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Spatial Distribution and Influencing Factors of High-Level Tourist Attractions in China: A Case Study of 9296 A-Level Tourist Attractions

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Abstract: The distribution pattern of high-level tourist attractions is crucial for the sustainable development of the tourism industry. However, few studies have explored the spatial distribution and dominant influencing factors of tourist attractions of different levels from a macro perspective in China. This study, which was based on large-scale multi-source data, involved the use of kernel density analysis, local spatial autocorrelation, and geographical detector analysis to explore the spatial distribution, spatial correlation, and dominant influencing factors of high-level tourist attractions in China. The study's results show that the spatial distribution of tourist attractions of different levels is polarized and regionally clustered, and there exist some spatial correlation effects among attractions of the same level. Additionally, different influencing factors play a different role in determining the spatial distribution of attractions of different levels. Based on market demand and tourism resources, it is necessary to regulate attractions of different levels to promote the sustainable development of high-level tourist attractions and provide a reference for the development of China's tourism industry.

Keywords: tourist attractions; influencing factors; spatial distribution; spatial correlation; geographical detector

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1. Introduction

Tourist attractions generally refer to geographically connected places with many common features, including transportation networks and tourist service facilities composed of regional units, which have the characteristics of consistency, relevance, and completeness [1,2]. Tourist attractions can be restricted by administrative regions or can break through the constraints of administrative regions; they can even be affected by topography, landscapes, and social relations [3]. Different tourist attractions have obvious differences in spatial span. Although there is no clear definition applicable to all tourist attractions, it is generally believed that tourist attractions are defined as areas or regions where tourism activities are the main function, areas or regions where natural and cultural attractions of certain values are relatively concentrated, and areas or regions with a certain scale and tourism conditions that can be visited and appreciated and/or perceived as relaxing, entertaining, or a good place to engage in tourism cultural activities [4,5].

A-level tourist attractions are the highest-level tourist attractions in China, according to the national standards created by China for a comprehensive evaluation of different tourist attractions' quality and grade. Creating A-level attractions is an important way to enhance the comprehensive quality of tourist attractions and attract tourists, which also helps to improve the regional tourism economy and thus promote local economic and social benefits [6]. The creation and improvement of A-level tourist attractions in China involve strict standards and requirements, including considering the advantages based on the scenic area's original humanistic and natural basis, as well as comprehensively considering the allocation of regional infrastructure and tourism resources [7,8]. Therefore, analyzing the distribution pattern of different A-level tourist attractions in China can help coordinate the distribution of tourist attractions at a macro scale in the country to improve the overall tourism resource effect and the balance between the region and tourism [9].

The spatial distribution of tourist attractions not only refers to the spatial locations of tourist attractions but also the attractions' interrelationship with the region. The influencing factors of the spatial distribution of tourist attractions are also a point of focus of contemporary tourism-based spatial studies [10]. The spatial structure of tourist attractions not only involves the distribution, taste, and quantity combination of the attractions but also often has a profound impact on tourism activities. Therefore, the spatial structure and distribution patterns of tourist attractions have always been one of the core research topics in the domain of tourism geography [11–13].

Initially, studies on tourist spatial structure mainly focused on the spatial analysis and measurement of the tourist source market, and there was less research on the spatial distribution of tourist attractions. It was not until the proposal of statistical theories based on the distribution model of tourists that scholars began using spatial dynamics methods to analyze the evolution process of destination tourism [14,15]. As a country with an especially high number of tourists, researchers in China mainly focus on the accessibility and traffic accessibility of tourist attractions, including their spatial distribution characteristics, spatial structure evolution patterns, and spatial pattern optimizations [16–18]. Regarding the spatial distribution of tourist attractions, more attention is being paid to the spatial structure characteristics of tourist regions, the influence of transportation infrastructure on the spatial structure of tourist attractions, and the spatial distribution rules of tourist attractions [19–21]. The analysis methods used in existing studies include fractal theory, geographic concentration index, spatial syntax, and spatial statistical analysis [22,23]. The biggest advantage of these spatial analysis methods is that spatial data can be processed, analyzed, and visualized to reveal the spatial relationships and trends concerning the data; for example, the level of geographic concentration index can be used to judge the degree of concentration of the elements within the space. However, these spatial analysis methods are currently more commonly used in the calculation of meso–micro scale spatial data, and they have certain limitations when calculating large-scale spatial data. For instance, spatial syntax can analyze spatial relationships based on road elements within a city, but excessive internal elements in large-scale urban spaces can interfere with calculation results. Therefore, currently, the most widely applied method in the calculation of large-scale spatial data is Kernel Density Analysis; the advantage of this method is that it is not affected by the amount of data, and the results only depend on the subjective setting of the bandwidth. Thus, this study also uses Kernel Density Analysis to analyze the distribution of scenic spots at the macro scale. The spatial distribution scale of tourist attractions ranges from a single attraction to the entire country. For China's tourist attractions, researchers generally believe that their spatial distribution presents a cluster pattern, with tourist attractions mainly being distributed in plain areas, areas near major rivers, and areas with high population density, a high level of economic development, and good transportation infrastructure [24,25]. Research on tourist attractions is constantly improving in terms of content and analysis methods [26]. However, there are still some issues that need to be addressed, mainly due to the limitations of data scale. Contemporary research mainly focuses on the spatial distribution of tourist attractions in individual cities, and there is a lack of research on the spatial distribution of tourism in multiple regions, especially in the context of the national-scale planning of tourism resources [27,28].

Tourist attractions all have their specific regional and core locations. According to contemporary research, the operation of tourist attractions depends on their popularity and whether they are managed efficiently. However, in actual tourism development and management, the current trend is to explore existing tourism resources. Nevertheless, the development of tourism resources should consider both economic benefits and social value, that is to say, if newly developed tourist attractions cannot create value, the development of scenic spots has no practical significance, and from the point of view of tourism management and operation, different tourist attractions exhibit significant differences in terms of regional development level, tourism industry infrastructure, tourist visitor numbers, and the quality and value created by the attractions. Therefore, the question of how to create as much value as possible for the tourist attractions through the coordination and management of tourism resources and upgrading the tourist attractions according to the actual situation of the tourist attractions needs to be comprehensively analyzed in terms of the factors affecting the tourist attractions in order to promote the sustainable development of the tourism industry.

