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Analysis of High-Quality Tourism Destinations Based on Spatiotemporal Big Data—A Case Study of Urumqi

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Abstract: Although high-quality tourism destinations directly determine the tourism experiences of tourists and the management focuses of tourism management departments, existing studies have paid little attention to the relationship between tourism destinations of differing quality and tourist experiences. This study analyzed the spatiotemporal distribution of tourists and the quality of tourism destinations in Urumqi based on Tencent migration big data and Weibo sign-in big data and ultimately determined whether there are spatial correlations between the two. The results show that there are large differences in quality between different tourist destinations, and although the spatial and temporal distribution of tourists is not strongly correlated with the quality of tourist destinations, we can divide tourist destinations into four categories based on the correlations between the two (e.g., high-quality tourist destinations with a low number of tourists). The results of this study provide tourists with examples of high-quality tourist destinations, thus improving their holiday experiences, and they also provide a basis by which tourism management departments can manage and develop tourist destinations. The results of this study can also be extended to other regions and play a positive role in promoting the development of the tourism industry.

Keywords: tourism destination; Tencent migration; Weibo sign-in; spatial correlation; tourism experience

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1. Introduction

With the rapid development of the economy and the continuous improvement in people's living standards, tourism has become a way of improving quality of life and expressing individuality [1–3]. A tourism destination is a region where tourist activities take place; this can be either a special tourist site or any area in a city where tourist activities occur. It is one of the most important parts of the entire tourism process [4,5]. Creating high-quality tourism destinations can provide tourists with high-quality experiences and improve the overall living environments in an area, thereby pleasing locals and attracting visitors from far and wide [6]. Therefore, for tourists, choosing high-quality tourism destinations is important for obtaining a good tourism experience [7,8].

The factors determining the selection of a tourism destination can be divided into two categories. One is the tourist's own motivation for travelling, which specifically includes factors such as escaping familiar environments, leisure and relaxation, expanding their horizons, pursuing physical and mental health, socializing, and nostalgia [9–11]. The other includes the individual characteristics of the tourist, such as gender, age, income, education level, and family commitments. These have important effects on an individual's choice of tourism destination [12–14]. Tourists may also develop a desire to travel due to the perceived attractions of a particular tourism destination [15]. This can be affected by information stimulus, i.e., various factors that affect the subjective perceptions, decisions, and behaviors of tourists such as advertising, online posts, word-of-mouth marketing

(WOMM), recommendations from friends and relatives, travelogues, and information published on various travel forums and in virtual communities [16–18]. Destination factors also play a role, and these can be divided into two categories: destination attributes and destination resources. Destination attributes are abstract summaries of the basic characteristics of a destination, including the destination's image, its perceived distance, its local social environment, its transportation conditions, the cost, etc. Destination resources are the specific tourism attractions that the destination possesses and the tourism products and services developed based on these. They can include natural resources, such as the seaside, forests, hot springs, and grasslands, as well as cultural resources, such as ethnic customs, folk activities, intangible cultural heritage, and corresponding tourism products [19–22]. Additionally, journey factors are a newly emerging type of influencing factor that are quite different from those traditionally affecting tourism [23,24]. The processes by which tourists choose tourism destinations are thus very important and complicated [25]. How to choose high-quality tourism destinations is an important consideration for the development of tourism-related studies, and it is also of great importance to tourists and tourism management departments (tourism management departments include administrative authorities responsible for local tourism industries, such as the Department of Culture and Tourism, as well as actual destination management organizations, such as scenic area operational departments) [26] (Table 1).

Table 1. Attractive elements of tourism destinations.

Attractive elements of tourism destinations	Destination information stimuli	Destination information stimuli encompass various factors that influence tourists' subjective perceptions and decision-making behaviors. These stimuli include destination advertisements, online posts, word-of-mouth marketing, recommendations from friends and relatives, travelogues, and travel guides posted on various tourism forums and in virtual communities.
	Destination attributes	Destination attributes are abstract summarizations of a destination's basic characteristics. These include destination image, perceived distance, local social environment, transportation conditions, and cost.
	Destination resources	Destination resources are the specific tourist attractions a destination possesses, as well as the corresponding tourism products and services. These can include natural resources, such as beaches, forests, hot springs, and grasslands, as well as cultural resources, such as ethnic customs, folklore activities, intangible cultural heritage projects, and corresponding tourism products.
	Travel factors	Travel factors specifically refer to the different influencing factors that lead tourists to choose different travel destinations during their travel experiences.

2. Literature Review

Tourists behave differently based on the quality of their tourism destination. Therefore, how to analyze the quality of tourism destinations has become the focus of many studies [27,28]. Currently, this analysis is mostly based on the number of visitors, that is, the quality of tourism destinations with more tourists is considered higher than those with fewer tourists [29–31]. However, from the perspective of actual tourism choices, this may not be entirely accurate. For example, the tourism experience at some niche tourism destinations is often better than that at well-known and popular mainstream tourism destinations [32]; therefore, tourism destinations with more tourists do not necessarily have higher quality [33]. As it is difficult to evaluate the quality of a tourism destination using traditional data, more and more scholars have started to pay attention to the big data generated when tourists share their tourism experience on social platforms such as Weibo and WeChat. These experiences can better reflect the quality of a tourism destination as evaluated by tourists [34–36] and provide valuable data for the quality analysis of tourism destinations.

