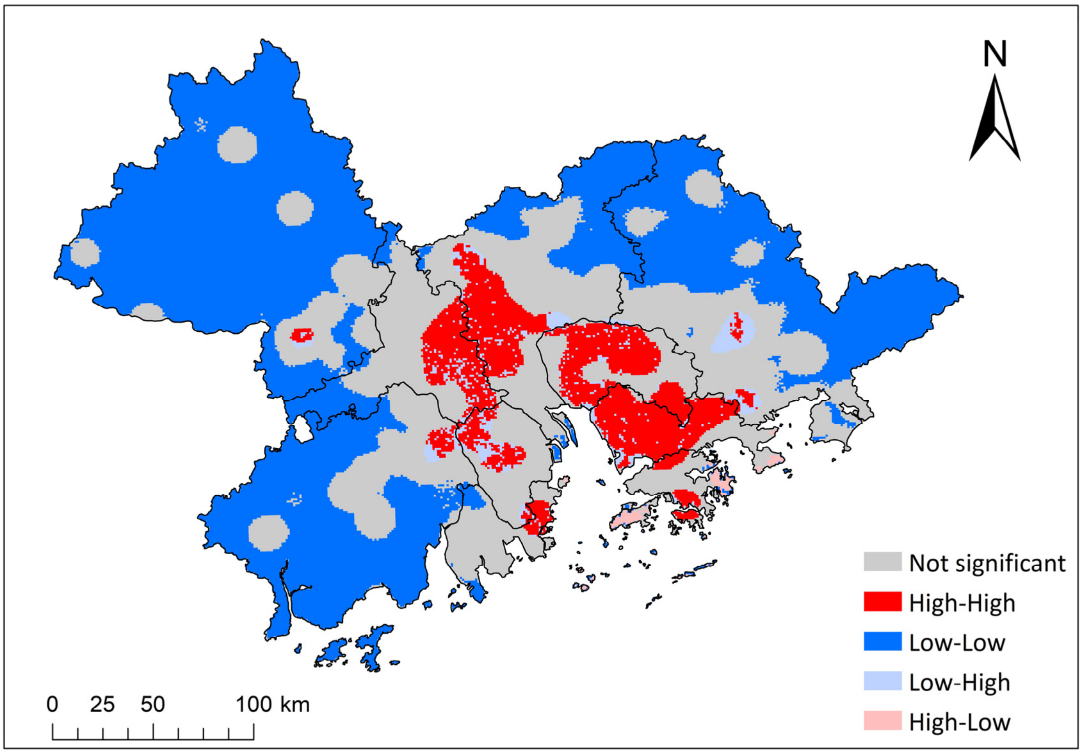
4.3. Bivariate Local Moran's Index and Cluster Analysis

The bivariate local Moran's index is used to test whether the distribution of tourism services has a spatial correlation with its neighbors for a different variable. (Here, we only tested tourism and GDP as an example.) As in Table 6, the bivariate local Moran's index revealed a significant spatial correlation between the four types of POI services and 1 km^2 GDP in the overall region. However, the Lisa cluster analysis exposed distinct clustering characteristics for each POI type and helps us identify different types of spatial correlations between tourism services and GDP (see Figure 4). For example, as for Figure 4a, the high–high aggregation means the highly dense distribution of catering services is spatially correlated with its neighboring area with a high level of GDP. In other words, catering services tend to concentrate in areas with a high level of GDP. Notwithstanding this spatial relationship, the bivariate local Moran's index cannot help us discern whether GDP is a driving force that influences the distribution of tourism services. This requires us to use spatial regression models and the coupling degree index to further detect this spatial relationship, which we will elaborate on later.

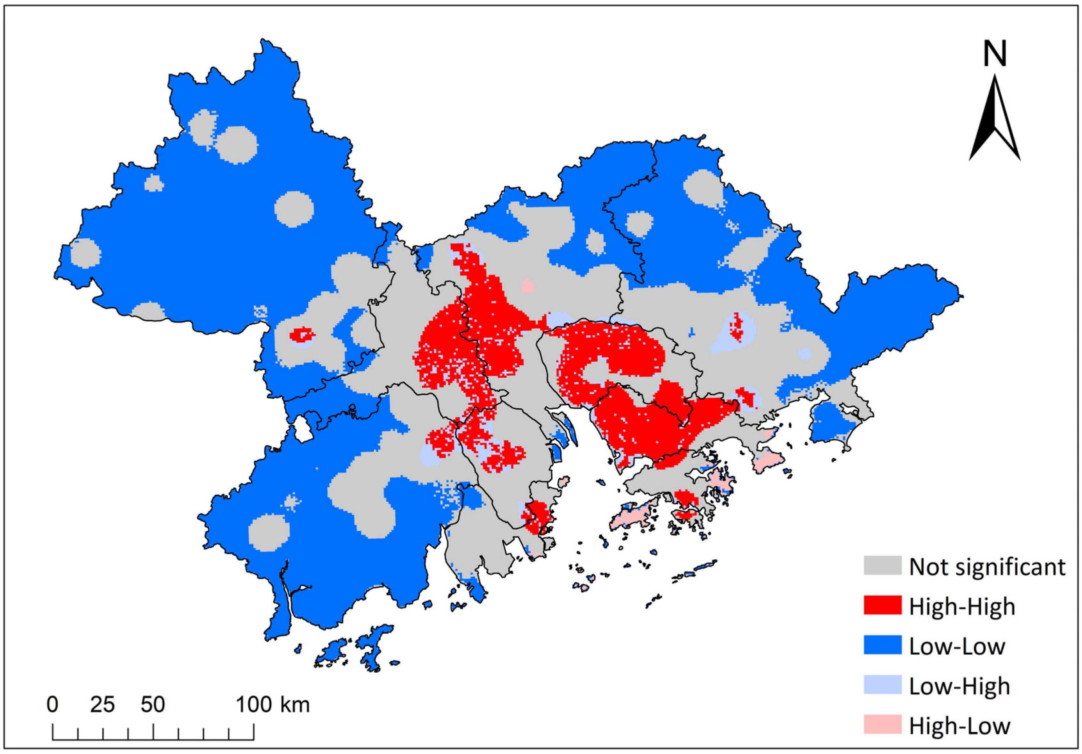
Table 6. Bivariate local Moran's index table (permutations: 999).

