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The Matching Relationship Between the Distribution Characteristics of High-Grade Tourist Attractions and Spatial Vitality in Xinjiang

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Abstract: The development of the tourism industry serves as a crucial pathway for guiding urban spatial vitality, making the study of the matching relationship between the spatial distribution characteristics of tourist attractions and regional spatial vitality particularly important for the advancement of the tourism sector. This study combines Amap POI data and Weibo sign-in data, employing various quantitative methods, including Kernel Density Estimation (KDE), Hotspot Analysis (Getis-Ord Gi*), and the Geographically Weighted Regression (GWR) model, to thoroughly explore the distribution characteristics of different grades of tourist attractions in Xinjiang and their matching relationship with spatial vitality. The findings indicate that AAAAA attractions are primarily concentrated in Urumqi and its surrounding areas, where spatial vitality highly matches the distribution of attractions. The distribution of AAAA attractions shows regional differences, exhibiting higher matching degrees in certain areas of southern and western Xinjiang, while some regions in northern Xinjiang demonstrate lower matching degrees. Conversely, AAA attractions are more widely distributed in remote areas, where the matching between vitality and attraction distribution is low, particularly in southern and eastern Xinjiang, revealing a notable mismatch between tourism resources and spatial vitality. By analyzing the matching relationship between tourism resources and spatial vitality, this study provides a scientific basis for optimizing the allocation of tourism resources in Xinjiang and enhancing regional tourism spatial vitality. Additionally, this study also offers valuable insights for tourism managers and planners to formulate more precise tourism development policies.

Keywords: tourist attractions; distribution characteristics; spatial vitality; degree of match; spatial mismatch

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1. Introduction

With the rapid development of China's economy, the tourism industry increasingly contributes to regional economic growth and optimizing spatial structures [1]. The 14th Five-Year Plan for National Economic and Social Development of the People's Republic of China explicitly states that tourism, as a strategic pillar industry, has become a crucial engine for enhancing regional economic vitality and promoting sustainable development [2]. The spatial pattern of tourist attractions, concerning their distribution and configuration in geographical space, influences resource usage efficiency and significantly contributes to the enhancement of regional economic, social, and cultural vitality. An effectively organized distribution of tourist attractions can enhance spatial vitality by attracting tourists, stimulating consumption, and promoting infrastructure development [3]. Regional spatial vitality reflects the dynamic performance of a region regarding economic activity, population mobility, and capital accumulation, hence suggesting the potential for overall regional development [4]. However, due to the uneven distribution of tourist attractions, particularly in resource-rich yet vast areas, a mismatch often exists between the spatial layout of attractions and regional spatial vitality, leading to underutilization or mismanagement of regional resources. In actuality, even high-grade tourist attractions within the same region exhibit varying impacts on enhancing regional spatial vitality due to disparities in their geographic location, transportation accessibility, and infrastructure levels. Certain attractions, despite being endowed with high-quality tourism resources, are located in remote areas or lack integration with surrounding regions, thereby constraining their capacity to effectively boost regional spatial vitality [5]. Therefore, it is of great significance to study the matching relationship between the spatial pattern of tourist attractions and regional spatial vitality. By elucidating the imbalances in the distribution of attractions and their impact on regional spatial vitality, this study will provide a scientific foundation for optimizing the allocation of tourism resources and the advancement of coordinated regional development. Furthermore, it will offer valuable insights for policymakers to design more precise regional planning and tourism development strategies, ultimately fostering sustainable and high-quality regional economic development.

Scholars, through the analysis of the spatial distribution characteristics of tourist attractions, have revealed their distribution patterns within regional contexts. Researchers employ various geographical analysis methods, including spatial autocorrelation analysis, Kernel Density Estimation (KDE), and geographically weighted regression [6–8], to assess the concentration and dispersion of tourist attractions across different geographic spaces [9]. Studies have indicated that tourist attractions are predominantly concentrated in economically developed, well-connected, or resource-rich areas, whereas their presence in less developed areas is relatively sparse, demonstrating a pattern of imbalance and clustering [10]. Specifically, some scholars have focused on regional scales (e.g., provincial or national), discovering that tourist attractions are often concentrated in eastern coastal areas and urban agglomerations, while western or remote regions exhibit a lower density of attractions [11]. However, studies on the spatial distribution differences among tourist attractions of different grades are relatively scarce. Tourist attractions are classified into different grades—AAA, AAAA, and AAAAA—according to their attractiveness, scale, and resource richness, and their spatial distribution exhibits certain disparities [12,13]. Studies indicate that AAAAA-grade attractions are typically located in regions with abundant national-level tourism resources and well-developed infrastructure, particularly in provincial capitals or key national development areas, where clustering effects are more evident [14]. In contrast, although AAA- and AAAA-grade attractions are more numerous, their distribution is relatively dispersed, particularly in areas with poor transportation and lower levels of economic development. These attractions tend to rely more on local resources and market demand, making it difficult to achieve economies of scale [15]. By analyzing the spatial distribution characteristics of attractions of different grades, scholars have further revealed their close relationship with regional development levels, contributing to a deeper understanding of the spatial allocation of tourism resources [16,17].

The study of regional spatial vitality can be traced back to Jane Jacobs' theory of urban vitality. She proposed that urban vitality stems from functional diversity and frequent human interactions, particularly in areas with convenient transportation and high spatial accessibility, which facilitate economic and social development. Building on this foundation, this study defines spatial vitality as a comprehensive reflection of the dynamic performance within a region, including economic activities, population movements, and tourist flows. In other words, a region's development potential and activity level are manifested through the concentration of human movements, financial flows, and tourism activities [18,19]. Regional spatial vitality is influenced by spatial structure as well as the flow and concentration of elements like population, capital, and information, serving as a core indicator for assessing regional economic and social dynamism [20]. Initial studies on regional spatial vitality primarily employed qualitative analysis, focusing on functional zoning, transportation infrastructure, and the effects of economic agglomeration [21]. The advent of big data technologies has led to a notable shift in research methodologies towards quantitative approaches. Scholars now analyze the activity levels of population mobility and economic activities within regions using new data sources, including mobile signaling data, social media data, and nighttime light data [22–24]. Through spatial statistics and spatiotemporal behavior analysis tools, researchers have revealed the spatiotemporal distribution characteristics of spatial vitality. Current studies utilize a variety of spatial analysis tools, including spatial autocorrelation analysis, fractal theory, space syntax, and entropy analysis [25–28]. These methods enable the quantitative analysis of regional spatial vitality's complexity and its temporal and spatial variation. Although these quantitative methods have significant advantages in revealing the spatiotemporal dynamics of spatial vitality, they also face certain limitations. For example, existing studies on spatial vitality largely rely on big data, and their analytical results are highly dependent on data quality and accessibility [29,30].