Currently, data collection from social media-based sharing of travel experiences primarily focuses on tourists' spatiotemporal behavior [37], including the use of images with geographic information to analyze tourist density, points of interest, and trajectories, and aims to obtain the length of stay of tourists in local tourism destinations to reveal their concentration and spatiotemporal flow characteristics [38]. Additionally, photos posted on social media are analyzed to obtain the different behavioral characteristics of tourists by examining their movement trajectories in space and time [39]. From the perspective of travel experiences, spatiotemporal big data based on social media can uncover valuable high-level information and thus play an important role in understanding tourists' spatiotemporal behavior [40]. As one of the most important social media platforms in China, Weibo sign-in data has the advantages of wide coverage, high accuracy, and easy access. Therefore, using Weibo sign-in data could provide a new perspective and approach for studying tourist activities [41,42]. It can be used to analyze tourists' spatiotemporal dynamics, including their emotional response to different tourism destinations, and thus obtain quality evaluations for these destinations [43]. This would be beneficial for tourism management departments to accurately grasp tourist flow trends and conduct customer monitoring, warning, and flow control management, thereby achieving balanced and sustainable development of tourism destinations. It could also be helpful in providing tourists with timely scenic spot travel strategies, making it easier for them to choose the best leisure route and improve their experience [44].

Many studies have shown that there is a certain correlation between the spatial distribution of tourists and the quality of tourism destinations. However, this spatial correlation is not necessarily positive, that is, it is not guaranteed that tourism destinations with more tourists are of higher quality [45,46], yet this finding has been mostly ignored in previous research. Data from such correlation studies are mostly based on the statistics of tourist numbers in different scenic spots or questionnaires taken by tourists [47]. However, the feedback time for these data is generally too long, and the analysis results are somewhat one-sided. The scope of a tourism destination often lacks clear boundaries, especially for destinations that are different from traditional tourist attractions [48], thus the spatiotemporal distribution of tourists at a tourism destination is an important prerequisite for analyzing the relationship with the tourism destination's quality [49]. Currently, many studies have determined the population distribution of regions using population big data, such as the data from the Baidu Heat Map and Tencent migration, etc. [50]. The Baidu Heat Map has high temporal resolution, but a limited pixel value range and low spatial resolution due to being grid data after grading, making it difficult to compare the population agglomeration degree of different city centers [51]. In comparison, although Tencent migration big data also represent a type of population distribution heat map, the data come from recording the location information of Tencent's related online products in the form of spatial point data (with a 25 m interval) [52]. Tencent migration has the characteristics of low acquisition cost, high spatial resolution, and real-time dynamic changes and can characterize the urban spatial structure from the perspective of population dynamic changes. This makes up for many deficiencies in traditional census data and existing big data, providing a new source for quantitatively identifying spatial patterns within cities [53,54]. Therefore, we attempt to use Tencent migration big data as a real-time feedback data source for the spatial distribution of tourists in different tourism destinations [51].

In terms of the bandwagon effect in tourism, there is a clear polarization in the choice of tourist destinations. The number of tourists visiting highly rated and high-quality tourist attractions is much higher than the number visiting those with average ratings and low quality, which is a result of the influence of normative social influences and receiving tourism information. Since the majority of tourists have limited knowledge about the tourist destinations they are heading to, and this knowledge mostly comes from other people or the internet, their understanding is vague when engaging in tourism activities. Therefore, they are more inclined to refer to the behavior of others. Additionally, tourists prefer affirmation, approval, and acceptance from others when engaging in tourism activities, in order to avoid violating certain normative expectations. Hence, when tourists are choosing tourist destinations, there is a clear polarization and it is crucial for tourists to know how to choose high-quality tourist destinations.

Urumqi is home to a large number of tourist attractions, and, with its unique location and abundant tourism resources, it has become an important region for the development of China's tourism industry [55]. Although still relatively scarce, research exploring the patterns between the spatial distribution of tourists and the quality of different tourism destinations using Tencent migration big data and Weibo sign-in big data can accurately predict tourist flow trends and highlight the preferences of different tourists, thus providing scientific and effective strategies and suggestions for the management and development of tourism destinations and the development of the tourism industry [56].

Therefore, based on spatiotemporal big data (Tencent migration big data and Weibo sign-in big data), this study explored the relationship between the spatial distribution of tourists and the quality of tourism destinations in Urumqi and puts forward strategies and recommendations for the future development of Urumqi's tourism industry based on the differences between the two. This will not only provide a reference for tourism management and planning, but also serve as an important basis for improving tourist experiences.

3. Materials and Methods

3.1. Study Area

Urumqi is the capital city of Xinjiang, China, located at 86°37′33″–88°58′24″ E, 42°45′32″–45°00′00″ N (Figure 1) with a total area of 13,800 km^2, a resident population of 4,082,400, and an urbanization rate of 96.1%, as of 2020. Urumqi received more than 80 million tourists in 2020, and the revenue from tourism-related industries accounted for nearly 30% of its GDP, making it one of China's primary tourist cities [57]. Although Urumqi has abundant tourism resources, different tourism destinations have environmental, geographical, and developmental differences, thus providing different travel experiences to tourists. Therefore, if the spatial correlation between the quality of Urumqi's different tourism destinations and the spatiotemporal distribution of its tourists could be analyzed, it would be of practical significance in improving the tourists' travel experiences and thus promoting local tourism development in Urumqi.