The distribution of tourism resources is a reflection of regional relations, and the emergence of tourist attractions is accompanied by many influencing factors that often determine the coordination of regional tourism resources [6]. Currently, it is believed that the spatial distribution of tourist attractions is influenced by factors such as topography, rivers, GDP, transportation infrastructure, and population distribution. Researchers have quantitatively analyzed these influencing factors in the context of the spatial distribution of tourist attractions using different methods [29], including OLS and GWR models, to analyze the spatial heterogeneity of different attractions' influencing factors [30] and propose factors that affect the creation and improvement of tourist attractions based on the characteristics of different attractions [31]. These studies have adequately explored the distribution patterns of regional tourist attractions. Regarding OLS and GWR models, they can both reveal the impact of explanatory variables on the dependent variable and make predictions. However, before using OLS and GWR models, it is necessary to test for whether there is spatial autocorrelation among the variables. This is because these models may suffer from multicollinearity during the variable computation process, where the input explanatory variables are highly correlated, resulting in ineffective estimates, insignificant significance tests, and reduced prediction accuracy under the assumption of collinearity. Based on this, this study uses a geographical detector for analysis. Compared with other models, a geographical detector has two advantages. First, a geographical detector can detect both numerical data and qualitative data. Second, it can detect the interaction of two factors in relation to the dependent variable. By calculating and comparing the individual factor's q-value and the q-value after adding the two factors, geographical detectors can determine whether there is an interaction between the two factors; if so, the strength, direction, and linearity or non-linearity of the interaction can be also determined. The addition of two factors includes both multiplication relationships and other relationships; as long as there is a relationship, it can be detected. However, on a national scale, there is a certain degree of heterogeneity in the spatial distribution of different attractions due to their own construction priorities, as evidenced by the distribution pattern of AAAAA-level attractions being quite different from that of AAAA- and AAA-level attractions [32], which requires the unified allocation of tourism resources on a national level [33]. Therefore, it is particularly important to analyze the inherent laws behind the distribution of tourist attractions at different levels.

Overall, the geographical spatial structure of tourist attractions is both a response to tourism demand and a manifestation of the continuous improvement of tourism supply levels [34,35]. Although many studies analyzing the spatial layout of tourist attractions and its influencing factors through mathematical statistics and spatial analysis have been conducted, previous studies have mainly focused on the spatial distribution of single tourist attractions or a certain type of tourist attraction [36], with little in-depth research being conducted on the distribution of different levels of tourist attractions and the inherent patterns on a national scale [37]. Therefore, this study aims to analyze the spatial distribution characteristics and influencing factors of AAAAA-, AAAA-, and AAA-level tourist attractions at the national level. On the one hand, analyzing the spatial characteristics of tourist attractions could help researchers clarify the distribution status of China's high-grade tourist attractions. On the other hand, a systematic analysis of the main reasons affecting the spatial differentiation of high-grade tourist attractions could improve the nationwide allocation of tourist resources and thus promote the sustainable development of China's tourism.

2. Materials and Methods

2.1. Study Area

China's tourist attractions are classified into five levels according to the national "Standard of Rating for Quality of Tourist Attractions" [38] (GB/T17775-2003); the five levels are as follows: AAAAA-, AAAA-, AAA-, AA-, and A-level tourist attractions. Among which, AAAAA-level tourist attractions are the highest evaluation standard for tourist attractions in China, representing the world-class boutique tourist attraction level and having high international market visibility. AAAA-level tourist attractions are well known nationwide, with high resource attraction and market appeal, while AAA-level tourist attractions have a certain market appeal in their surrounding provinces and cities [32]. Overall, the AAAAA-level, AAAA-level, and AAA-level tourist attractions all have the characteristics of strong tourism resource quality, perfect infrastructure, good service quality, high management level, great market visibility, and wide influence and are favored by tourists, reflecting the higher level of China's tourism reception capacity, service level, and tourism construction capacity and tourism resource development capacity in China. Therefore, this study selects tourist attractions of AAA-level, AAAA-level, and AAAAA-level as the study objects for analyzing high-level tourist attractions' spatial distribution (Figure 1).

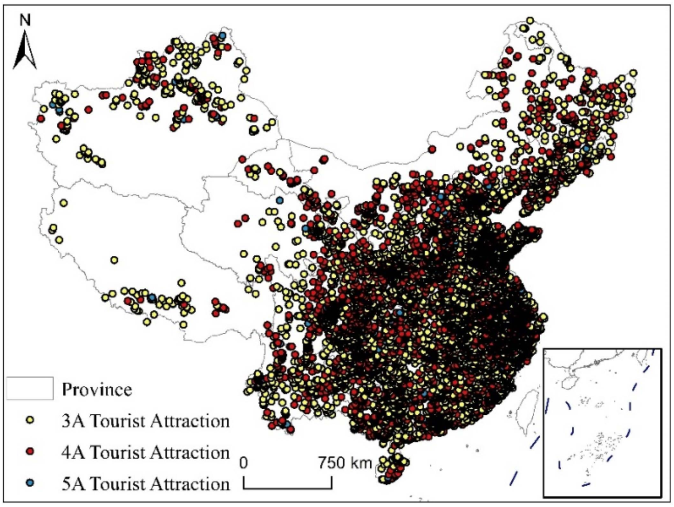

Figure 1. Spatial distribution of high-level tourist attractions.

2.2. Study Data

The data involved in this study mainly include high-level tourist attractions and factors that influence their distribution.

High-level tourist attractions were sourced from the tourism bureaus of various provinces in China. Due to the existence of new establishments and the continuous upgrading and downgrading of A-level tourist attractions, this study concerns all of the AAAAA-level, AAAA-level, and AAA-level tourist attractions considered as such by each province as of the end of 2022. By the end of 2022, through accessing the official websites of the tourism bureaus of different provinces and regions in China, we obtained a total of 9296 high-grade tourist attractions, of which 319 are AAAAA-level scenic spots, 3857 are AAAA-level scenic spots, and 5120 are AAA-level scenic spots. Since the tourism bureaus only provide information on the quantity and names of attractions without specific locations, we preprocessed the data. To represent the spatial locations of these attractions, we used geocoding based on their names to obtain latitude and longitude coordinates. Finally, we mapped these coordinates onto a geographic space to visualize the spatial distribution of the different tourist attractions, as shown in Figure 2.