The rapid development of the tourism industry has led researchers to acknowledge that, although some attractions possess abundant natural and cultural resources, their economic benefits or tourist attraction (i.e., regional spatial vitality) are often not fully realized [31]. This phenomenon reflects a mismatch between the spatial distribution of resources and actual vitality: some resource-rich attractions exhibit low vitality, while certain highly vibrant attractions have relatively limited resources [32]. The causes of this mismatch are complex and multifaceted, involving the combined effects of transportation conditions, regional economic development levels, resource distribution, and policy planning [33,34]. To investigate this phenomenon, researchers have employed spatial mismatch models, spatial statistical analysis, and spatiotemporal behavior analysis to explore the relationship between attraction vitality and the distribution of spatial resources [35–37]. However, current research predominantly utilizes static data, failing to fully account for the dynamic changes in tourist behavior, making it difficult to explain vitality fluctuations caused by seasons, holidays, or policy shifts. Additionally, many studies emphasize the match between attractions and the number of visitors, overlooking the diversity of tourist behavior and individualized needs, which limits the understanding of the subtle differences in tourism appeal [38,39].

This study seeks to investigate the relationship between the spatial patterns of various grades of tourist attractions and regional spatial vitality in Xinjiang, considering the identified issues and the existing research landscape. This study examines the spatial patterns of different grades of tourist attractions in Xinjiang, emphasizing the geographic distribution characteristics of AAA, AAAA, and AAAAA attractions. Second, by analyzing tourist sign-in data from social media, it captures the spatiotemporal dynamics of tourist movements and identifies the spatial vitality characteristics related to tourism in different regions of Xinjiang. Finally, the study conducts a spatial matching analysis, aligning the spatial patterns of different grades of tourist attractions with regional spatial vitality to evaluate the match between attraction grades and regional vitality. By comparing the vitality performance of attractions of various grades, the study assesses the efficiency of resource utilization and their contribution to regional spatial vitality, revealing the correlations between attraction vitality and their resources, location, and grade, hoping to provide data support and theoretical reference for the optimization of tourism resource allocation.

2. Materials and Methods

2.1. Study Area

The Xinjiang Uygur Autonomous Region (Xinjiang) is located in the northwest of China, situated between 73°40′ to 96°18′ E and 34°25′ to 48°10′ N (Figure 1). Xinjiang is rich in tourism resources, currently hosting 17 AAAAA-grade attractions, 143 AAAA-grade attractions, and 350 AAA-grade attractions, ranking among the top in the country in terms of the number of attractions. Notably, Xinjiang ranks third nationwide for the number of AAAAA-grade attractions. Furthermore, the region encompasses 56 types of national tourism resources, accounting for 83% of all resource types in China. Recently, Xinjiang's abundant tourism resources have attracted a large number of visitors, leading to a significant increase in spatial vitality for certain attractions [40]. However, despite the overall diversity and abundance of tourism resources, there is a clear imbalance in the development of tourism resources and spatial vitality across different regions of Xinjiang.

Therefore, this study focuses on all AAA-grade and higher attractions in Xinjiang, analyzing their spatial distribution characteristics, spatial vitality, and the matching relationship between the two. The objective is to optimize the rational allocation of Xinjiang's tourism resources, enhance the vitality of its attractions, and promote the sustainable development of the regional tourism industry.

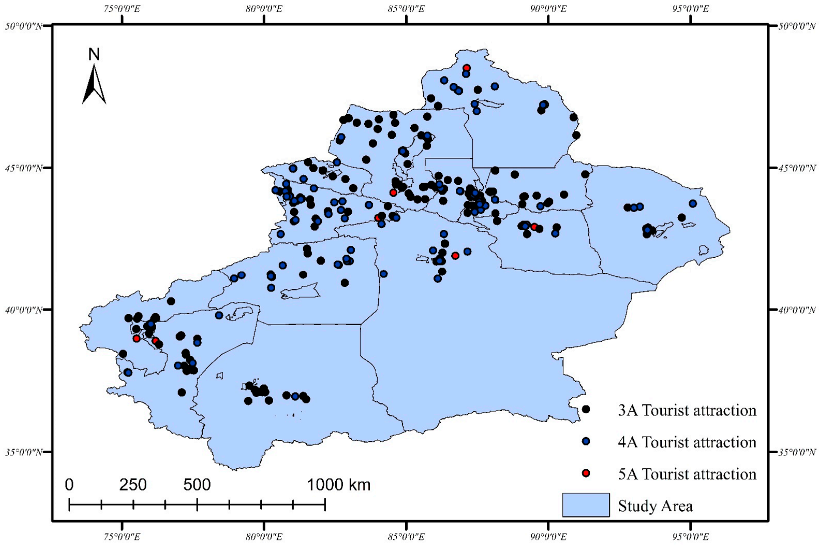

Figure 1. Study area and distribution of tourist attractions.

2.2. Study Data

The data used in this study primarily consist of POI (Point of Interest) data and social media data, with different methods of data collection and processing outlined as follows.