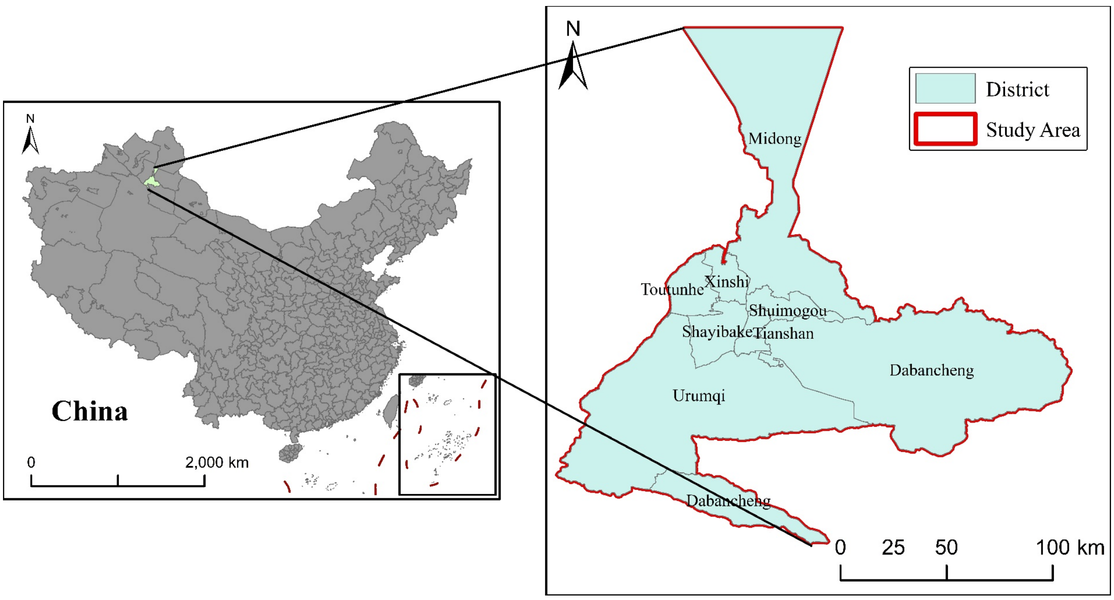

Figure 1. Study area.

The Tianshan District is the administrative center of Urumqi and the main location of government offices. The Shayibake District is the economic and trade center of Urumqi, while the Shuimogou District is the cultural and leisure center of the city. The Xinshi District is a new research and development center and also contains the largest concentration of Urumqi's relevant educational institutions. The Midong District has a high concentration of traditional manufacturing activities and serves as the manufacturing base of Xinjiang's characteristic industries, while the Economic and Technological Development Zone (Toutunhe District) is the integration area of the local and Xinjiang Production and Construction Corps (China's special administrative division). The Dabancheng District is the largest district in Urumqi, which mainly focuses on animal husbandry. Urumqi County includes the main tourist attractions of Urumqi, such as National Forest Park and Regional Forest Park.

3.2. Study Data

As this study aims to analyze the relationship between the quality of different tourism destinations in Urumqi and the distribution of tourists, we selected two types of big data, Tencent migration big data and Weibo sign-in big data, to conduct a comprehensive analysis of the spatiotemporal distribution of Urumqi's tourists and the quality of scenic spots, respectively [58].

Based on the real-time location of Tencent app users, Tencent migration data display the regional population flow and highlight the correlation between the designated area and the geographical area where the population resides. The data provide a simulation of the population relationship and can more realistically reflect the spatial patterns of population movement compared to other similar big data [51,52]. This study obtained the Tencent migration data of all tourism destinations in Urumqi for a total of 6 months, from September 2022 to February 2023, by visiting Amap API. The data attributes of Tencent migration big data include the starting and ending points of the migration data, migration city codes, data latitude and longitude coordinates, data timestamps, and total migration data. After processing the six-month Tencent migration data, we obtained the six-month average migration volume from September 2022 to February 2023, which totaled 21,462,500 tourists. According to the official statistics of Urumqi, in 2022, the city received a total of 51,537,100 tourists, and the data obtained by us in the first half of the year accounted for 41.65%, which means that, excluding the elderly and children who were not counted by Tencent's migration big data, the sample number we obtained exceeded more than 85% of the actual number of tourists. Therefore, the results can be used to represent the tourism industry of Urumqi, and our analysis based on Tencent migration big data can also accurately and objectively reflect the tourism frequency at different scenic spots during the six-month period.

Weibo sign-in data come from the sign-in information that users post on Weibo. The content of Weibo sign-in data can be used to reflect the degree of user preference for the sign-in area, and thus reflect tourists' evaluation of the quality of different tourism destinations [59,60]. By using the Weibo open API, we obtained all Weibo sign-in data for Urumqi from September 2022 to February 2023, a total of 6,172,500 sign-ins. The data attributes included the geographic location (latitude and longitude), sign-in location, Weibo link, blogger homepage link, text content, image and video links, publishing time, number of reposts, comments, likes, and followers. In order to exclude sign-in data from Urumqi residents, this study cleaned the Weibo sign-in data, which reflect the number of people who checked in on Sina Weibo within the Urumqi city area. As the data we obtained included the blogger's homepage link, which revealed their location, we analyzed their location and set the filtering criteria to exclude those who had stayed in Urumqi City throughout the period from September 2022 to February 2023. The remaining users were those who traveled from outside Urumqi to Urumqi during this time period, indicating tourism activity in Urumqi City. After the cleaning process, we were left with 4.2219 million records of Weibo check-in data. With this cleaned dataset, we could comprehensively analyze the quality assessments of tourists regarding Urumqi City.

3.3. Methods

3.3.1. Kernel Density Analysis

Kernel density analysis simulates the distribution of points and line sets in space by calculating their distribution density in geographic space to objectively reflect the agglomeration form of different elements [61]. Kernel density analysis was used to visualize the tourism frequency and quality of different scenic spots in Urumqi, as seen in Equation (1):

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

where p_i is the kernel density value of the spatial position; D_{ij} is the distance between the spatial point i and the study object j; n is the distance less than or equal to the spatial position 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 the highest in each core, and the increase in spatial distance will lead to the decrease in density until the kernel density value is 0. In addition, a different search radius will lead to different results of kernel density analysis.

We used the default research radius computed for the dataset based on the spatial variant of Silverman's rule of thumb (Equation (2)):

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

where n is the count of input points; D_m is the median of the distance from the mean center; and SD is the standard distance.

3.3.2. Bivariate Moran's I analysis

Bivariate Moran's I has a similar working mechanism to univariate Moran's I spatial autocorrelation. Instead of analyzing the spatial relationships between variables of interest and their surrounding variables of interest, bivariate Moran's examines the spatial relationship between independent variables and their surrounding outcome variables. To define spatial weights, we used the Queen's Case and assigned all the fishnet units that connect with the analyzed fishnet unit either by edge or corners as 1. The bivariate global Moran's I coefficient was calculated using Equation (3) [62,63]:

$$I_{GB} = \frac{\sum_i (\sum_j w_{ij} y_j \times x_i)}{\sum_i x_i^2} \tag{3}$$

where I_{GB} is the global bivariate Moran's I coefficient; i represents the ith feature unit (a fishnet grid); j represents the neighbor units of i; w_{ij} is the spatial weight of j to i (spatial weights matrix); x_i is the independent variable value (count of boba or coffee shops) in the analyzed fishnet unit; and y_j is the outcome variable value of neighborhood units. All variables were in standardized form, and spatial weights were row standardized (means were 0 and variances were equal to 1).