Category	Bivariate Local Moran's Index	*p*-Value	Z-Score
Catering services	0.511	<0.01	289.293
Shopping services	0.454	<0.01	262.477
Scenic spot services	0.582	<0.01	325.311
Sports and leisure services	0.574	<0.01	319.485

Like catering services, other tourism service categories of shopping, scenic spots, leisure, and sports services share similar characteristics of spatial correlation. However, in the periphery of the GBA, these services belong to low–low aggregation, with rare instances of other aggregation patterns observed. Unlike the kernel density estimation map, the high–high aggregation areas extend across municipal boundaries in the economic field, indicating significant development potential in the Pearl River Delta region. The non-significant areas surround the core high–high aggregation areas, indicating that these types of areas are discrete, with no obvious spatial bivariate correlation. They are randomly distributed, and there is a random pattern of aggregation of high and low values within each area, which does not effectively indicate the direction of development.

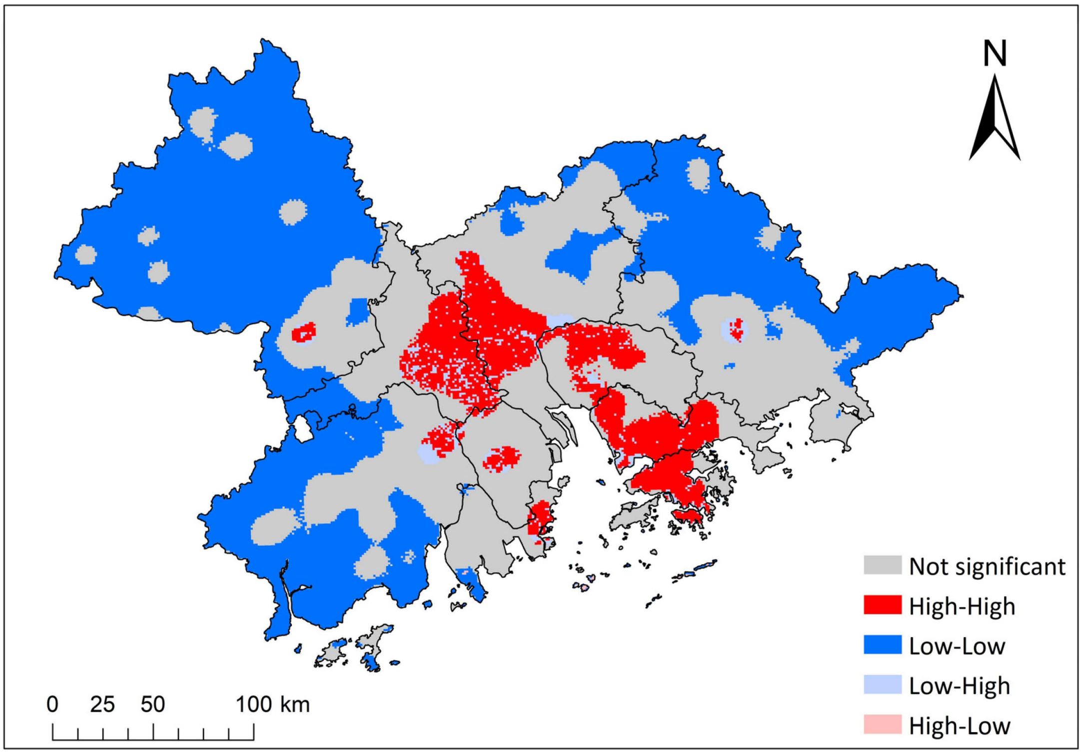


(a)

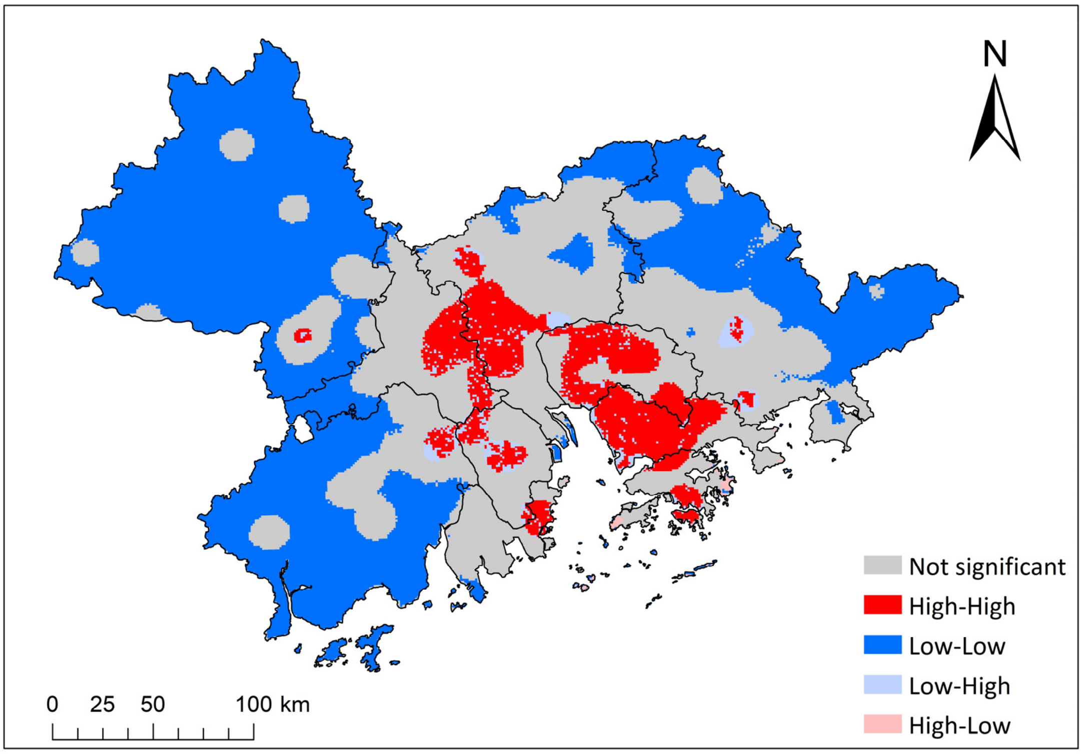


(b)

Figure 4. *Cont.*



(c)



(d)

Figure 4. The POI Lisa cluster analysis consists of four categories: (**a**) catering services Lisa cluster, (**b**) shopping services Lisa cluster, (**c**) scenic spot services Lisa cluster, and (**d**) sports and leisure services Lisa cluster.