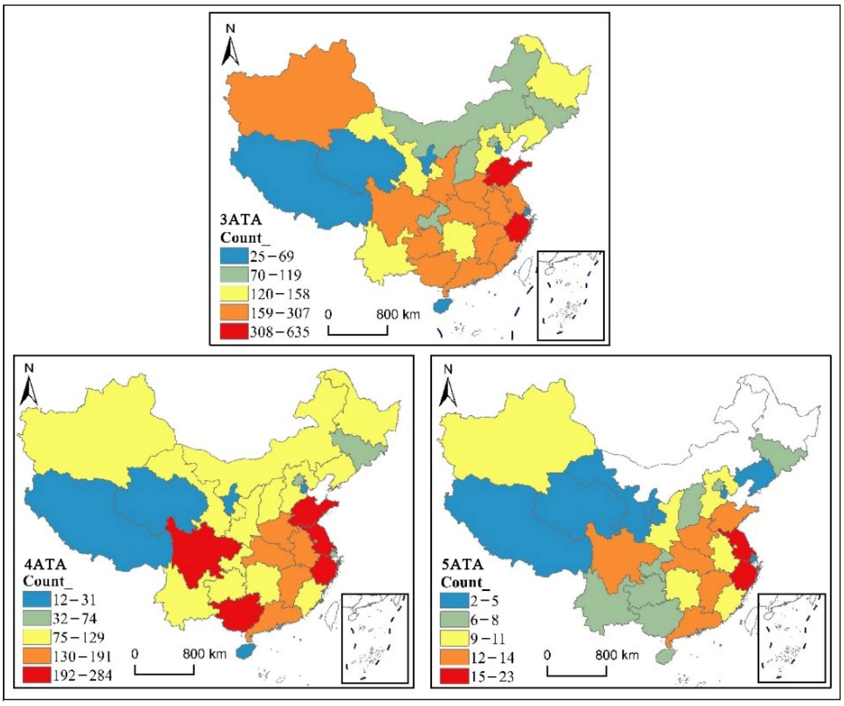

Figure 2. Distribution statistics of the high-level tourist attractions of different Chinese provinces.

The influencing factors affecting the spatial distribution of tourist attractions are different for various reasons. On the one hand, there are differences in the tourist attractions themselves. For example, some attractions highlight natural landscapes, while others focus on culture and history. As a result, the factors that influence the spatial distribution of these two types of attractions are quite different. On the other hand, China has significant regional differences due to economic and geographic variations between its eastern and western regions. Consequently, the factors that cause spatial differentiation in tourism resources are not the same. Therefore, the selection of factors that affect the spatial distribution of tourist attractions will directly determine the subsequent development of tourism resources [28]. As our study involved focusing on the spatial distribution differences among tourist attractions of different levels, we selected factors such as population distribution [21], topography [20], distribution of river systems [39], economic foundation [40], transportation facilities [25], market demand [41], resource allocation [42], and policy support [43] to explore the reasons for the spatial differentiation of different-level attractions based on the existing literature and the general characteristics of high-level tourist attractions in China.

Population distribution: From the perspective of supply, considering the distance decay effect, consumers' distance sensitivity makes them more inclined to visit tourist attractions that are closer in proximity to them, which implies that tourist attractions are typically not located too far from population centers. Moreover, from a demand perspective, the operation of tourist attractions relies on tourism professionals with different levels of skills and qualifications. A large number of tourists and related industry practitioners are attracted to China's tourist attractions, leading to the development of China's substantial tourism industry. Therefore, in order to reflect the relationship between population distribution and tourist attractions, we used the 2022 dataset of China's spatial population distribution as a proxy for population distribution. The 2022 population spatial dataset was sourced from the Chinese Academy of Sciences; it takes into account multiple factors for weighted allocation to convey the spatial distribution of the population. This dataset facilitates data sharing and spatial statistical analysis, making it one of the most precise population datasets currently available for studying the population of China. The dataset is in raster format and can be saved in the form of a geotiff file. We conducted spatial resampling of the acquired data to a resolution of 1 km.

Topography, along with other geographic elements, can enhance the ornamental and taste properties of tourism resources, which can further breed different types of tourism landscapes, enhance the spatial hierarchy of tourist attractions, and enhance the visual impact of tourism landscapes. The topographic data used in the present study was obtained from the advance spaceborne thermal emission and reflection radiometer global digital elevation model website. The original data were in raster format and tiff format, with each scene covering a latitude and longitude of 1 degree. The horizontal and vertical accuracy of the data ranged from 7 to 50 m, with a horizontal resolution of approximately 30 m. To maintain consistency with the spatial resolution of the study, we also resampled the Digital Elevation Model (DEM) to 1 km and extracted slope and aspect information from the resampled DEM using the slope and aspect tools in Arcgis.

River systems and water resources, which directly affect the quality of tourist resources and are also fundamental elements that attract tourists and promote the development of tourist attractions, are important foundations for nurturing different types of landscapes, exerting a strong influence on the location selection of tourist attractions. We used ArcGIS to perform hydrological analysis on elevation DEM data, establish models for surface water flow, and obtain hydrological information for the area. This information was subsequently combined to create a network of river systems in China.

Regional economic foundations and socioeconomic conditions are decisive factors that drive the development of the tourism industry and the development and construction of tourist attractions. The production element supply capacity determined by the regional economic level constrains the scale and quality of regional tourist attractions and plays an important driving role in the spatial structure changes of the attractions. Urban lights can reflect the energy consumption level of a country or region, which is closely related to economic activity. Generally, higher energy consumption indicates more active economic activity, higher productivity, and a higher standard of living. Therefore, by comparing the urban light intensities of different countries or regions, we can roughly determine their level of economic development. Despite not being able to fully represent economic differences, nighttime light data can effectively reflect regional economic development. Therefore, we used nighttime light (NTL) data to roughly indicate the trend of economic development. Since the NPP/VIIRS NTL data have a higher spatial resolution with a wider range of radiation detection compared to other data, we used it to determine the economic development level trend by visiting https://eogdata.mines.edu/download_dnb_composites.html (accessed on 18 August 2023). The obtained data were remote sensing data in raster format. We preprocessed the data; first, this involved removing noise from the data. Then, we gridded the light data, meaning that the original data were converted into grid format for subsequent analysis. Following that, we statistically analyzed the light intensity within the grid data. Afterwards, we labeled geographical information for each grid to facilitate our geographic spatial analysis. Next, we processed the data for visualization in order to enable a more intuitive understanding and analysis. Lastly, the data were resampled to a resolution of 1 km to match the spatial resolution of the other data.