The output of bivariate local Moran is the local indicator of spatial association (LISA), which captures the association between the independent value in the fishnet unit i and the outcome values of the neighboring unit j (Equation (4)). The LISA index produced scatter plots in four quadrants, and the H-H, H-L, L-H, and L-L zones were generated according to the positive or negative signs of x_i and $\sum_j w_{ij} y_j$ (all variables were standardized).

$$I_{LB} = c x_i \sum_j w_{ij} y_j \tag{4}$$

Here, I_{LB} is the local bivariate Moran's I coefficient; c is a constant scaling factor; w_{ij} is the spatial weight of j to i (spatial weights matrix); y_j is outcome value of neighborhood units; and x_i is the independent value in the analyzed fishnet unit. All variables were in standardized form, and spatial weights were row standardized (means were 0 and variances were equal to 1).

4. Results

4.1. Temporal and Spatial Distribution of Tourists at Different Tourism Destinations

Tourist destinations refer to specific regions with certain tourism resources and attractions that are capable of attracting a certain number of tourists for travel activities. This makes their definition more extensive compared to traditional tourist attractions [64]. Due to the lack of studies on the spatial division and identification of tourist destinations in Urumqi, we used the distribution range of tourists in Urumqi to define the spatial scope of tourist destinations. Based on the characteristics of Tencent migration big data, we selected the data with migration destinations within the Urumqi urban area, while migration origins outside the Urumqi urban area served as the data source for incoming tourists. To avoid errors, we conducted a comprehensive average analysis of the monthly number and distribution range of tourist migration, ultimately obtaining the spatial distribution of tourists and tourist destinations from September 2022 to February 2023. According to the Tencent migration data reflecting the number of tourists, there were obvious differences in tourist numbers during different periods, indicating that different tourist destinations in Urumqi have varying degrees of attractiveness to tourists during different periods. Furthermore, by analyzing the Tencent migration data origins and destinations during different periods, it was found that, overall, from September 2022 to February 2023 tourists came to Urumqi primarily from the eastern coastal regions of China, such as Guangdong, Fujian, and Zhejiang, while in the specific months of October and November 2022, tourists mainly came from Fujian, Zhejiang, Shandong, and Shanghai. After December 2022, more tourists came from Guangdong and Zhejiang. The origin of tourists also reflected local epidemic policies, particularly during the period from October to December 2022 when Guangdong and other regions implemented strict epidemic prevention and control measures, resulting in a significant decrease in the number of tourists from those regions. On the other hand, it can be seen that tourist flows were not only related to regional population and economic levels but also influenced by unexpected events. Additionally, the behaviors and characteristics of tourists from different regions can have different effects on tourist attractions.

The spatial distribution characteristics of Urumqi's tourism destinations show that they were mainly concentrated in the Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District, while their concentrations in the Midong District, Urumqi County, and the Dabancheng District were relatively low. Additionally, there was a significant difference between the spatial distribution of tourism destinations and that of tourist attractions. This was mainly due to the fact that tourist attractions were generally more scattered, while tourism destinations in Urumqi were relatively concentrated, indicating that tourists' choices of tourism destinations did not directly depend on the distribution of tourist attractions. In terms of the spatial distribution of tourists, from September 2022 to February 2023, tourists were mainly concentrated in the Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District, but the number and distribution range of tourists during different periods differed significantly. Considering the characteristics of different districts in Urumqi and the spatial distribution of tourists, it can be seen that Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District are the main areas in Urumqi with significant economic, cultural, and ethnic features. These areas offer ethnic scenery that cannot be experienced elsewhere, making them particularly attractive to visitors. However, some more common landscapes, such as the Forest Park in Urumqi County, are often overlooked.

The tourists' aggregation showed a trend of first decreasing and then increasing, especially in October and November 2022, which is the golden season for tourism. The number of tourists in Urumqi was relatively low due to the strict control measures against the COVID-19 pandemic but increased significantly after the pandemic eased in December.

In terms of the distribution range, from September to December 2022, more tourists were distributed in the Tianshan District and the Xinshi District, while in January and February 2023, more tourists were distributed in the Shuimogou District and the Shayibake District (Figure 2).