4.4. Discussion on the Driving Forces of Tourism Space in the Guangdong–Hong Kong–Macao Greater Bay Area

4.4.1. Overall Examination

The maximum likelihood estimation method was employed to analyze the factors influencing the spatial distribution of tourism services, using the OLS model, spatial lag model, and spatial error model (Table 7). The mean variance inflation factor was calculated to be 1.77, with a maximum value of 2.76, indicating no significant issues of multicollinearity in the models. To facilitate a quantitative comparison of the influence of different factors on tourism service distribution, each independent variable was standardized to account for extreme differences. The explanatory power of all the models exceeded 72.0%. After comparing log likelihood values and variable significance across the three models, it was observed that the spatial error model exhibited the fewest large likelihoods and better significance for each variable. As a result, the spatial error model was selected as the benchmark model to analyze the influencing factors.

Regarding demographic factors, the model results show that population size has a significant positive effect on tourism services distribution. In terms of economic factors, this study shows a weak negative correlation between tourism services and the level of regional GDP at a network scale of one square kilometer.

Regarding transportation factors, the study found that superior transportation conditions promote tourism agglomeration, but the extent of the effect varies by the mode of transportation. The number of parking lots reflects the scale of tourism services accessible by automobile, which is significantly and positively correlated with tourism service density. Additionally, bus stops also show a significant positive relationship with tourism service density, as convenient public transportation helps to increase tourism service density. However, according to the spatial error model analysis, subway stations exhibit a negative correlation with tourism service density.

Regarding the facilities of hospitality, the Guangdong–Hong Kong–Macao Greater Bay Area has formed a spatial structure with the clustering of tourism facilities, clustering of tourism industry enterprises, and clustering of talents and employment. It is worth noting that both travel agencies and accommodation services have a positive effect on the distribution of tourism services.

Table 7. Results of OLS, SLM, and SEM for tourism services.

Variable Plates	Variable Settings	OLS	SLM	SEM
Independent variable (X)	X_{eco}	−0.0001 *** (−0.0717)	−0.0002 *** (−0.0829)	−0.0001 *** (−0.0335)
	X_{pop}	0.0033 *** (0.1451)	0.0012 *** (0.0529)	0.0017 *** (0.0742)
	X_t	16.5405 *** (0.2476)	16.7242 *** (0.2503)	14.7736 *** (0.2211)
	X_{pa}	4.9244 *** (0.3497)	3.7247 *** (0.2645)	5.2303 *** (0.3714)
	X_{pu}	22.4442 *** (0.1133)	17.8142 *** (0.0899)	17.0724 *** (0.0862)
	X_s	−8.4521 *** (−0.0427)	−5.2823 *** (−0.0267)	10.9028 *** (0.0550)
	X_a	3.1083 *** (0.3462)	2.8906 *** (0.3220)	3.1302 *** (0.3486)
	Spatial lag term (SLT)	-	0.3118 ***	-
	Spatial error term (SET)	-	-	0.5617 ***
Sample size (SS)		55,654	55,654	55,654
Log likehood (LL)		−329,853	−327,712	−326,131
R^2		0.7207	0.7450	0.7678

Note: *** indicates that the variable is significant at 99% confidence level; normalization factors are in parentheses.

4.4.2. Categorical Examination

To further explore the variability of the spatial distribution of different categories of tourism services, namely catering, scenic spots, shopping, and sports and leisure, they were extracted as important components for analyzing and comparing influencing factors (Tables 8 and 9).

Table 8. OLS, SLM, and SEM results for catering services and scenic spots.

VP	VS	Catering Services			Scenic Spots		
		OLS	**SLM**	**SEM**	**OLS**	**SLM**	**SEM**
X	X_{eco}	−0.00002 *** (−0.0398)	−0.00003 *** (0.0638)	−0.00001 *** (−0.0245)	−0.00001 *** (0.1688)	0.000003 *** (0.0916)	0.000006 *** (0.1360)
	X_{pop}	0.0008 *** (0.1432)	0.0003 *** (0.0602)	0.0005 *** (0.0895)	0.0001 *** (0.1634)	0.00004 *** (0.0897)	0.0001 *** (0.1098)
	X_t	4.7543 *** (0.2877)	4.8066 *** (0.2909)	4.1474 *** (0.2510)	0.2513 *** (0.1701)	0.1996 *** (0.1351)	0.1919 *** (0.1299)
	X_{pa}	1.5021 *** (0.4313)	1.2187 *** (0.3499)	1.6457 *** (0.4725)	0.0154 *** (0.0496)	0.0068 *** (0.0219)	0.0160 *** (0.0513)
	X_{pu}	6.6844 *** (0.1364)	5.5531 *** (0.1133)	5.1473 *** (0.1050)	0.0899 *** (0.0205)	0.0610 *** (0.0139)	0.0746 *** (0.0170)
	X_s	−2.7575 *** (−0.0563)	−2.2017 *** (−0.0449)	2.1807 *** (0.0445)	−0.1262 *** (−0.0288)	−0.1281 *** (−0.0293)	−0.0832 *** (−0.0190)
	X_a	1.1838 *** (0.5332)	1.1254 *** (0.5069)	1.2119 *** (0.5458)	0.0174 *** (0.0878)	0.01427 *** (0.0719)	0.0158 *** (0.0794)
	SLT	-	0.2454 ***	-	-	0.4684 ***	-
	SET	-	-	0.5129 ***	-	-	0.4683 ***
SS		55,654	55,654	55,654	55,654	55,654	55,654
LL		−263,753	−262,446	−260,705	−120,196	−117,163	−117,697
R^2		0.7363	0.7505	0.7732	0.2531	0.3524	0.3398

Note: *** indicates that the variable is significant at 99% confidence level; normalization factors are in parentheses.

Table 9. OLS, SLM, and SEM results for shopping services and sports and leisure services.