Transportation facilities and networks are important components of the tourism system, and their accessibility directly affects the accessibility of tourist attractions and the time and economic costs tourists must spend to visit them. Transportation conditions refer to the mapping of the spatial layout of tourist attractions, and they have an important controlling role in tourists' behavioral decisions. The transportation road data used in this study were sourced from Open Street Map, which is one of the most detailed sources of local scale map data available, featuring wide coverage and full data volume, and is a non-profit open data source that is completely free to use. We downloaded and obtained all the road data in China as vector line segments by accessing the following website: www.openstreetmap.org/ accessed on 1 June 2023; we corrected the road data using Google Earth and subsequently conducted statistical analysis within spatial grids of 1 square kilometer, obtaining the total length of roads per square kilometer as the transportation condition factor.

The rapid expansion of market demand and tourism demand can provide a good market environment for the development of tourist attractions, driving the continuous appreciation in their quality and quantity. As an important sector of tourism market supply, the rapid development of tourist attractions can stimulate the generation of tourism market demand. We used the number of tourist visits received by different scenic spots within a year to represent their market demand. The number of tourist visit values were sourced from the official websites of the tourism bureaus in the different regions. The data were in tabular format and considered official. In order to maintain consistency with the spatial resolution of other data, we divided the tourist visits received by different scenic spots by the area of the scenic spot; this meant that we could obtain the tourist arrivals per unit square kilometer of the scenic spot, that is, the market demand of the different scenic spots.

The allocation of tourism resources is the foundation for the development and construction of tourist attractions, and to some extent, it determines the competitiveness of tourism destinations. The quality of tourism resources is closely related to the attractiveness and development prospects of tourist attractions, and the allocation of resources in different regions has an essential influence on the spatiotemporal evolution of tourist attractions. To assess the resource allocation of different scenic areas, we calculated it using the resource advantage index. The advantage index for tourist attractions includes both resource abundance and resource quality. Resource abundance refers to areas that are rich in the types of tourism resources that are more attractive than that of areas that are rich in tourism resources of a lower quality; high-quality tourist resource areas are more appealing than areas with numerous general-grade tourist resources. The formula for calculating the abundance of tourism resources is as follows: $R_i = \frac{M_i}{\sum_i M_i}$. In this formula, R_i is the abundance of tourism resources in area i, and M_i is the number of tourism resource types in area i. The classification of the tourism resource types was carried out according to the standard of "Classification, Investigation, and Evaluation of Tourism Resources in China" [44] (GB/T18972-2003). The higher the number and diversity of tourism resource types, the greater the abundance value. The studied tourism resources included A-level and above scenic areas, national scenic spots, national nature reserves, national forest parks, national key cultural relics protection units, historical and cultural cities, and national industrial tourism demonstration zones. These data were obtained from statistical surveys and were in tabular format. Tourism resource quality is an indicator that measures the level of quality of the tourism resources within a region, which can be calculated by summing up the weighted quantity of high-quality tourism resources in the region, reflecting both the quantity and quality characteristics of the tourism resources. This was represented by using the following formula: $Q_i = \frac{P_i}{\sum_i P_i}$. Here, Q_i is the tourism resource quality of region i, and P_i is the quantity of high-level tourism resources (scenic areas) in region i. For calculating the quality, AAAAA-level and AAAA-level scenic areas, national scenic spots, national key cultural relics protection units, national nature reserves, national forest parks, and national industrial tourism demonstration zones were considered as high-level scenic areas. The quantity of high-quality tourism resources (scenic areas) was calculated by taking a weighted sum of the quantity of high-level resources, where AAAAA-level and AAAA-level scenic areas were multiplied by 5 and 4, respectively; national scenic spots, national nature reserves, national forest parks, national industrial tourism demonstration zones, and national historical and cultural cities were multiplied by 1; and national key cultural relics protection units with a higher tourism value were multiplied by 1, and the rest were multiplied by 0.5. These data were obtained from statistical surveys (in tabular format). By combining the tourism resource abundance and quality, the degree of regional tourism resource advantage can be obtained using the following formula: $A_i = R_i \times Q_i \times 100\%$. In this formula, A_i is the resource allocation level of different scenic areas.

Policy support and guidance are reflected not only in macro-level planning differences but also in the governance of regional tourism regulations. Thus, government policy bias and incentive mechanisms often greatly promote the formation of the spatial distribution pattern of tourist attractions. For this study, we represented local policy support for tourism and related industries by using the public fiscal expenditures of different local governmental levels. Policy support is generally provided in the form of funding and policies. Since it is difficult to quantitatively measure the results achieved by policies, we used the public financial expenditure of the relevant governing bodies of different scenic areas as a proxy for local support for the tourism industry. Data on public financial expenditure were sourced from local statistical yearbooks; these data are presented herein in tabular format. Based on these statistical yearbooks, we obtained the public financial expenditure of different prefecture-level cities for their respective regions. Finally, we mapped the financial expenditure results onto spatial grids of 1 square kilometer.

For these influencing factors, since raster data, vector data, and tabular data were used to represent the factors, in order to process these data and make the spatial resolution uniform and convenient to calculate, we spatially resampled the raster data to 1 km, while the vector data and tabular data were factored into the spatial grid of 1 square kilometer, respectively, and the spatial resolution of the final data obtained were all 1 km.

2.3. Study Method

2.3.1. Kernel Density Analysis

Kernel density analysis is a method that can be used to simulate the spatial distribution of geographic points and lines by calculating their density, reflecting the aggregation form of point and line features in space [45]. The formula for kernel density analysis is as follows:

$$p_i = \frac{1}{n\pi R^2} \times \sum_{j=1}^{n} k_j \left(1 - \frac{D_{ij}^2}{R^2}\right)^2 \tag{1}$$

where p_i is the kernel density value of spatial location, D_{ij} is the distance between spatial point i and study object j, n is the spatial location with distance less than or equal to to D_{ij}, k_j is the spatial weight, and R is the search radius. The geometric meaning of kernel density analysis is that the density value is highest in each core, and spatial distance increases will lead to a decrease in density until the kernel density value is 0. In addition, different search radii will lead to different kernel density analysis results; thus, we determined the results of our kernel density analysis by verifying the search radius, which was calculated by using the following formula:

$$0.9 \times min\left(SD, D_m \times \sqrt{\frac{1}{ln2}}\right) \times n^{-0.2} \tag{2}$$

where SD is the standard distance, D_m is the median distance, and n is the number of event points. We used kernel density analysis to reflect the spatial distribution characteristics of different levels of tourist attractions on a national scale. We implemented kernel density analysis by using Arcgis 10.5. In Arcgis 10.5, we imported a total of 9296 high-level tourist attractions, 319 AAAAA-level tourist attractions, 3857 AAAA-level tourist attractions, and 5120 AAA-level tourist attractions, respectively, and carried out a total of four calculations to obtain spatial distribution results for tourist attractions of different levels.