2.2.1. Tourist Attraction Data

The data on AAA, AAAA, and AAAAA tourist attractions in Xinjiang used in this study are sourced from Amap (15.02.0.2032)'s POI data. POI data refers to a collection of geographic entities or locations characterized by specific functions within geographic space, commonly encompassing attractions, restaurants, hotels, and similar establishments. We filter the Amap POI data in the "attraction" category to extract pertinent information regarding AAA, AAAA, and AAAAA attractions within Xinjiang [41]. To ensure the accuracy and applicability of the data, we apply strict cleaning and preprocessing procedures to the raw data. First, we remove duplicate entries by cross-referencing attraction names, geographic coordinates, and grades to eliminate redundant records, ensuring each attraction retains a unique data entry. Second, we correct the grade classification by comparing the dataset with the official list of A-grade attractions published by the National Tourism Administration to ensure the accuracy of attraction grades in the POI data. Next, we verify spatial accuracy by overlaying the attraction point data onto the administrative boundary maps of Xinjiang and satellite imagery to further confirm the correctness of attraction coordinates. For attractions with significant spatial deviations, we make manual corrections to adjust their accuracy. Finally, we standardize the data to ensure consistency in format, which facilitates subsequent data processing by standardizing non-uniform fields in the POI data. This process results in the spatial distribution of AAA, AAAA, and AAAAA tourist attractions in Xinjiang (as shown in Figure 1).

2.2.2. Weibo Sign-In Data

The analysis of regional spatial vitality in this study uses Weibo sign-in data. By the end of the first quarter of 2024, Sina Weibo's daily active users have increased to 255 million, with more than 588 million monthly active users, making it one of the most influential social media platforms in China. Weibo sign-in data not only reflects users' activity trajectories at specific times and locations but also provides dynamic information on social interactions and tourist behavior. Given the platform's broad user base and high-frequency sign-in behaviors, Weibo sign-in data effectively captures tourists' spatiotemporal behavior patterns and reflects regional spatial vitality [42,43]. In the process of collecting Weibo sign-in data, we use the platform's open API to extract tourism-related sign-in records in the Xinjiang region from January to December 2023, using keywords such as "tourism", "scenic spot", "sign-in", "travel", "vacation", and "sightseeing" as filtering criteria. A total of 125,474 records are obtained. The selection of these keywords aims to capture common tourism activities while minimizing confusion with non-tourism activities. However, potential biases and limitations exist in the choice and application of these keywords, which may affect the reliability of the data. Firstly, the scope and specificity of keyword selection directly impact the accuracy of the data. Although the keywords cover the most common tourism scenarios, certain specific activities, such as adventure tourism, cultural experiences, or sign-ins at non-popular sites frequently visited by locals, may be overlooked. As a result, tourism activities not associated with the selected keywords may be underrepresented, limiting the data's representativeness. Secondly, selective user behavior may introduce bias into the data. Not all tourists use Weibo to sign in, meaning the data primarily reflect the activities of users who prefer social media, particularly younger individuals or frequent Weibo users. Consequently, the activities of older tourists or those less inclined to share their travel experiences online may be underestimated in this dataset. Thirdly, noise in the keyword filtering process also presents a potential issue. For instance, some Weibo sign-in records may use tourism-related keywords without actually reflecting genuine tourism activities (such as briefly signing in at a scenic spot during work). We attempt to exclude such irrelevant records during data cleaning, but completely eliminating false positives remains challenging. Additionally, the risk of geographical location offset may also affect data accuracy. For example, users might sign in around a scenic area rather than inside it, causing some records to deviate from actual tourism activities. These factors collectively indicate that, while we strive to ensure data relevance through keyword filtering, caution is still needed in data analysis and interpretation, fully considering these potential biases and limitations. Future research can address this limitation by incorporating more data sources, such as mobile signaling or consumer data, to provide a more comprehensive reflection of tourist behavior patterns. The final result of the Weibo sign-in data preprocessing is shown in Figure 2.

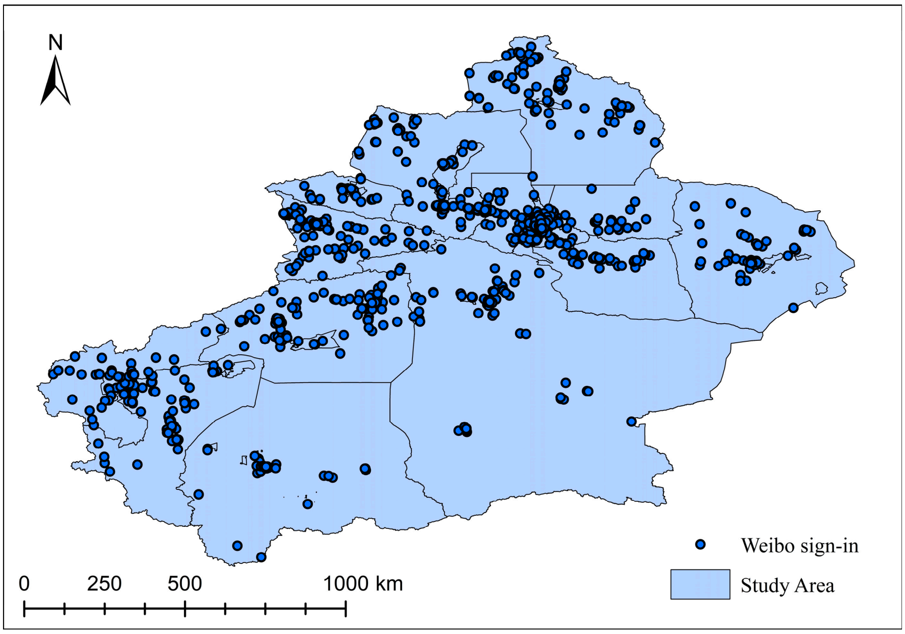

Figure 2. Distribution of Weibo sign-in data.

2.3. Study Method

This study employs various quantitative analysis techniques, including Kernel Density Estimation (KDE), hotspot analysis (Getis-Ord Gi), regional statistical analysis, and the Geographically Weighted Regression model (GWR), to analyze the spatial distribution characteristics of different levels of tourist attractions in Xinjiang and their matching with regional vitality.