VP	VS	Shopping Services			Sports and Leisure Services		
		OLS	**SLM**	**SEM**	**OLS**	**SLM**	**SEM**
X	X_{eco}	−0.0001 *** (−0.0743)	−0.0001 *** (−0.0756)	−0.0001 *** (−0.0346)	0.000002 *** (0.0386)	0.0000002 *** (0.0039)	0.000002 *** (0.0305)
	X_{pop}	0.0023 *** (0.1122)	0.0006 *** (0.0304)	0.0011 *** (0.0528)	0.0001 *** (0.1466)	0.0001 *** (0.0792)	0.0001 *** (0.0982)
	X_t	10.5476 *** (0.1753)	10.8012 *** (0.1795)	9.7103 *** (0.1613)	0.9872 *** (0.4309)	0.9404 *** (0.4105)	0.8279 *** (0.3614)
	X_{pa}	3.2262 *** (0.2543)	2.2832 *** (0.1800)	3.3546 *** (0.2644)	0.1807 *** (0.3743)	0.1497 *** (0.3100)	0.1972 *** (0.4084)
	X_{pu}	15.3030 *** (0.0857)	11.6404 *** (0.0652)	11.6805 *** (0.0654)	0.3670 *** (0.0540)	0.2965 *** (0.0437)	0.2888 *** (0.0425)
	X_s	−5.5784 *** (−0.0313)	−2.5848 *** (−0.0145)	8.2475 *** (0.0462)	0.0100 *** (0.0015)	−0.0302 *** (−0.0044)	0.2263 *** (0.0333)
	X_a	1.7908 *** (0.2214)	1.6342 *** (0.2021)	1.7888 *** (0.2212)	0.1162 *** (0.3774)	0.1089 *** (0.3538)	0.1133 *** (0.3681)
	SLT	-	0.3708 ***	-	-	0.2367 ***	-
	SET	-	-	0.5694 ***	-	-	0.4453 ***
SS		55,654	55,654	55,654	55,654	55,654	55,654
LL		−314,895	−312,212	−311,009	−139,545	−138,282	−137,365
R^2		0.6448	0.6839	0.7069	0.7571	0.7697	0.7820

Note: *** indicates that the variable is significant at 99% confidence level; normalization factors are in parentheses.

It can be observed that the spatial distribution of the three types of tourism services (catering, shopping, and sports and leisure) exhibited similarities, with the models explaining over 64.0% of the spatial distribution for these categories. However, the R-square value for attraction services was relatively lower. As shown in the table below, all four categories of tourism services were positively influenced by factors such as population distribution, the number of parking lots, bus stops, travel agencies, and accommodation services. However, the strength of the influence varied among the different categories. For instance, population and travel agency density had the highest contribution coefficient to sports and leisure service density, and only the subway station contribution coefficient for sports and leisure services was positive, while for the other three categories, the subway station contribution coefficient was negative. On the other hand, parking lots, bus stops, and accommodation service density had the highest contribution to catering service density, indicating a significant positive driving effect of accommodation services on catering services, which was closely related to people's dining and accommodation needs. Furthermore, GDP only showed a positive influence on attraction and sports and leisure services, while it was negatively correlated with the other two categories of services.

4.5. Analysis of the Coupling of Tourism Space with Economy and Population

The comprehensive evaluation model was employed to calculate the comprehensive evaluation value of GDP, population, and tourism services for each sample. Subsequently, correlation analysis was conducted in SPSS to assess the relationship between GDP, population, and tourism services. The Pearson correlation coefficient between GDP and tourism services was found to be 0.447, while the Pearson correlation coefficient between population and tourism services was 0.579. Both correlations were significant at the 0.01 level, indicating a high degree of synchronization between GDP, population, and tourism services.

Further data processing was performed according to the chosen theory and research method, resulting in the determination of the coupling degree of GDP, population, and tourism services at the 1 km^2 level, represented as images in ArcGIS (Figure 5). The levels of coupling degree were classified as follows (Tables 10 and 11).

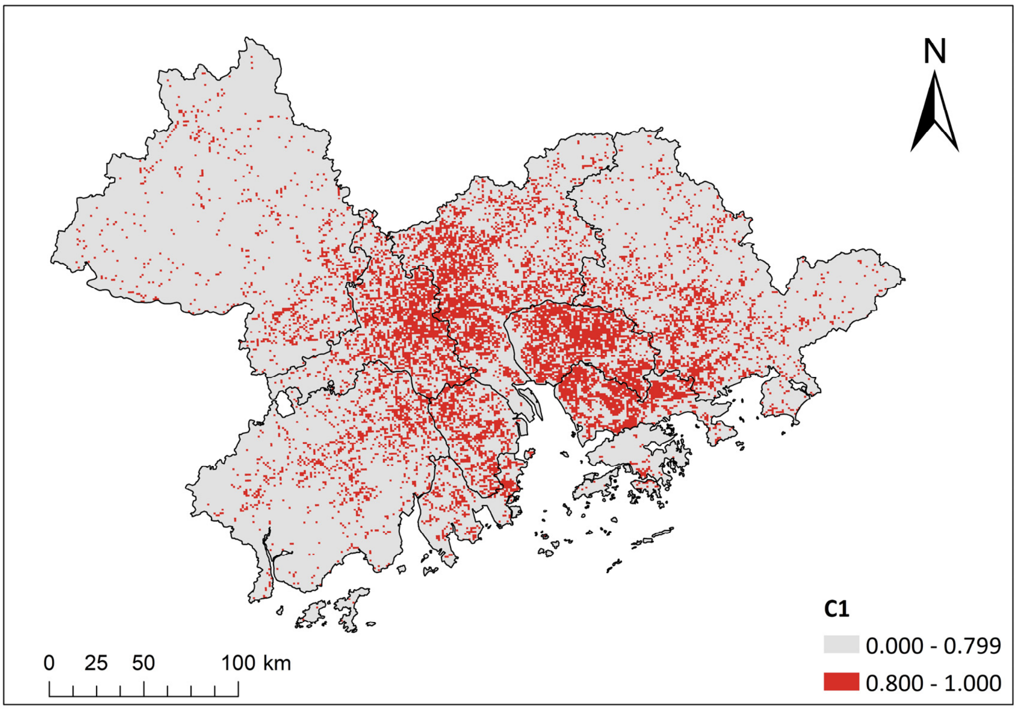
Analysis of the results indicates that the coupling effect of population and tourism services surpassed that of GDP and tourism services. The high-value areas of GDP and tourism service coupling were primarily concentrated in Guangzhou, Foshan, Zhuhai, Dongguan, and Shenzhen, signifying strong interdependence and mutual influence in these regions. Notably, the regions with a high coupling degree displayed dense clustering, such as the Liwan, Yuexiu, Haizhu, and Baiyun Districts in Guangzhou, as well as the Nanhai, Chancheng, Shunde Districts, among others. Additionally, large portions of Dongguan and most areas of Shenzhen exhibited high coupling degrees. However, in the fringe areas of the Guangdong–Hong Kong–Macao Greater Bay Area, connectivity was poor, resulting in low-value gathering areas for the coupling of GDP and tourism services.