2.3.2. Local Spatial Autocorrelation

To explore the spatial patterns or distribution characteristics of the different-level tourist attractions, we used a spatial autocorrelation index to measure their spatial correlation. The degree of correlation can reflect the spatial patterns and distribution characteristics of the attribute. Anselin Local Moran's I can be used to test whether there is variable clustering in a local area, as well as the degree and significance of spatial differences between its surrounding units [46,47]. Local indicators of spatial association (LISA) are commonly used in analyses. LISA decomposes Global Moran's I into each spatial unit and forms a LISA aggregation map through verification, which can reflect the specific location of spatial aggregation or the differentiation of variables in the research unit and its neighborhood, revealing the regions that have a greater impact on the overall correlation. The formula for local spatial autocorrelation is as follows:

$$I_i = \frac{(x_i - \overline{x})}{S^2} \sum_j w_{ij} (x_j - \overline{x}) \quad (3)$$

Anselin Local Moran's I can be combined with Z-tests in statistical analysis to identify the spatial correlation patterns with a 95% confidence level, such as HH (high–high clusters), LL (low–low clusters), LH (high-value outliers surrounded by low values), and HL (low-value outliers surrounded by high values). For our local spatial autocorrelation analysis, we used Geodata to calculate the local spatial autocorrelation; in Geodata, we first set the spatial weights based on different high-level scenic area data, and the weight field was ID. Then, we imported the spatial locations of AAAAA-level, AAAA-level, and AAA-level scenic areas to facilitate the local autocorrelation calculation and cluster mapping of the obtained results, respectively.

2.3.3. Geographical Detector

Geographical detector models contain a set of statistical methods that reveal the driving forces of geographic features or phenomena by detecting their spatial differentiation. A geographical detector can explore the geographic correlations between different phenomena and allow researchers to use its advantage in spatial regression to explore the spatial heterogeneity of the effects of influencing factors. Due to the lack of excessive assumptions, a geographical detector has a clear advantage in dealing with different types of data [48,49]. In this study, a geographical detector model was used to explore the heterogeneous characteristics that influence the differentiation of mining development in different levels of tourist attractions. The formula for the geographical detector used is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{m=1}^{L} N_m \sigma_m^2 \quad (4)$$

where q is the explanatory power of regional geographic environmental factors; m equals to 1, 2,. . .; L is the number of categories; N_m and N are the number of layers m and the number of cells in the whole region, respectively; and σ^2 is the variance of the index. The value of q ranges from 0 to 1, and the larger the value of q, the stronger the explanatory power of spatial heterogeneity. In the process of data processing, population distribution, topography, river system distribution, economic foundation, transportation facilities, market demand, resource allocation, and policy support were processed into 1 km spatial data; thus, we could first perform spatial sampling on different influencing factors and then output sampling points. Subsequently, we employed Geodetector_2018_Example software for geodetector operation purposes, for the setting of independent variables and dependent variables, and for obtaining the results.

3. Results

3.1. Spatial Distribution Differences of High-Level Tourist Attractions

This study analyzes the spatial layout characteristics of Chinese tourist attractions of AAA-level, AAAA-level, AAAAA-level and presents them visually. The results show that the density of tourist attractions is higher in the east and south, gradually decreasing from east to west. The density of tourist attractions in the west and north is relatively low, with only a certain size in Xinjiang and Ningxia provinces. From a provincial perspective, the more concentrated distribution is in Beijing, Shandong, Henan, Shanxi, Jiangsu, Zhejiang, Anhui, Hubei, Hunan, Shaanxi, Guangdong, Guangxi, Fujian, Chongqing, and Sichuan. The density of Yunnan, Guizhou, Hainan, and other provinces and cities is relatively uniform. Xinjiang, Qinghai, Gansu, and Tibet do not show a large-scale aggregation of distribution. Overall, the geographic distribution of AAA-level, AAAA-level, AAAAA-level tourist attractions in China exhibits a regional differentiation feature, with an uneven distribution, and the proportion of tourist attractions in the eastern and western regions is extremely imbalanced.

The spatially concentrated distribution areas of China's AAAAA-level tourist attractions include eastern regions such as Beijing and Shanghai, where the AAAAA-level attractions are relatively clustered. The number of AAAAA-level attractions in the northwestern provinces is relatively low, which may be attributed to factors such as the vast territories, sparse populations, underdeveloped transportation facilities, and lagging economies in these regions.

China's AAAA-level tourist attractions are distributed along the Yangtze River and Yellow River water systems. They are concentrated in the Chongqing–Hubei–Anhui–Jiangsu–Shanghai axis along the Yangtze River and the Shaanxi–Shanxi–Henan–Shandong axis along the Yellow River, as well as other contiguous areas such as Beijing and Guangdong. In general, AAAA-level attractions are mainly located in the central and eastern regions of China, followed by the northeastern region; very few attractions are located in the western region.

The distribution of China's AAA-level tourist attractions shows a linear distribution along the coastline, with the most dense provinces in Beijing and Shandong, followed by Jiangsu, Anhui, Chongqing, and Guangdong, and again by Liaoning, Shaanxi, Shanxi, Hunan, Hubei, and Henan, while the western region remains sporadically distributed. Compared with the AAAAA-level and AAAA-level attractions, the concentration of AAA-level attractions has increased in the northeastern region, and their concentration in other areas has also seen a relative increase (Figure 3).