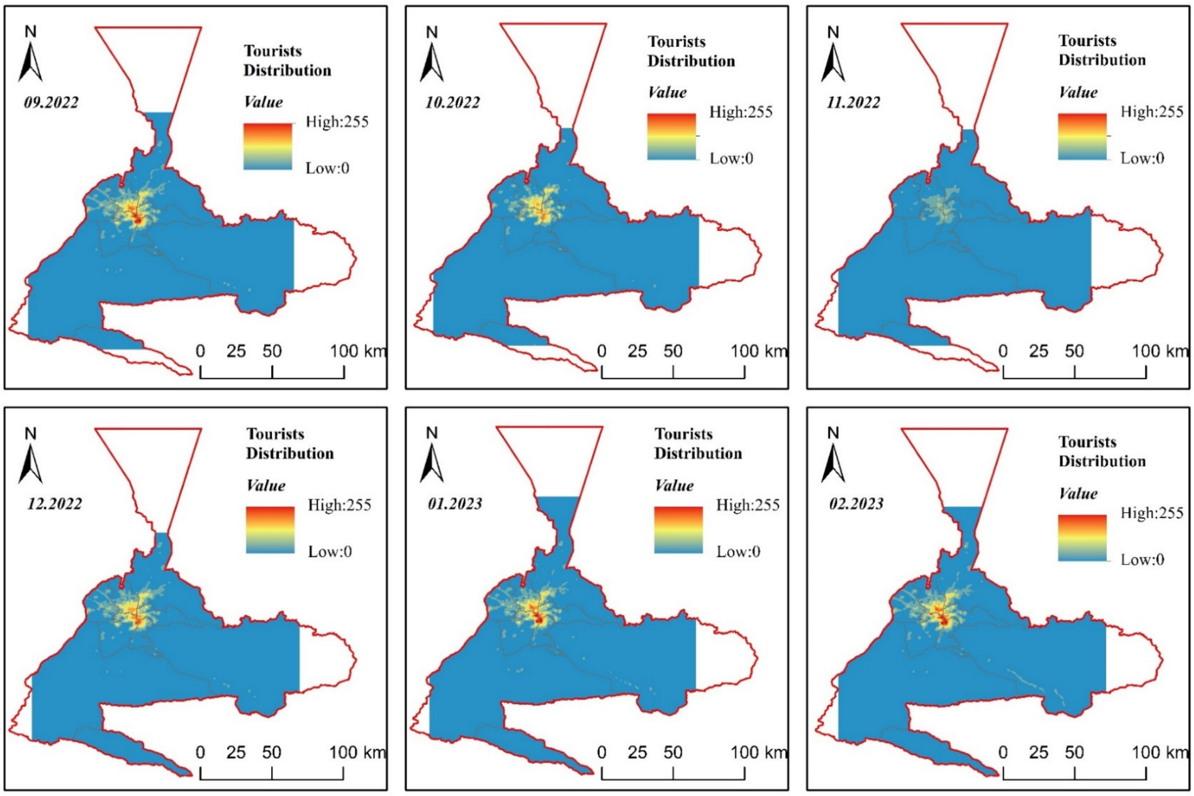

Figure 2. The temporal and spatial distribution of tourists in Urumqi.

4.2. Quality Analysis of Different Tourism Destinations

The quality of a tourism destination generally depends on the tourists' comprehensive experience, including food and consumption, which is often difficult to express quantitatively [65]. However, Weibo sign-in big data include sign-in content and number of followers, so we selected the positive evaluation data in regard to the tourism destination based on the characteristics of the Weibo sign-in big data, where a higher number of followers indicated a higher quality evaluation of the tourism destination [66]. We summarized and analyzed all sign-in data from September 2022 to February 2023 to obtain the quality evaluation results of different tourism destinations in Urumqi.

From the quality analysis using the Weibo sign-in big data, it can be seen that the tourism destinations with higher quality were mainly distributed in the Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District, and there were also many high-quality tourism destinations in the Dabancheng District. The spatial distribution was comparable to the spatial distribution of tourists, indicating that the number of tourists does indeed correlate with the quality of tourism destinations to some extent. However, high-quality tourism destinations were more often found in the Xinshi District, the outer areas of Tianshan District, and the Dabancheng District, a distribution pattern that showed some differences compared to the spatial distribution of tourists. This is most likely because foreign tourists are often attracted to non-homogeneous and niche tourism destinations, which often provide different experiences, and they may recommend these tourism destinations on social platforms. From the quality analysis of tourism destinations during different periods, it can be seen that from September 2022 to February 2023 there was an obvious decline in the quality evaluations for the same tourism destinations, which was due to the fact that various tourism facilities had not been restored promptly after the COVID-19 pandemic, resulting in a less satisfactory experience for tourists in Urumqi. Overall, the quality analysis of tourism destinations reflected the degree of attraction of tourists to different tourism destinations and the tourists' travel experience (Figure 3).

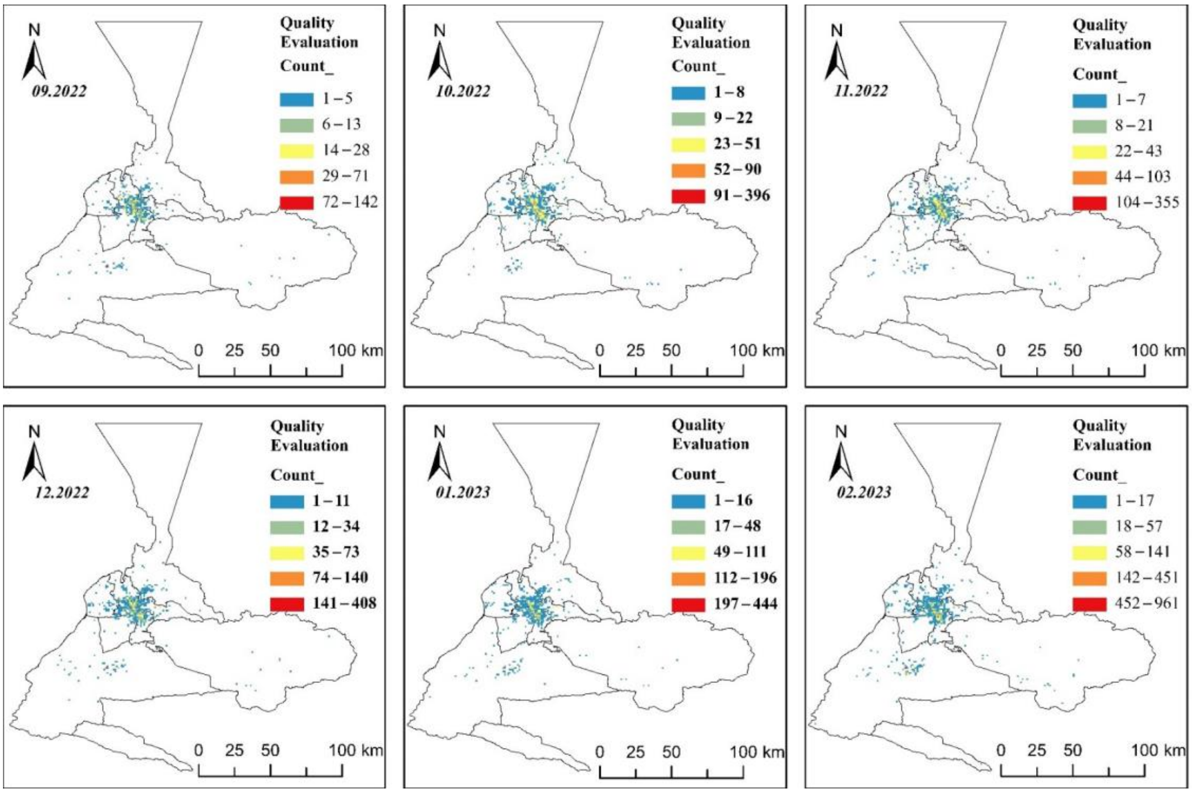

Figure 3. Quality analysis of Urumqi's tourism destinations.