Table 10. Coupling level classification criteria.

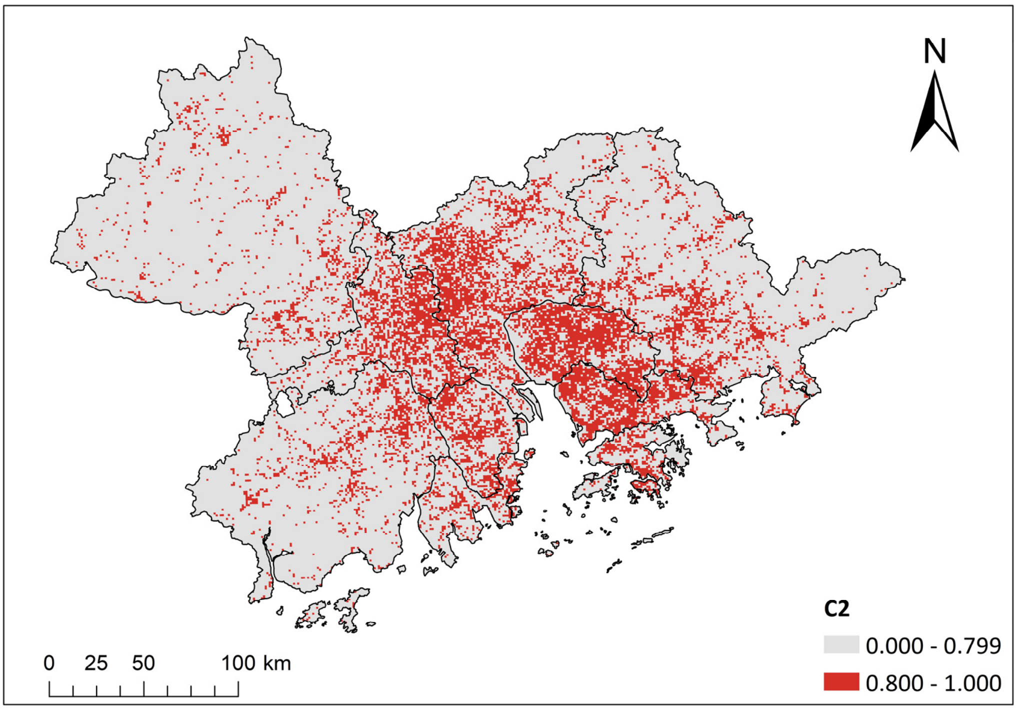
Serial Number	Coupling Degree Interval	Coupling Phase	Custom Classification
1	[0.000, 0.299]	Low level	Low level
2	[0.300, 0.499]	Antagonistic	
3	[0.500, 0.799]	Break-in	
4	[0.800, 0.990]	High level	High level
5	[0.990, 1.000]	Extremely high	

Table 11. Sample number statistics for different coupling types.

Serial Number	Coupling Degree Classification	Sample Size
GDP–tourism service coupling	0.800<	45,212
	≥0.800	10,442
Population–tourism service coupling	0.800<	44,230
	≥0.800	11,424



(**a**)



(**b**)

Figure 5. Diagram of coupling degree: (**a**) tourism with GDP; (**b**) tourism with population.

5. Discussion

With the help of ArcGIS, SPSS, and GeoDa, this paper analyzed the tourism spatial pattern characteristics of cities in the Guangdong–Hong Kong–Macao Bay Area by using a variety of methods and reveals some new findings that research based on traditional census statistics failed to discover. In what follows, we further respond to the three research questions outlined in the beginning of this paper.

5.1. The Spatial Patterns of Tourism

The nearest neighbor ratio of tourism space of the GBA in 2019 was 0.140, which shows that the tourism service facilities in the GBA exhibited noticeable spatial aggregation. Catering and shopping services had a much higher degree of spatial aggregation than that of sports and leisure services.

Combined with the imbalance index S, the geographic concentration index G, and the local Moran's index, it was found that the distribution of different types of POI data was imbalanced and clustered at the same time. This also manifested in the analysis of kernel density: (1) Catering, shopping, and sports and leisure services were spatially clustered in groups within the cities' downtown areas where population concentrated. It was also illustrated in the regression model that population density positively correlated with the density of tourism services. (2) The distribution of scenic spots was not fully consistent with that of catering, shopping, and sports and leisure services, as many historical heritage sites or zoos are normally located in the old town or the suburb of the cities. Yet, all categories of tourism services tended to correlate with variables of economic level and population density in the grid of 1 km^2. In conclusion, the distribution of tourism services is highly dependent on the economy and population density.

5.2. Driving Forces of Tourism Space

This paper also examined what factors may influence the spatial distribution of tourism services in the GBA. Regarding demographic factors, the model results show that population density has a significant positive effect on the distribution of tourism services. Yet, the positive correlation between population and tourism services is often not singular but mutually reinforced. As Rapport's research suggests, the consumption of tourism services relies on the high density of the population, while tourism services themselves can also be the amenities that become an important determinant of where people choose to live [32].

Regarding economic factors, this study found a weak and negative correlation between tourism services and regional GDP at the scale of 1 km^2. This finding is in contrast with conventional studies based on city- or provincial-level census data, which show a positive correlation between GDP and tourism services. This is attributed to the micro-scale spatial panel data (1 km^2) of GDP that we used in this paper. The development of the tourism economy or services may be spatially exclusive with other economic sectors and industries like manufacturing, technological industries, and finance in the spatial unit of 1 km^2. Moreover, some scenic spots or areas do not necessarily have significant "economic spillover" effects on local development [33]. This, therefore, requires us to further examine the coupling relationship of tourism and GDP, which will be elaborated on in this section.

The effect of transportation on tourism services is diverse. The models show that areas with a high number of parking lots tend to have a higher density of tourism services. From the spatial error model, the effect of bus stops is significant, while the effect of metro stops is not significant. Most of the current suburban areas are still outside the reach of the metro, and some metro stations may be located in non-tourist areas of the city or have poor connectivity to major tourist attractions. Yet, the density of metro stations is positively related to sports and leisure services, probably because it can improve people's accessibility to stadiums, parks, and other sports and leisure facilities [34].