2.3.1. Kernel Density Estimation (KDE)

KDE is a method used to analyze the distribution density of specific phenomena within a spatial dataset. Its principle involves setting a search radius and generating a kernel function centered on each data point (the location of tourist attractions). Based on the distance to surrounding points, different weights are assigned, with the contribution of each point decreasing as the distance increases, ultimately producing a smooth density surface map. In this process, KDE extends the influence of each point across the entire analysis area, allowing us to calculate the distribution density of tourist attractions within a specific region [44]. The formula for KDE is as follows:

$$f(s) = \sum_{i=1}^{n} \frac{1}{j^2} k\left(\frac{S - C_i}{h}\right) \tag{1}$$

where $f(s)$ is the kernel density estimation function value at a spatial location, j is the distance decay threshold, and n refers to the number of points within a distance less than or equal to the decay threshold. K is the spatial weighting function. The choice of search radius h has a significant impact on the results; therefore, this study adopts an appropriate method to determine the search radius value as follows:

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

In this formula, h is the search radius, n is the number of features within the space, SD is the standard distance, and D_m is the median distance. KDE serves to reveal the spatial distribution patterns of tourist attractions, highlighting areas of high concentration. However, the results of KDE depend on the choice of search radius: an excessively large radius may lead to an overly smoothed density map, while a smaller radius may overlook agglomeration patterns.

2.3.2. Hotspot Analysis (Getis-Ord Gi*)

Weibo sign-in data exhibit significant spatial clustering characteristics. These data can reflect the level of tourist activity in a particular area during a specific time period. Getis-Ord Gi* is a technique used in spatial data analysis, primarily for identifying clustering patterns of values in geographic data. It helps to determine which areas show clusters of high or low values, often referred to as "hotspots" or "coldspots". The Gi* statistic calculates a z-score for each feature in the dataset (e.g., points or areas on a map) [45]. This z-score is used to assess whether there is significant clustering of high or low values around that location. Due to its statistical significance, the final visualization of hotspot analysis is more objective. In this study, Getis-Ord Gi* is used to calculate the attribute value of each spatial unit, and the surrounding values are evaluated to determine whether the unit is a hotspot or coldspot [46]. If the value of a unit and its neighboring areas is significantly higher than the average, the unit is marked as a hotspot; otherwise, it is marked as a coldspot. The formula for Getis-Ord Gi* is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}} \tag{3}$$

where G_i^* is the Gi statistic for unit i; x_j is the observation value at location j (the number of Weibo sign-ins); $w_{i,j}$ is the spatial weight between locations i and j; $\overline{X}$ is the mean of all observation values; n is the total number of observation units; and S is the standard deviation of the observation values. The Getis-Ord Gi* method is suitable for identifying clustering patterns in tourist behavior, aiding in the analysis of attraction appeal. However, the results are constrained by the timeliness of the data and the self-selection bias inherent in sign-in behavior.

2.3.3. Regional Statistical Analysis

To more clearly assess the vitality level of different regions and facilitate comparisons across regions, we use regional statistics to summarize the number of coldspots and hotspots, calculating a regional vitality index to quantify the spatial vitality level of each area. The formula is as follows:

$$Vitality\ Index = \frac{Number\ of\ Hotspots - Number\ of\ Coldspots}{Total\ Number\ of\ Units} \quad (4)$$

In the formula, a vitality index greater than 0 indicates that the vitality level of the area is high, with a greater number of hotspots than coldspots. Conversely, a vitality index less than 0 signifies that the vitality of the area is weak, with a higher number of coldspots than hotspots. Using ArcGIS 10.4, hotspots and cold spots are statistically aggregated within each region, and a vitality index is calculated for each area to generate a distribution map illustrating varying vitality levels across regions. The vitality index enables the direct quantification of regional vitality, revealing the matching between tourist attractions and vitality levels.

2.3.4. Geographically Weighted Regression (GWR)

GWR is an extended regression analysis method particularly suited for addressing spatial heterogeneity in geographic data [47]. It is highly useful in studying the relationship between the spatial patterns of tourist attractions and regional spatial vitality, as GWR allows regression coefficients to vary with spatial location, revealing differences in the factors influencing vitality across different areas [48]. This flexibility makes GWR an ideal tool for analyzing the match between tourist attractions and vitality. The formula for geographically weighted regression is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (5)$$

where y_i is the dependent variable for the i-th unit; $\beta_0(u_i, v_i)$ is the intercept at location i, which varies with spatial coordinates (u_i, v_i); x_{ik} is the k-th independent variable for the i-th spatial unit; $\beta_k(u_i, v_i)$ is the regression coefficient for the independent variable x_{ik}, reflecting the influence of the independent variable on the dependent variable, and it varies with spatial coordinates (u_i, v_i), capturing local spatial heterogeneity; and ε_i is the error term. By calculating the regression coefficients for each spatial unit, GWR generates local regression coefficient maps that reflect the degree of contribution of tourist attractions to vitality in different areas. A larger local regression coefficient indicates that the density and grade of attractions in that area have a significant positive impact on regional vitality, suggesting a good match between vitality and attractions. Such regions typically feature high-grade attractions or exhibit pronounced agglomeration effects in tourism points. Conversely, a smaller or negative local regression coefficient indicates that while the density or grade of attractions in the area may be high, vitality performance is poor. This situation may point to issues such as the underutilization of resources or inadequate infrastructure, reflecting a phenomenon of spatial mismatch. The number and level of tourist attractions, along with regional vitality data, are imported into ArcGIS. Using the Geographically Weighted Regression (GWR) tool in ArcGIS, the dependent and independent variables are set to run the model, producing a distribution map of regression coefficients to identify the matching between tourist attractions and vitality levels. GWR reveals the impact of attraction layout on regional vitality and identifies areas of resource mismatching; however, it depends on the spatial completeness of the data and is sensitive to data noise.