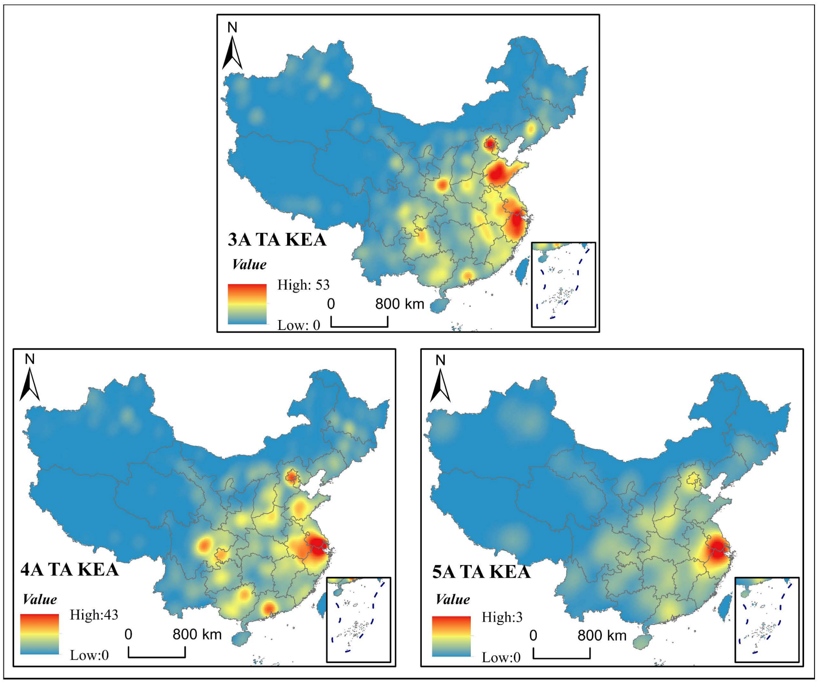

Figure 3. Kernel density analysis of China's AAA-level, AAAA-level, and AAAAA-level tourist attractions.

We also analyzed the clustering relationships between different tourist attractions through local spatial autocorrelation. The HH cluster indicates that there are high densities of tourist attractions in its own area as well as in the surrounding provinces, where there are also other tourist attractions with high densities. The LH cluster represents areas with low tourist attraction densities but with high densities in the surrounding areas, where development is restricted by the "siphon effect" of the surrounding HH cluster. The HL cluster represents areas with high tourist attraction densities but with low densities in the surrounding areas, and the driving effect on the development of the surrounding tourist attractions is not significant. The LL cluster represents areas where both its own and surrounding tourist attraction densities are low. As shown in Figure 4, HH-clustered AAAAA-level tourist attractions are mainly distributed in central provinces such as Hunan, Hubei, Jiangxi, and Fujian, while HL-clustered tourist attractions are distributed in Hebei and Beijing. HH-clustered AAAA-level tourist attractions are mainly distributed in Jiangxi, Hubei, Jiangsu, and Guizhou, while LH clusters are distributed in Fujian, Hunan, Chongqing, and Yunnan. HH-clustered AAA-level tourist attractions are mainly distributed in Henan, Jiangxi, Zhejiang, and other places. In terms of the cluster distribution of different tourist attractions, the HH clusters are generally located in the east–central part of China, east of the Hu line. Generally speaking, the spatial correlation of tourist attractions in the eastern region is the strongest, and the correlation effect gradually weakens towards the western region. Therefore, in the future, it is necessary to focus on the growth of key clusters of tourist attractions to promote tourism development.

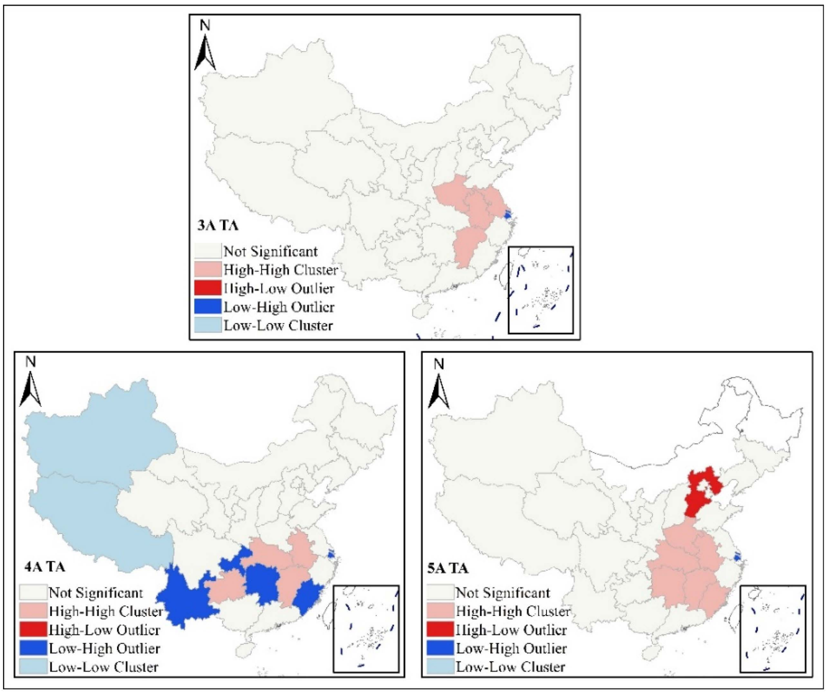

Figure 4. The spatial clustering of China's AAA-level, AAAA-level, and AAAAA-level tourist attractions.

3.2. *Factors Influencing the Spatial Differentiation of High-Level Tourist Attractions*

Geodetector can be used to detect spatial variations and reveal the driving forces behind them. Its core idea is based on the assumption that if an independent variable has a significant influence on a dependent variable, their spatial distributions should exhibit similarity. Geodetector is adept at analyzing categorical variables, but for ordinal, ratio, or interval variables, appropriate discretization can be applied to conduct statistical analysis using geodetector as well. Regarding the results derived from the use of geodetector, their significance lies in analyzing the spatial heterogeneity of the detection variable Y and examining to what extent a factor X explains the spatial variation of variable Y (measured by the q-value). If the stratification is generated by the independent variable X, a larger q-value indicates a greater consistency between the spatial distributions of X and Y, demonstrating the stronger explanatory power of the independent variable X on the attribute Y and vice versa. Another unique advantage of geodetector is its ability to detect the interaction between two factors on the dependent variable. The typical approach used to identify interaction effects involves including the product term of the two factors in a regression model and testing its statistical significance. However, the interaction between two factors is not necessarily a multiplicative relationship. Geodetector can determine whether there is an interaction between two factors and whether the interaction is strong, weak, directional, linear or nonlinear, etc., by calculating and comparing the q-value of each single factor and the q-value of the superposition of the two factors, respectively. Therefore, from the results derived from the use of geodetector, we can deduce the impact of the factors involved in our study and their relationship with each other.