Regarding hospitality facilities, the GBA has now formed a spatial structure with a concentration of tourism facilities, industry enterprises, and talent employment [35–37]. Travel agents and accommodation services have a positive impact on the distribution of tourism services, as both can provide hospitality support and guidance for tourism services. They can provide tourists with convenient access to dining, leisure, shopping, and attractions, and this convenience can lead to the aggregation of tourism services [34,38]. In sum, we identify GDP, transportation, and hospitality facilities in a grid of 1 km^2 as three important drivers for the distribution of tourism services. Because of the limitation of data sources, other factors which were not included in this paper, such as the GDP of the service industry and the number of visitors, may also influence the distribution of tourism services.

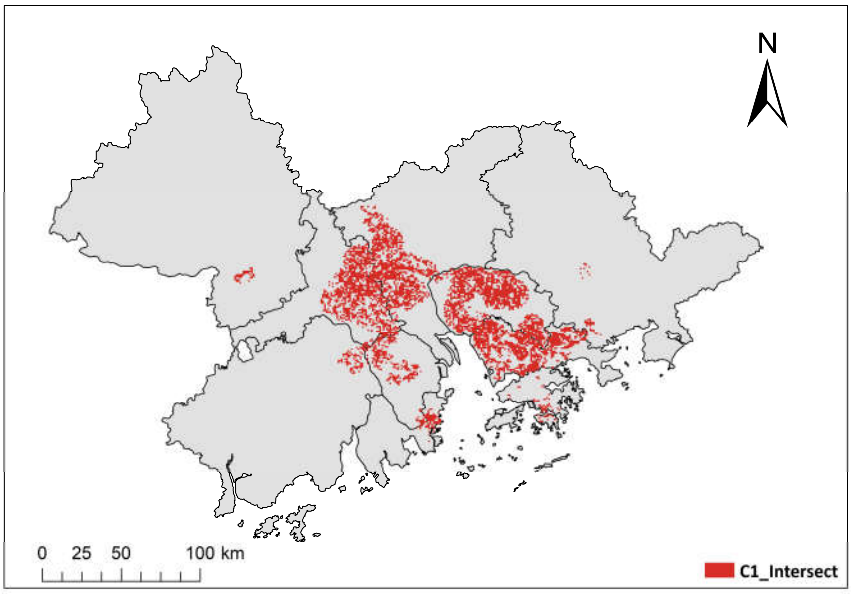
Future research can use more comprehensive variables to examine the factors influencing the distribution of tourism services.

5.3. The Coupling of Tourism with GDP and Population

As the economy and population are crucial factors influencing the distribution of tourism services, it is important to evaluate the extent to which tourism services are coordinated with the index of GDP and population. The coupling degree, therefore, offers us a method to classify the areas in which tourism services have good interactions with GDP and population.

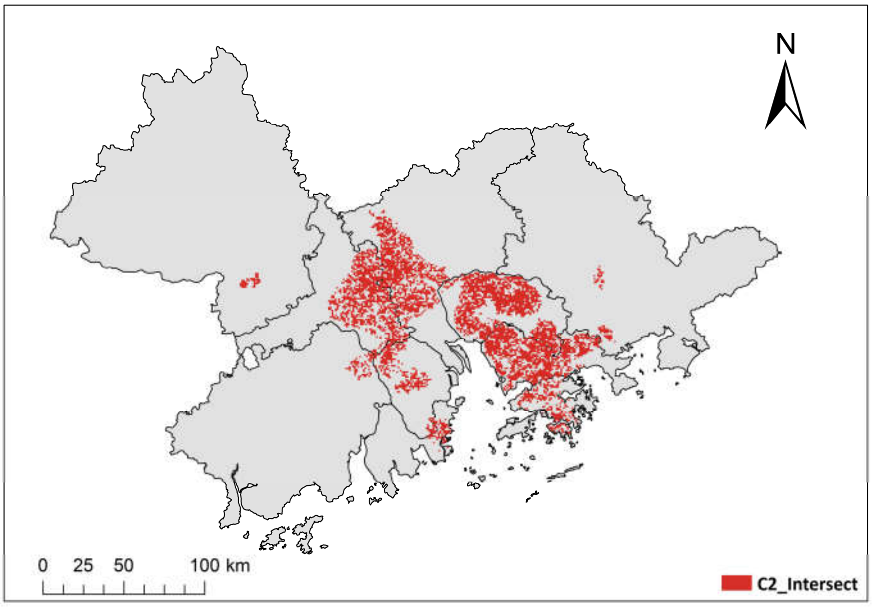
In general, the coupling effect of tourism services with population is better than the coupling effect of tourism services with GDP. In this sense, population density is fundamental for consumption-oriented tourism services. A high coupling degree between tourism services and population (see Figure 5b) indicates that (1) population and tourism can mutually facilitate each other; (2) the distribution of tourism services or amenities is consistent with the distribution of population and, therefore, is reasonable.

We also classified the areas in which tourism services had a high degree of coupling with GDP. It can be seen that the high-value areas with a coupling between GDP and tourism services are principally located in Guangzhou, Foshan, Zhuhai, Dongguan, and Shenzhen, indicating that tourism and GDP are highly dependent on each other. However, areas with a high degree of coupling do not necessarily indicate that tourism services can be a driving force of GDP; as we discussed before, tourism economy may be exclusive with other economic sectors on a scale of 1 km^2. Yet, if we combine and overlap the areas with high–high aggregation measured using the local Moran's index and the areas with a high coupling degree between tourism services and GDP, we can clearly identify the areas where tourism services are not only highly developed but also have a positive interaction with local GDP (see Figure 6a,b). We also offer the methodological process for identifying hotspots for tourism development in Figure 7. In this sense, such areas can be considered as suitable for the development of tourism because tourism can promote GDP growth, bring higher flows of people, and, therefore, create "spillover efforts" on the local economy. This growth relationship is bidirectional because such areas are both highly coupled and highly interactive and, therefore, are important areas for urban and tourism planning.



(**a**)

Figure 6. *Cont.*



(**b**)

Figure 6. Diagram of overlay of Moran and coupling degree: (**a**) tourism with GDP; (**b**) tourism with population.