4.3. Spatial Correlation between the Quality of Different Tourism Destinations and the Spatial-Temporal Distribution of Tourists

For tourists, finding high-quality tourism destinations generally involves information from two sources: official and private. Official information generally comes from tourism departments that introduce tourism destinations. These departments mainly focus on high-class scenic areas, such as China's 3A-, 4A-, and 5A-rated scenic spots (in China, tourist attractions are classified into five levels of quality, ranked from highest to lowest as follows: AAAAA, AAAA, AAA, AA, and A, and the level of an A-rated attraction is an important indicator of its quality in China), and the introductions are often one-sided for the sake of attracting more tourists. The private information pathway generally involves tourists finding relevant information about tourism destinations on the internet; however, the information on the internet is generally mixed, so being able to access high-quality tourism destinations can greatly improve their travel experience [34]. Tourism management departments manage the operation of different tourism destinations; however, they generally focus on developing high-class tourist attractions, leaving the development and management of some ordinary tourism destinations somewhat lacking. If tourism management departments can obtain information on high-quality tourism destinations, it will have great benefits for the development and management of tourism.

Therefore, in order to better understand the relationship between the spatial distribution of tourists and high-quality tourism destinations, this study used Bivariate Moran's I analysis. The results of the Moran scatter plot and spatial interaction indicate the correlation between high-quality tourism destinations and the spatial distribution of tourists [62]. It can be seen that there was not a strong correlation between the spatial distribution of tourists and the overall evaluation of the tourism destination. Areas with a more concentrated distribution of tourists did not necessarily have higher tourism quality. Furthermore, according to the result of the Moran scatter plot, the Moran index showed a trend of first decreasing and then increasing, which indicates that the COVID-19 epidemic may have had an important impact on tourists' choices of destinations. In addition, some tourism destinations may not have opened due to epidemic prevention and control measures (Figure 4).

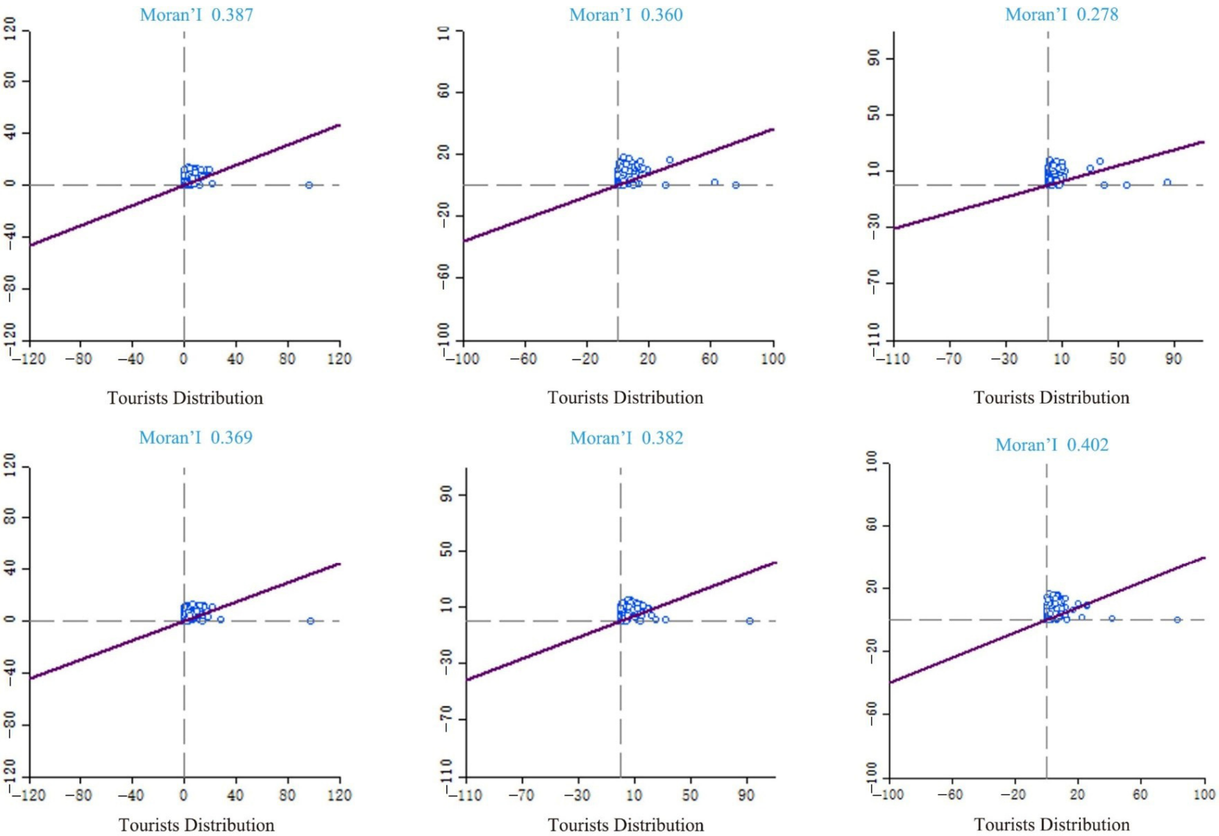

Figure 4. Moran scatter plot.