From the results of our geographical detector analysis, the influencing factors of different level tourist attractions distribution are different. Overall, population distribution, economic foundation, and transportation facilities are the main influencing factors that affect the spatial distribution of high-level tourist attractions. However, the effects of different factors on the distribution of tourist areas vary (Figure 5). The main influencing factors for the distribution of AAAAA-level tourist attraction are population, economy, transportation facilities, and policy support. The main factors for the distribution of AAAA-level tourist attraction are population, economy, transportation facilities, and market demand. The primary factors for the distribution of AAA-level tourist attraction are population, economy, and transportation facilities. The role of topography and river systems in the distribution of different levels of tourist attractions is roughly the same, mainly affecting tourism resource quality, while administrative division often causes the fragmented development of resources for the same large natural geographical entity, leading to similar results in spatial analysis.

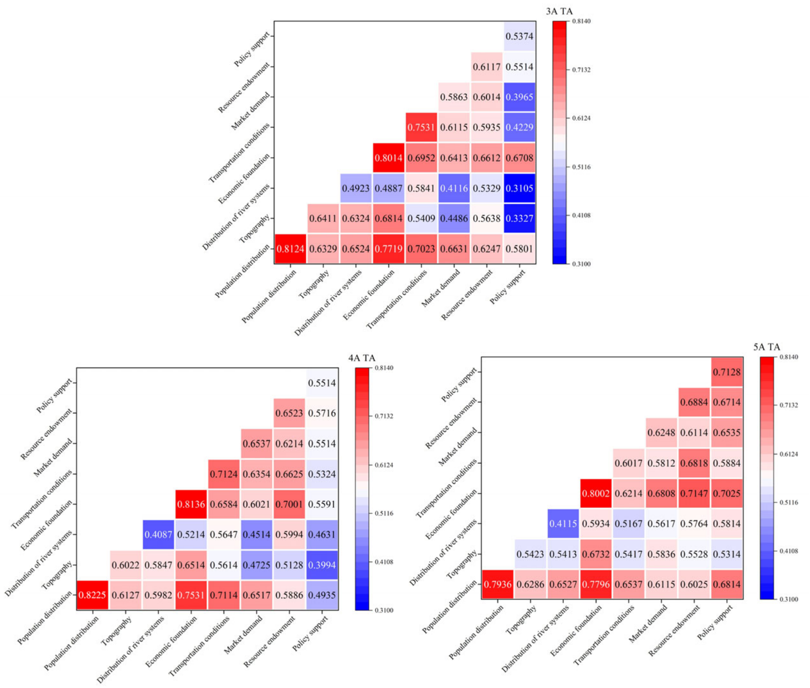

Figure 5. Influencing factors of spatial distribution of high-level tourist attractions in China (based on the results derived from using geodetector, there are horizontal and vertical coordinates in the graph; when the horizontal and vertical coordinates are the same, it indicates the degree of the effect of a single factor, and when the horizontal and vertical coordinates are different, it indicates the interaction between the two factors. Higher values indicate that the interaction has a higher degree of influence on the spatial distribution of the scenic area).

Combining the results of geographical detector analysis and the actual development of tourist attractions, population and economic development levels are the two main factors that determine the scale required for the operation of tourist attractions. That is, when the economic development level reaches a certain level, there will be sufficient demand for tourism consumption, so the total population size of the region is usually the first factor to consider in the construction of high-level tourist attractions. Therefore, more than 50% of high-level tourist attractions are distributed in the eastern region, where the population and economic development are higher. Transportation facilities also have a significant impact on the distribution of tourist attractions, and this is because high-level tourist attractions have regions with greater tourism resources, especially AAAAA- and AAAA-level tourist attractions. The construction of these tourist attractions mainly considers the traffic conditions of airports, railways, and expressways at the provincial and municipal levels. Among them, cities with better accessibility are mainly distributed in the central and eastern regions, and AAAAA-level and AAAA-level tourist attractions also are mainly distributed in these regions. Finally, for tourism management departments and governments, policies are often made with AAAAA-level tourist attractions in mind, as AAAAA-level tourist attractions represent the tourism image of the country and region to a certain extent.

In order to verify the accuracy of the results of the spatial distribution of the factors influencing the spatial distribution of higher-level tourist attractions in China based on our geodetector analysis, we used an alternative approach to validate our research results. Due to its ability to effectively explain spatial non-stationarity, the Geographically Weighted Regression (GWR) model was utilized. The GWR model estimates parameters by borrowing data from neighboring sample points while considering multiple bandwidths to address this limitation, thus identifying the scale effects of different variable influences. Therefore, in this study, we used GWR to investigate the spatial non-stationarity and scale effects between the spatial distribution of different-level attractions in China and other factors. The results are presented in Table 1.

Table 1. Results of geographically weighted regression analysis for influencing factors.

5A TA		4A TA		3A TA	
Variable	**Mean Value**	**Variable**	**Mean Value**	**Variable**	**Mean Value**
Population distribution	4.361	Population distribution	5.014	Population distribution	4.715
Topography	2.354	Topography	0.758	Topography	0.968
Distribution of river systems	−1.047	Distribution of river systems	−1.217	Distribution of river systems	−2.113
Economic foundation	3.142	Economic foundation	4.109	Economic foundation	5.221
Transportation facilities	2.001	Transportation facilities	3.247	Transportation facilities	1.589
Market demand	0.907	Market demand	2.991	Market demand	2.674
Resource allocation	1.671	Resource allocation	2.178	Resource allocation	3.008
Policy support	0.117	Policy support	0.469	Policy support	3.447

The results of our geographical weighted regression analysis include average value, maximum value, minimum value, etc. The average value is generally used to reflect the results of its influencing factors, that is, in the average value, a higher value in the average indicates a higher degree of influence.

From the results of our geographically weighted regression analysis, the influence patterns and trends of different factors align with those derived from the use of the geodetector, demonstrating the validity of using geodetector calculations in this study. Regarding the results of the influencing factors, overall, although China currently has a large number of high-level tourist attractions, the distribution of tourist attractions is uneven [50]. Moreover, the main factors influencing the spatial distribution of different-level attractions are not exactly the same. Based on the results derived from our use of the geographical detector, in subsequent tourism development plans, more attention should be given to the actual market demand and the balance of resources among regions to develop and enhance high-level tourist attractions and thus promote sustainable tourism development.