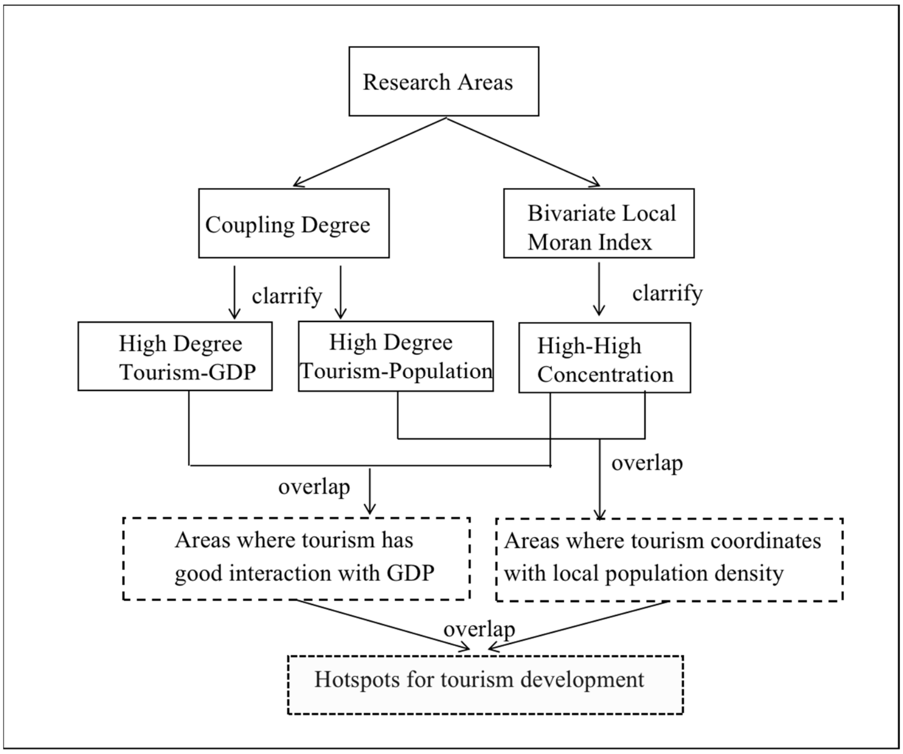


Figure 7. Methodological process for identifying hotspots for tourism development.

6. Conclusions and Policy Engagement

This study analyzed the spatial distribution and agglomeration of tourism services in China's Great Bay Area and explored the coupling of tourism space with the local economy and population. The major research findings can be summarized as follows: (1) Tourism services exhibited noticeable spatial aggregation within the cities' metropolitan areas. Yet, catering and shopping services had a much higher degree of spatial aggregation than that of sports and leisure services and scenic spots. (2) Through 1 km^2 scale panel data analysis, it was found that population density, transportation, and hospitality facilities were positively associated with the distribution of tourism services, but tourism services may be spatially exclusive with other economic sectors like industries and, therefore, show a negative association with local GDP. (3) We identified the areas in which tourism services developed in tandem with the local economy and population density, and consider them as hotspots suitable for the development of tourism.

This paper also offers important policy implications for tourism development in the GBA. First, the planning of tourism services and facilities should be consistent with population density as it is an important supply-side indicator of the tourism market. Tourism services should also be supported by transportation and hospitality facilities, as they influence the movement and stasis of tourism flows. This is particularly important for some less developed areas that intend to use tourism as an economic facilitator: tourism needs to be developed in a holistic sense with the support of economic and transportation systems. Second, policymakers should pay special attention to the areas with a high degree of coupling between tourism, the economy, and population density in order to maximize the spatial–economic effects of tourism. As visualized in Figure 6, which shows hotspot areas, tourism investment and the planning of tourism facilities should look towards these areas so that the socio-economic benefits of tourism can be optimized.

However, this paper also has some limitations. First, the POI data can capture the category and number of tourism services but fail to reflect the quality of the specific spatial unit. For example, different scenic spots may have quite different capacities for attracting visitors and have different economic outputs. Second, the variables of transportation in the regression model can be improved by measuring the degree of accessibility that POI data cannot simply address. In this sense, future research should use multiple sources of data to address the limitations of POI data so as to more comprehensively cover both the quality and quantity of tourism services.

Author Contributions: Conceptualization, Q.G.; methodology, L.L.; software, L.L.; validation, L.L.; formal analysis, Q.G. and L.L.; investigation, L.L.; resources, Q.G.; data curation, Q.G.; writing—original draft preparation, L.L.; writing—review and editing, Q.G.; visualization, L.L.; supervision, Q.G.; project administration, Q.G.; funding acquisition, Q.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China (grant number: 42201240) and The Young Elite Scientists Sponsorship Program by CAST (grant number: 2022QNRC001).

Data Availability Statement: Data are available from the corresponding author upon request.

Acknowledgments: We want to offer appreciation for Jing Xie for his guidance in data analysis and paper revision.

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

References

1. Shaw, G.; Bailey, A.; Williams, A. Aspects of service-dominant logic and its implications for tourism management: Examples from the hotel industry. *Tour. Manag.* **2011**, *32*, 207–214. [CrossRef]
2. Frisch, T.; Sommer, C.; Stoltenberg, L.; Stors, N. Chapter one. In *Tourism and Everyday Life in the Contemporary City*, 1st ed.; Frisch, T., Sommer, C., Stoltenberg, L., Stors, N., Eds.; Routledge: Oxford, UK, 2019; pp. 1–23.
3. Edensor, T. Performing tourism, staging tourism: (Re)producing tourist space and practice. *Tour. Stud.* **2001**, *1*, 59–81. [CrossRef]
4. Oppermann, M. Tourism space in developing countries. *Ann. Tour. Res.* **1993**, *20*, 535–556. [CrossRef]
5. Kytzia, S.; Walz, A.; Wegmann, M. How can tourism use land more efficiently? A model-based approach to land-use efficiency for tourist destinations. *Tour. Manag.* **2011**, *32*, 629–640. [CrossRef]
6. Zhang, S.; Zhang, G.; Ju, H. The spatial pattern and influencing factors of tourism development in the Yellow River Basin of China. *PLoS ONE* **2020**, *15*, e0242029. [CrossRef]
7. Dinu, A.-M. The importance of transportation to tourism development. *Acad. J. Econ. Stud.* **2018**, *4*, 183–187.
8. Liao, K.-C.; Chen, C.-H.; Lin, C.-H.; Chen, S.-H. An evaluation of coupling coordination between tourism and finance. *Sustainability* **2018**, *10*, 2320. [CrossRef]