3. Results

3.1. Spatial Distribution of Tourist Attractions in Xinjiang

After visualizing the AAA and above-grade tourist attractions in Xinjiang, the spatial distribution map of these attractions is presented in Figure 3. The AAA attractions in Xinjiang exhibit a relatively broad spatial distribution characterized by a multi-point dispersed layout. High-density clusters of AAA attractions are primarily concentrated in Urumqi and its surrounding areas in northern Xinjiang. This region exhibits a notable agglomeration effect, likely associated with transportation convenience, economic development levels, and a relatively advanced tourism infrastructure. Other scattered high-density areas appear in the western and southern fringe regions of southern Xinjiang; however, the density of attractions in these areas is relatively low. The distribution of AAAA attractions is more concentrated than that of AAA attractions, particularly exhibiting clear agglomeration characteristics in the Urumqi area of northern Xinjiang. Urumqi, the capital of Xinjiang, features a well-developed transportation network and a dynamic economy, leading to an increased number of AAAA attractions. This reflects the strong agglomeration effect of AAAA attractions in relatively developed regions. Additionally, there is a small cluster of AAAA attractions in the Kashgar region of southern Xinjiang; however, the degree of agglomeration and density in this area is significantly lower than that around Urumqi. In contrast, the distribution of AAAAA attractions is extremely sparse, primarily concentrated in Urumqi and its surrounding areas, where the agglomeration effect is most pronounced. Compared to AAA and AAAA attractions, the number of AAAAA attractions is limited, and their spatial distribution is relatively confined. This agglomerated distribution indicates that AAAAA attractions typically rely on richer tourism resources, high-end infrastructure, and significant tourist flow, leading to a tendency to cluster in economically vibrant and well-connected central areas. Furthermore, there is a certain distribution of AAAAA attractions in the Yili region of western Xinjiang, although their activity level and density remain low.

Overall, the spatial distribution of AAA, AAAA, and AAAAA attractions in Xinjiang demonstrates a pattern where higher-grade attractions exhibit stronger agglomeration. High-grade attractions are primarily concentrated in Urumqi and its economically developed surrounding areas, reflecting the relative advantages of infrastructure, economic levels, and tourism resources in this region. In contrast, lower-grade attractions are more dispersed, with some scattered distribution in remote areas. This indicates that the spatial distribution of attractions of different grades is closely related to the economic, transportation, and infrastructure conditions of the region.

3.2. Influencing Factors of Travel Behavior Choices at Different Distances

We utilized hotspot analysis (Getis-Ord Gi*) and regional statistical methods to analyze the spatial vitality index in the Xinjiang region, producing the spatial vitality index distribution map presented in Figure 4. The map indicates that high vitality indices are concentrated in Urumqi and its surrounding areas. The significantly high vitality of Urumqi suggests that the frequency of tourist sign-ins in this region exceeds that of others, highlighting Urumqi's function as a transportation hub and economic center in Xinjiang, which draws a substantial number of visitors and tourism activities. The high vitality of Urumqi is closely related not only to its function as a tourism distribution center but also to its well-developed infrastructure, high levels of socioeconomic development, and convenient transportation network, which draw many tourists for visits or transit. Regions exhibiting elevated sign-in frequencies can be considered core regions of tourist aggregation. The Yili region in northern Xinjiang and the eastern areas also exhibit relatively high spatial vitality. The analysis of Weibo sign-in data indicates that although these regions are not the most frequently visited for tourism sign-ins, they still demonstrate a relatively high level of tourist activity. This moderate distribution of vitality is related to the richness of local tourism resources, the grade of attractions, and a certain economic foundation. For example, the Yili region may possess abundant natural resources and several attractions, attracting a certain number of visitors; however, its sign-in vitality is relatively lower than that of Urumqi, likely due to less convenient transportation conditions compared to the central city, resulting in shorter visitor stays. In contrast, the remote areas of southern, western, and eastern Xinjiang show the lowest levels of spatial vitality. These regions exhibit low spatial vitality, as indicated by Weibo sign-in data, reflecting a relatively low frequency of visitor sign-ins. This phenomenon can be attributed to poor infrastructure in remote areas and low accessibility for tourists, leading to fewer sign-ins. Additionally, low-vitality regions often lack economic resources and have inadequate service facilities, resulting in shorter visitor stays or poorer tourism experiences, making it difficult to attract large numbers of tourists.