4. Discussion

Since the distribution pattern of tourist attractions is related to the macro allocation of tourism resources and the sustainable development of tourist attractions, the distribution pattern of tourist attractions has always been the focus of tourism-related studies [36]. Based on the spatial distribution of high-level tourist attractions in China, this study explores the spatial correlation between tourist attractions and the factors that influence the distribution of tourist attractions of different levels. Compared with previous studies on tourist attractions, this study is more comprehensive and in-depth, which makes our explorations of the distribution patterns of tourist attractions more accurate, and analyzing the development of tourist attractions and the allocation of tourism resources based on these patterns at a national level is more reasonable.

The level of tourist attractions determines the scale and flow of regional tourism, thereby guiding the direction of the consumption of regional tourism [51]. Our analysis of different-level tourist attractions shows a significant differentiation in the spatial distribution of high-level tourist attractions [52]. Among them, AAAAA-level attractions are mainly distributed in areas with larger populations, more developed economies, and superior transportation facilities. AAAA-level attractions are mainly distributed in the central and eastern regions, with a stronger correlation with landscape elements, while AAA-level attractions are mainly distributed in the eastern region, with a stronger correlation with economic development [53,54]. Although the results of this study are generally similar to the results of other studies on the spatial distribution of tourist attractions, we also analyzed the correlation effect between different tourist attractions on the basis of their spatial distribution, which has significant implications for the coordinated construction of different-level tourist attractions.

From the perspective of the dominant influencing factors of the distribution of tourist attractions at different levels, market demand and the allocation of tourism resources are important factors for the sustainable development of China's high-level tourist attractions in the future. From the perspective of market demand and tourism resources, the scale of high-level tourist attractions is actually limited, and different levels of tourist attractions should be classified and regulated with a focus on optimization [55,56]. For AAAAA-level attractions, the total balance should be maintained and effectively controlled on a national scale, shifting from mass approval to focusing on improving the quality of AAAAA-level attractions and optimizing and enhancing the driving force of the attractions on surrounding tourism resources, thus building high-quality attractions that can truly reflect the image of China. For AAAA- and AAA-level attractions, the aim should be to meet the increasingly growing demand for leisure tourism and cultural consumption, and special attention should be paid to the construction of facilities and service capabilities to better serve tourists and achieve the sustainable development of tourist attractions [57].

Regarding analyses of the factors that influence the spatial distribution of tourist attractions, due to the availability of data, they are still mainly regional and qualitative. In this study, we analyzed the distribution differences of China's high-level tourist attractions in a detailed and comprehensive manner, considering aspects such as population distribution, topography, river system distribution, economic foundation, transportation facilities, market demand, resource allocation, and policy support. We also summarized the main factors affecting the distribution of different-level attractions. There are few studies on the spatial distribution of high-level tourist attractions across China that adopt a smaller-scale approach (e.g., examining the spatial distribution characteristics of tourist attractions in certain provinces and regions). In terms of influencing factors, compared to other studies, this study does not simply qualitatively analyze the potential effects of different factors on the distribution of tourist attractions from different perspectives. Instead, it quantitatively and uniformly expresses the different influencing factors in certain regions and derives different influencing factors from spatial calculations. In addition, factors such as market demand and the allocation of tourism resources, which have been less extensively considered in the literature but have significant effects on the spatial distribution of tourist attractions, are quantitatively expressed. This is rarely reflected in contemporary studies on the spatial distribution of tourist attractions and the and the factors that influence their distribution.

This study focused on analyzing the spatial distribution of tourist attractions in China and their influencing factors. We believe our study has made a worthwhile contribution to the literature; however, it still has certain limitations and aspects that could be improved in future. Firstly, regarding the classification of tourist attractions, this study considered different-level tourist attractions, but in reality, tourist attractions can be further subdivided based on their different attributes (e.g., natural attractions and cultural attractions), and their spatial distribution and influencing factors may have significant differences. Secondly, to a certain extent, the construction of high-level attractions relies on the changes in the assessment indicators and the cumulative cycle triggered by the development timeline. With the implementation of high standards for China's A-level attractions, the assessment indicators for construction and approval increasingly focus on supporting facilities and service functions. In the central and eastern regions, where the quality of resources is generally average, it is not difficult to achieve high-level attraction status through careful design and construction. However, in the western regions, which are more remote, have poor accessibility, are less attractive to investors, and have greater market barriers, only some areas that have particularly exceptional resources and/or landscapes enter the high-level attraction category, and this was scarcely considered in the present study. Therefore, the spatial distribution of Chinese tourist attractions still requires a detailed and comprehensive analysis to rationally promote the sustainable development of tourism resources.

5. Conclusions

Based on the spatial distribution characteristics of tourist attractions of different levels and the dominant influencing factors of tourist attractions, this study focused on exploring the distribution pattern of high-level tourist attractions in China. The spatial distribution features of high-level tourist attractions in China are polarization and regional clustering, and there exist certain spatial correlation effects among these attractions, with the distribution of high-level tourist attractions being closely related to population distribution, economic development, and transportation facilities. However, different influencing factors play different roles in determining the spatial distribution of attractions of different levels.

This study has positive practical significance for the development of China's tourism sector and its related industries. Firstly, regarding the development of new tourist attractions, we found that the total scale of high-grade tourist attractions has achieved a balance when considering market demand and tourism resources. In the future, more focus should be placed on classifying and regulating tourist attractions at different levels to promote the sustainable development of higher-level tourist attractions. Secondly, in terms of the management of tourist attractions, factors such as population distribution, economic development levels, and transportation facilities are all important factors that influence the distribution of tourist attractions. Therefore, to achieve the efficient management of tourist attractions, the relevant stakeholders should focus on improving the attractiveness of the attractions, accelerating the development of the regional economy, and improving public infrastructure. It is also important to provide comprehensive supporting facilities for tourism-related industries. Lastly, in terms of the operation of tourist attractions, their operation should not only consider individual attractions but also take into account the advantages and distribution characteristics of different attractions at a regional scale, which involves efficiently allocating tourism resources to maximize the utilization of tourism-related resources. This study has provided an in-depth discussion on the distribution pattern of tourist attractions in China, and its results could have important implications for the future development of China's tourism industry and the optimal deployment of tourism-related resources.

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