9. Xie, X.; Li, J.; Zhang, J.; Wang, Y. Spatiotemporal differentiation of coupling and coordination relationship of tourism–urbanization–ecological environment system in China's major tourist cities. *Sustainability* **2021**, *13*, 5867. [CrossRef]
10. Lai, Z.; Li, X.; Wang, Y.; Zhang, Y. Coupling coordination between environment, economy and tourism: A case study of China. *PLoS ONE* **2020**, *15*, e0228426. [CrossRef]
11. Law, R.; Leung, R.; Lo, A.; Leung, D.; Fong, L.H.N. Distribution channel in hospitality and tourism: Revisiting disintermediation from the perspectives of hotels and travel agencies. *Int. J. Contemp. Hosp. Manag.* **2015**, *27*, 431–452. [CrossRef]
12. Santana-Jiménez, Y.; Hernández, J.M. Estimating the effect of overcrowding on tourist attraction: The case of Canary Islands. *Tour. Manag.* **2011**, *32*, 415–425. [CrossRef]
13. Čada, V.; Marvalová, J.; Musilová, B. *The Rise of Big Spatial Data*, 1st ed.; Igor, I., Alex, S., Jiří, H., Tomáš, I., Eds.; Springer: Berlin, Germany, 2016; pp. 315–335.
14. Tang, Z. An integrated approach to evaluating the coupling coordination between tourism and the environment. *Tour. Manag.* **2015**, *46*, 11–19. [CrossRef]
15. Zhou, Z.; Yang, Q.; Kim, D.J. An empirical study on coupling coordination between the cultural industry and tourism industry in ethnic minority areas. *J. Open Innov.* **2020**, *6*, 65. [CrossRef]
16. Gal, Y.; Gal, A.; Hadas, E. Coupling tourism development and agricultural processes in a dynamic environment. *Curr. Issues Tour.* **2010**, *13*, 279–295. [CrossRef]
17. Akama, J.; Kieti, D. Tourism and socio-economic development in developing countries: A case study of Mombasa Resort in Kenya. *J. Sustain. Tour.* **2007**, *15*, 735–748. [CrossRef]
18. PwC. Interpretation and Suggestions on the Development Plan Outline of Guangdong-Hong Kong-Macao Greater Bay Area. *Sci. Technol. China* **2019**, *1*, 30–38.
19. McCarty, D.A.; Kim, H.W. A standardized European hexagon gridded dataset based on OpenStreetMap POIs. *Data Brief* **2023**, *14*, 49. [CrossRef]
20. Resource and Environmental Science Data Center. Available online: http://www.resdc.cn/DOI (accessed on 7 July 2023).
21. Yang, C.; Yang, H.; Han, H.; Yang, G. Spatial layout characteristics and influencing factors of knowledge innovation service industry based on POI data: A case study of Hefei City. *Geogr. Res.* **2023**, *42*, 682–698.
22. Lefever, D.W. Measuring geographic concentration by means of the standard deviational ellipse. *Am. J. Sociol.* **1926**, *32*, 88–94. [CrossRef]
23. Tan, J.; Lin, Q. Research on the spatiotemporal distribution and evolution of traditional villages in Guangxi Zhuang Autonomous Region. *J. Green Sci. Technol.* **2023**, *25*, 234–238.
24. Läuter, H.; Silverman, B.W. *Density Estimation for Statistics and Data Analysis*; Chapman & Hall: London, UK; New York, NY, USA, 1986; pp. 876–877.
25. Anselin, L. A local indicator of multivariate spatial association, extending Geary's c. *Geogr. Anal.* **2019**, *51*, 133–150. [CrossRef]
26. Tang, J.; He, Y.; Ta, N. Spatial Distribution Patterns and Factors Influencing the Shanghai Catering Industry Based on POI Data. *Trop. Geogr.* **2020**, *40*, 1015–1025.
27. Hu, Z.; Kumar, J.; Qin, Q.; Kannan, S. Assessing the coupling coordination degree between all-for-one tourism and ecological civilization; case of Guizhou, China. *Environ. Sustain. Indic.* **2023**, *19*, 100272. [CrossRef]
28. Wang, S.; Kong, W.; Ren, L.; Zhi, D.; Dai, B. Misunderstandings and Corrections of Domestic Coupling Coordination Models. *J. Nat. Resour.* **2021**, *36*, 793–810.
29. Zhang, H.; Geng, C.; Xie, S. Analysis of population factors in the development of China's tourism industry. *Math. Pract. Theory* **2018**, *48*, 74–87.
30. Lei, P.; Shi, Z. The study on China's domestic tourist demand and its influential factors. *Hum. Geogr.* **2009**, *24*, 102–105.
31. Wang, Z.; Luo, Y. Analysis of the response mechanism of Zhangjiajie transportation under tourism driving. *Sci. Geol. Sin.* **2015**, *35*, 1397–1403.
32. Liang, Y.; Yang, X.; Ma, X. Grey correlation analysis of influencing factors of tourism development. *Hum. Geogr.* **2006**, *21*, 37–40.
33. Rasool, H.; Maqbool, S.; Tarique, M. The relationship between tourism and economic growth among BRICS countries: A panel cointegration analysis. *Future Bus. J.* **2021**, *7*, 1. [CrossRef]
34. He, L.; Zhang, H. Analysis of Factors Influencing the Quality of Sports Tourism Services in Cities Hosting Sports Events in China. *J. Beijing Sport Univ.* **2014**, *6*, 16–20.
35. Yuan, J.; Zhou, Y.; Liu, Y. Convergence Evaluation of Sports and Tourism Industries in Urban Agglomeration of Guangdong–Hong Kong–Macao Greater Bay Area and Its Spatial-Temporal Evolution. *Sustainability* **2022**, *14*, 10350. [CrossRef]
36. Tian, G. *A Review of Research on Tourism Integration in Guangdong-Hong Kong-Macao Greater Bay Area*; Atlantis Press: Amsterdam, The Netherlands, 2019; pp. 253–262.
37. Zhou, L.; Wang, S.; Long, X.; Li, Y. Research on the Spatial Structure of Grade A Tourist Attractions in the Guangdong-Hong Kong-Macao Greater Bay Area. *Geospat. Inf.* **2020**, *18*, 9–12.
38. Zhang, C.; Xiang, F. A Preliminary Study on the Influence of Travel Agencies on Tourist Behavior. *J. Tour. Sci.* **2002**, *17*, 35–39.