The spatial interaction results are shown in Figure 5, which demonstrates four different clustering patterns, HH, HL, LH, and LL. These clustering patterns were used to represent the spatial relationship between the distribution of tourists and the quality of tourism destinations. The HH clustering result represents areas with high tourist density and high tourism quality, HL represents areas with high tourist density but low tourism quality, LH represents areas with low tourist density but high tourism quality, and LL represents areas with low tourist density and low tourism quality. During the period from September 2022 to February 2023, there were some differences in the spatial clustering results, especially in the HH clustering and LH clustering. The HH clustering was mainly concentrated in the Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District. However, the range of HH clustering showed a trend of first shrinking and then expanding from September 2022 to February 2023, and the main HH clustering gradually shifted from the Xinshi District to the Tianshan District. The LL clustering was mainly distributed in the Xinshi District and the outer areas of the Tianshan District, as well as in the Dabancheng District. Furthermore, there was greater LH clustering in the Dabancheng District, and the spatial range was relatively stable across different periods.

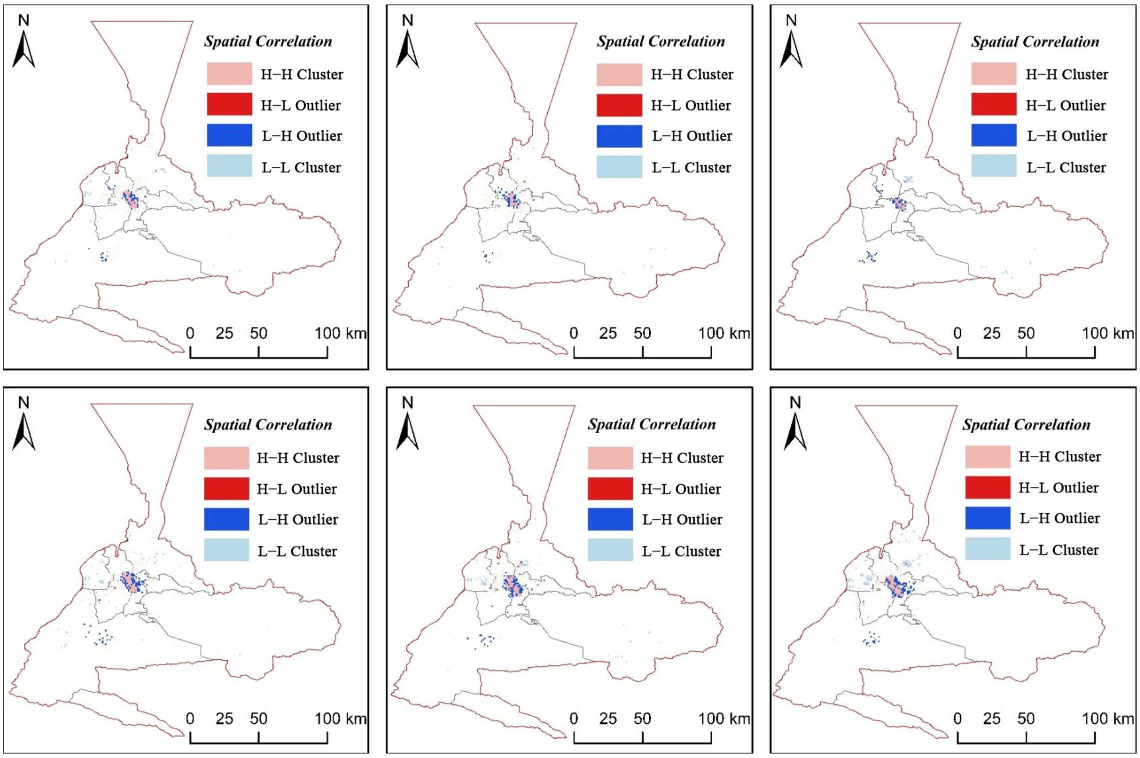

Figure 5. Spatial clustering results.

In terms of the characteristics of district divisions in Urumqi, the main areas where the population is concentrated are the Xinshi District, Shuimogou District, Toutunhe District, Shayibake District, and Tianshan District. These areas are also the main gathering and dispersing points for foreign tourists. Many tourists who come to Urumqi may not stay for a long time; therefore, they may focus on experiencing the ethnic customs in these areas, resulting in a higher tourist concentration. On the other hand, the outskirts of Xinshi District, Tianshan District, and Dabancheng District had a lower distribution of tourists. However, the vast pastoral landscapes in these areas can offer a different kind of experience, making these areas very appealing to tourists. Therefore, there was a higher concentration of LH class tourists in these areas. The clustering results of different districts are shown in Table 2.

Table 2. Statistical Results of Clustering Information.

September 2022	HH	HL	LL	LH	January 2022	HH	HL	LL	LH	November 2022	HH	HL	LL	LH
Xinshi	7	10	7	0	Xinshi	5	9	7	0	Xinshi	2	8	7	0
Shuimogou	9	8	3	0	Shuimogou	7	8	3	0	Shuimogou	7	8	3	0
Toutunhe	0	3	0	1	Toutunhe	0	3	0	1	Toutunhe	0	3	0	1
Shayibake	4	0	0	0	Shayibake	4	0	0	0	Shayibake	3	0	0	0
Tianshan	17	5	5	2	Tianshan	16	5	4	2	Tianshan	15	5	4	2
Dabancheng	0	0	10	12	Dabancheng	0	0	10	11	Dabancheng	0	0	10	12
Urumqi	3	8	0	0	Urumqi	1	7	0	0	Urumqi	1	7	0	0
2022.12	HH	HL	LL	LH	2023.01	HH	HL	LL	LH	2023.02	HH	HL	LL	LH
Xinshi	2	8	7	0	Xinshi	8	12	7	0	Xinshi	8	13	7	0
Shuimogou	7	8	3	0	Shuimogou	10	8	3	0	Shuimogou	11	8	3	0