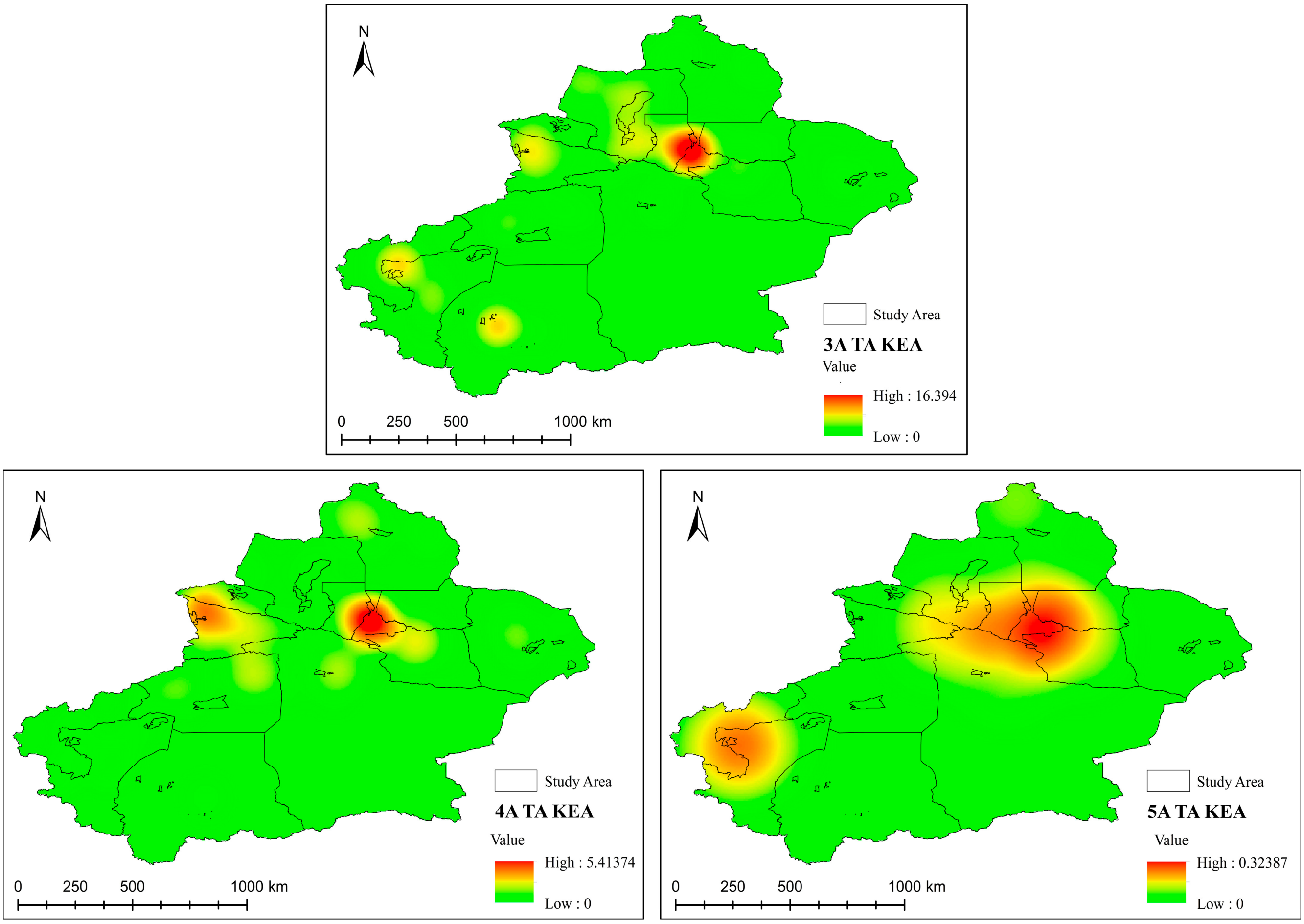

Figure 3. Spatial distribution of AAA, AAAA, and AAAAA tourist attractions in Xinjiang.

Overall, the spatial vitality distribution of tourist attractions in Xinjiang presents a pattern characterized by strong vitality in the north and weak vitality in the south, with a concentration in the central region and differentiation between the east and west. Aside from Urumqi, the Yili River Valley in northern Xinjiang and the central areas also demonstrate relatively high vitality. In contrast, the spatial vitality of attractions in southern and eastern Xinjiang is generally lower than that in northern and central Xinjiang. The findings indicate a trend of uneven and highly clustered spatial vitality distribution throughout the Xinjiang region.

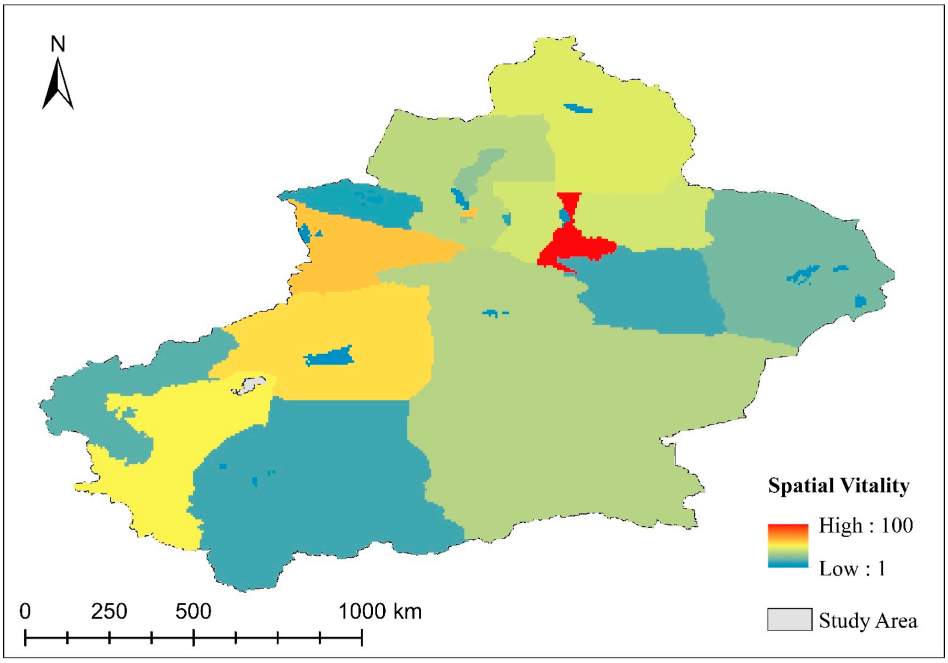

Figure 4. Spatial vitality distribution of tourist attractions in Xinjiang.

3.3. Analysis of the Match Between Spatial Distribution and Spatial Vitality of Tourist Attractions in Xinjiang

Through matching analysis using the Geographically Weighted Regression (GWR) model, we find significant regional differences in the matching between various levels of tourist attractions and regional spatial vitality across Xinjiang. The match is highest in Urumqi and its surrounding areas, as Urumqi serves as Xinjiang's transportation hub, featuring an international airport, highways, and railway systems that considerably reduce travel time and enhance tourist mobility. Additionally, the area provides comprehensive facilities, including hotels, dining, and shopping centers, offering a comfortable experience that attracts more visitors to stay longer. Furthermore, as Xinjiang's economic center, Urumqi possesses strong market appeal and allocates more resources to promote and support high-level attractions. Thus, high-level attractions in this region not only benefit from rich natural and cultural resources but also leverage transportation and service advantages to attract substantial visitor numbers, significantly enhancing regional spatial vitality. The northern Xinjiang region shows a moderate level of matching between tourist attractions and regional vitality. Although northern Xinjiang boasts numerous natural landscapes, such as grasslands, lakes, and forests, the distances between attractions are considerable, requiring visitors to spend more time on transportation. While some main roads and railways connect cities like Ili, transportation to more remote attractions remains challenging, limiting tourist mobility. Additionally, northern Xinjiang's attractions mainly attract visitors in summer, with a marked decrease in winter, leading to considerable fluctuations in overall matching. Despite abundant resources, the dispersed distribution and seasonal nature of attractions constrain efficient matching with regional vitality. In contrast, southern and eastern Xinjiang exhibit lower matching, indicating that attractions in these areas fail to effectively drive regional spatial vitality. The remote locations of southern and eastern Xinjiang, coupled with limited transportation networks, require visitors to spend substantial time reaching attractions, which significantly reduces visitor numbers. Moreover, these areas have limited hotel, dining, and leisure facilities, with relatively low service quality, making it difficult to encourage extended stays. Additionally, the lagging economic development and limited market support in these regions constrain further attraction development and promotion. Lastly, some attractions face slower development due to cultural or policy constraints, preventing the full utilization of tourism resources. These factors result in a mismatch in southern and eastern Xinjiang, where numerous attractions exist, yet tourist mobility remains low, reflecting an underutilization of regional vitality.