Table 2. *Cont.*

September 2022	HH	HL	LL	LH	January 2022	HH	HL	LL	LH	November 2022	HH	HL	LL	LH
Toutunhe	0	3	0	1	Toutunhe	0	3	0	1	Toutunhe	1	3	0	1
Shayibake	3	0	0	0	Shayibake	4	0	0	0	Shayibake	5	0	0	0
Tianshan	14	5	5	2	Tianshan	19	5	6	2	Tianshan	21	5	7	2
Dabancheng	0	0	10	14	Dabancheng	0	0	10	15	Dabancheng	0	0	10	15
Urumqi	1	8	0	0	Urumqi	3	10	0	0	Urumqi	3	13	0	0

5. Discussion

One of the focuses of tourism-related study is the evaluation of the quality of different tourism destinations, which often comes from tourists' emotional perception of the destination [67]. This is different from previous evaluations of scenic area grades, which often have large discrepancies, i.e., tourists' emotional perceptions are not solely based on the size of the scenic area [68,69]. Therefore, based on Weibo sign-in big data, this study determined the degree of attraction of tourists to different tourism destinations using the positive evaluation content they posted while visiting the sites and the number of forwards and follows these posts generated [69]. This kind of evaluation of tourism destination quality based on tourists' sharing their own travel experiences is often more objective and accurate.

Many studies have concluded that the number of tourists determines the quality of a tourism destination because, in theory, the higher the quality of a tourism destination, the more tourists it will attract [70]. However, these studies generally ignore the fact that few tourists revisit a previously visited tourism destination, making this conclusion not fully consistent with reality [71]. For example, in addition to some higher-rated scenic spots that attract a large number of tourists, there are also many niche and small destinations that have attracted a large number of tourists in recent years, so the relationship between the size and rating of tourism destinations and the spatial distribution of tourists is not necessarily positive [71,72]. This study analyzed the spatial distribution of tourists and tourism destination quality over a specified period and found that there were four possible relationships between tourist distribution and destination quality, namely, areas with high tourist density and high tourism quality, areas with high tourist density but low tourism quality, areas with low tourist density but high tourism quality, and areas with low tourist density and low tourism quality. For the four types of tourism destinations, the areas with high tourist density and high tourism quality were traditionally considered to be of high quality. However, based on current tourism trends, tourists often prefer to visit small niche attractions with low tourist density but high tourism quality for a better travel experience.

From the tourists' point of view, more and more tourism destinations are becoming homogenized, with tourists being more concentrated in certain famous tourism destinations [73]. However, these tourism destinations are often accompanied by overdevelopment, lack of unique characteristics, and excessive concentration of tourists, which may lead to a less satisfying travel experience [74]. Therefore, in addition to traditional, high-quality, and well-known tourist attractions, small niche tourism destinations can often bring tourists completely different travel experiences, thus influencing tourists' subsequent tourism-related behaviors [75,76]. From the perspective of tourism management departments, the management costs of different tourism destinations vary, and some traditional tourism destinations have gradually lost their tourism value due to excessive development [77,78]. Therefore, tourism management departments need to develop new tourist destinations and manage them efficiently to promote sustainable development of regional tourism industries [79]. This study analyzed the relationship between the quality evaluation results of tourism destinations and the spatiotemporal distribution of tourists in Urumqi from September 2022 to February 2023 based on Tencent migration big data and Weibo sign-in big data. Four types of relationships between the spatiotemporal distribution of tourists and the quality of tourism destinations were identified, which have practical significance for both tourists and tourism management departments.

This study conducted a detailed analysis of the spatiotemporal distribution of tourists, the quality of tourism destinations, and the relationship between the two. It not only analyzed the distribution of different quality tourism destinations from the perspective of spatiotemporal data but also creatively explored the differential relationship between the spatiotemporal distribution of tourists and the distribution of tourism destination quality. Based on this, high-quality tourism destinations and niche tourism destinations in Urumqi were summarized, which may have a significant promoting effect on tourism development in the city. Furthermore, for different tourism destinations, an evaluation methodology was proposed that can be promoted as a positive reference for tourists [80].

6. Conclusions

This study analyzed the temporal and spatial distribution of tourists with different travel purposes in Urumqi City, as well as the quality evaluation of tourist destinations based on Tencent migration big data and Weibo sign-in big data. It also compared the correlation between the two in spatial terms. The results revealed significant differences in the spatial distribution of tourists at different periods and variation in the quality of different tourist destinations. Additionally, we found that the spatial distribution of tourists did not show a significant positive correlation with the quality of tourist destinations. The study ultimately discovered the coexistence of tourist destinations with both high tourist distribution and high quality and those with low tourist distribution and high quality, which has important reference value for future tourism development and construction.

This study focused on analyzing high-quality tourist destinations, but there were some limitations. Firstly, Tencent migration big data and Weibo sign-in data may not fully reflect the actual tourism situation in Urumqi, as these social media platforms are primarily used by young people. The travel frequency of young people is far lower than that of middle-aged and elderly people, which means that the results of this study were only based on the real feedback at the data level. Secondly, the evaluation of the quality of tourist destinations was related to the level of consumption; however, many tourists tend to avoid high-consumption tourist destinations, which leads to certain deficiencies in the evaluation. Therefore, future studies should address these two aspects and continue to explore the correlation between high-quality tourist destinations and tourists.

Tourism has been revealed to be one of the most important means to improve quality of life, and the quality of tourism destinations is receiving attention from both tourists and tourism management departments. This study focused on the importance of the quality of tourism destinations to tourists and tourism management departments. Based on the correlation between the spatial distribution of tourists and the quality evaluation results of tourism destinations, four kinds of relationships were proposed. In addition to high-quality tourism destinations with high tourist density, we found some niche tourism destinations with lower tourist density but higher tourism destination quality. For tourists, this not only improves the choice of tourism destination, but also indirectly improves the tourism experience. For the tourism management department, it provides an important reference for the management and development of regional tourism. Finally, although this study takes the tourism destination of Urumqi, China as a case study, the research results can be extended to other tourism destinations, which is of great significance to the development of tourism-related industries.

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