Overall, the matching degree between tourist attractions and spatial vitality significantly varies with the grade of the attractions. AAA attractions tend to rely more on external conditions, such as the economy and transportation in their surrounding areas, resulting in higher matching degrees in regions with convenient transportation and strong vitality. In contrast, in remote areas, the matching degree of AAA attractions is lower, indicating that the vitality of these attractions is primarily constrained by local transportation and infrastructure conditions. The matching degree of AAAA attractions exhibits considerable regional variation, with some areas showing a high degree of matching with vitality, particularly in southern and western Xinjiang, where AAAA attractions play a relatively significant role in boosting local vitality. For AAAAA attractions, their higher visibility and appeal lead to outstanding matching degrees in more developed areas, such as northern Xinjiang. However, in some remote regions, despite the presence of high-grade AAAAA attractions, the lack of corresponding infrastructure support fails to fully stimulate local vitality, resulting in weaker matching degrees (Figure 5).

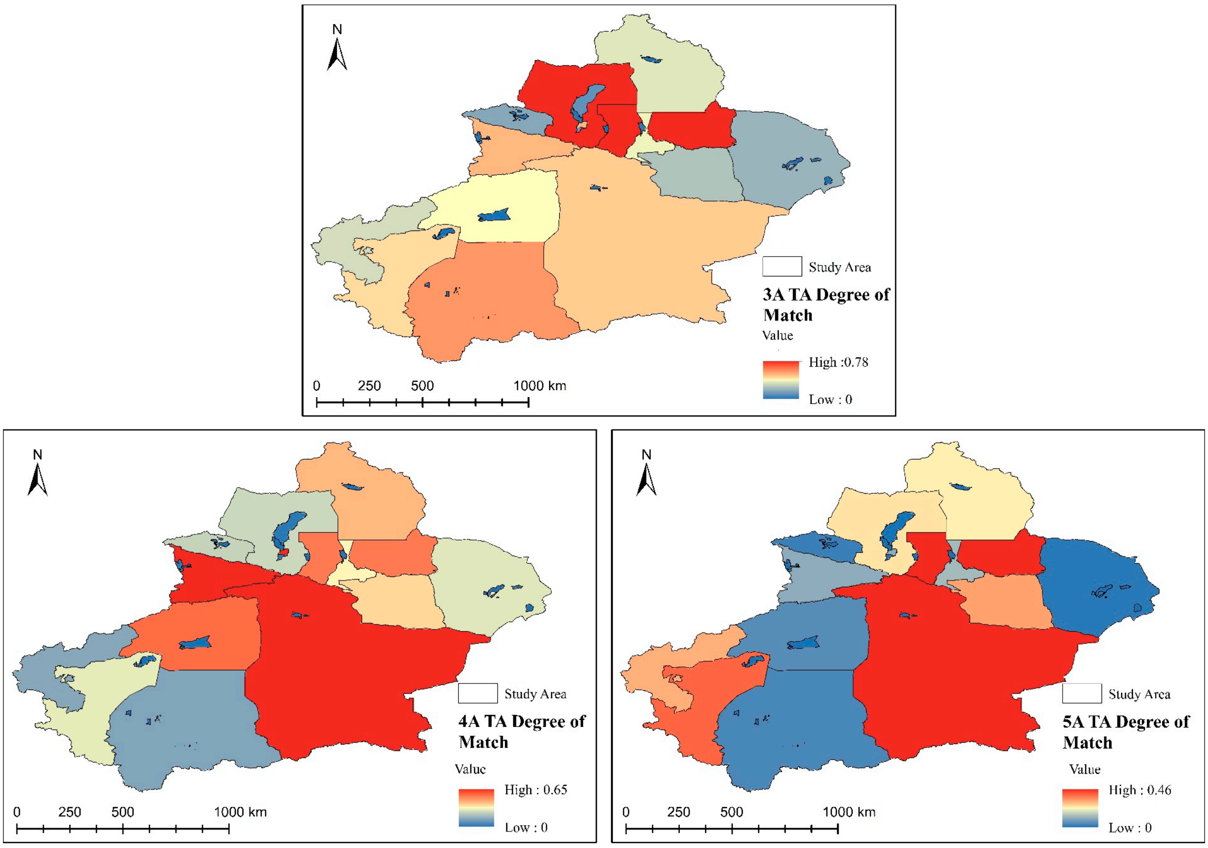

Figure 5. Matching degree between tourist attractions of different grades and spatial vitality.

4. Discussion

This study investigates the relationship between the spatial distribution of tourist attractions of different grades and regional spatial vitality in Xinjiang. By combining Amap POI data and Weibo sign-in data, we employ methods such as KDE, hotspot analysis (Getis-Ord Gi*), and spatial matching models to comprehensively analyze the spatial vitality distribution and matching degree of AAA, AAAA, and AAAAA attractions in Xinjiang and adjacent regions. We find that high-grade attractions are primarily concentrated in Urumqi and its surrounding areas, exhibiting a high degree of spatial agglomeration and a strong matching degree. In contrast, although there are many low-grade AAA attractions, they are mainly distributed in areas with relatively poor transportation, resulting in a lower matching degree, indicating that these attractions do not adequately stimulate regional vitality. Northern and central Xinjiang demonstrate higher vitality with a dense distribution of attractions, where spatial vitality and attraction distribution are relatively well matched. However, in certain areas of southern and eastern Xinjiang, the presence of tourism resources is undermined by inadequate infrastructure and economic conditions, resulting in a disparity between the distribution of vitality and attractions. This suggests that the capacity of tourism resources is insufficient to enhance spatial vitality.

Compared to other studies, the majority of research on tourist attractions typically relies on tourism yearbooks, official statistical data, or survey questionnaires [49–51]. Although such data can provide an overview of attraction distribution, they lack real-time and dynamic characteristics, making it difficult to reflect the actual spatial activities and movement behaviors of tourists [52]. This study integrates Amap POI data and Weibo sign-in data, facilitating a more accurate reflection of the real-time distribution of attractions and the dynamic changes in spatial vitality. Specifically, Amap POI data cover a wide area and can precisely locate the geographical positions of attractions [53]; Weibo sign-in data capture the fluidity and timeliness of tourism activities through real-time sign-in behaviors of visitors [54]. Compared to traditional static data, the data sources in this study offer higher timeliness and dynamism, allowing the research findings to better reflect the actual state of attraction vitality [55]. Additionally, research has found that areas in eastern China with concentrated tourism resources generally exhibit a high degree of match between attraction distribution and vitality, whereas remote areas in the western region often struggle to leverage their numerous attractions due to inconvenient transportation [7,56]. Similarly, this study identifies a strong match between high-grade attractions and spatial vitality in northern Xinjiang, indicating that high-grade attractions typically rely on well-developed infrastructure and economic conditions to attract visitors, resulting in high-vitality agglomeration [36]. However, this study also reveals a significant mismatch between tourism resources and spatial vitality in southern and eastern Xinjiang, which differs from other regions. Despite having certain natural resources and a foundational presence of attractions, these areas fail to stimulate the expected vitality due to inadequate infrastructure and underdeveloped economic conditions, resulting in vitality levels that are significantly lower than those in northern Xinjiang. This mismatch phenomenon is relatively uncommon in existing research. In comparison with studies from other regions and countries, research in the Yangtze River Delta and Pearl River Delta shows a generally high match between high-level tourist attractions and regional vitality. This matching largely benefits from the eastern region's extensive highway and high-speed rail networks, which allow visitors easy access to various attractions and enhance regional vitality. Additionally, the high economic development level in these coastal areas strongly supports infrastructure construction and marketing for attractions. Finally, the market-driven operation of attractions and the active development of diversified tourism products increase visitor appeal [57,58]. In contrast, southern and eastern Xinjiang exhibit lower matching due to transportation challenges and insufficient infrastructure. This finding indicates that attraction development in less-developed areas requires greater policy support to address gaps in infrastructure and marketization. In studies from developed regions like Europe and North America, matching between high-level attractions and regional vitality typically correlates closely with transportation accessibility, infrastructure completeness, and policy support. For example, remote mountain attractions in Switzerland and Austria attract large numbers of visitors due to comprehensive transportation facilities such as cable cars and railways, demonstrating high matching. Research on Yellowstone National Park shows that even attractions far from urban centers achieve high matching through well-developed service facilities and clear marketing strategies [59,60]. Compared to Xinjiang, attractions in Europe and North America overcome locational barriers by optimizing transportation infrastructure and strengthening market promotion. This suggests that attractions in remote areas of Xinjiang also have the potential to improve matching by enhancing transportation infrastructure and optimizing marketing strategies.

Unlike many studies that rely solely on static data [61], this study combines Amap POI data with Weibo sign-in data to address the shortcomings of traditional data, which are often delayed and lack dynamic changes [62]. Weibo sign-in data can reflect the real-time spatial movement of visitors, and this innovative data fusion provides the possibility for precise analysis of spatial vitality [63]. Moreover, this study, in contrast to prior research that mainly focuses on the agglomeration effect of attractions, examines the southern and eastern regions of Xinjiang and identifies shortcomings in attraction development in areas characterized by inadequate spatial vitality. The tourism resources in these regions have not been sufficiently transformed into vitality, which facilitates the development of more effective practical recommendations.

Although Weibo sign-in data provide real-time insights into visitor movement, these data only cover a portion of internet users and may not comprehensively reflect the behavior of all tourists, particularly in remote areas where the use of social media is relatively limited, potentially leading to insufficient data coverage [64,65]. Future research should consider integrating additional data sources, such as mobile signaling data and consumer data, to improve data coverage [66,67]. Furthermore, this study does not adequately account for the impact of seasonal factors, which are crucial to the tourism industry in Xinjiang [68]. Significant variations in tourist flow across different seasons may have important implications for vitality measurements. Subsequent research could incorporate time series analysis to capture the tourist movement patterns during different seasons and holidays, thereby enabling a more accurate assessment of the dynamic changes in regional vitality.

In terms of the methods used in this study, KDE aids in identifying spatial clustering patterns of tourist attractions, yet its results are highly sensitive to the choice of search radius: an overly large radius may obscure local details, while a smaller radius can lose the ability to display overall trends. Additionally, KDE assumes a smooth, continuous influence range for data points; however, in tourism, attraction appeal may vary discretely due to geographic and cultural factors, limiting its explanatory power [69]. Hotspot analysis effectively quantifies active and inactive tourism areas, but it relies on data completeness and coverage. Since Weibo sign-in data primarily reflect a social media-oriented demographic, potential biases may affect representativeness. Moreover, the selection of the spatial weight matrix significantly influences results, especially in a geographically extensive region like Xinjiang, where different weighting models may alter analysis outcomes [70]. The Geographically Weighted Regression (GWR) model effectively captures the spatial heterogeneity of attraction impacts on regional vitality, but it is sensitive to multicollinearity; when strong correlations exist among independent variables, model results may become unstable. Furthermore, this model requires high spatial data completeness; inadequate data quality in certain regions can lead to distorted outcomes [71]. Future research may consider introducing more control variables, such as economic level, policy support, and tourist type, to enhance model robustness.

To better enhance the matching degree between tourist attractions and spatial vitality, future efforts can focus on improving infrastructure. In regions with low vitality and low matching degrees, particularly in southern and western Xinjiang, it is essential to strengthen infrastructure development and improve transportation accessibility to promote tourism in these areas, thereby increasing the attractiveness of attractions to visitors and enhancing spatial vitality. Furthermore, in areas with high vitality but low matching degrees, it may be beneficial to optimize attraction development by improving service quality and increasing marketing efforts, allowing existing spatial vitality to be better integrated with attraction resources to further enhance compatibility. Additionally, regions with a dense distribution of AAAAA attractions can integrate resources and strengthen the linkages with surrounding lower-grade attractions, thereby enhancing the spillover effects of high-grade attractions and stimulating spatial vitality in the surrounding areas, ultimately improving the overall matching degree.

5. Conclusions

This study combines Amap POI data and Weibo sign-in data to conduct an in-depth analysis of the matching relationship between the spatial distribution of tourist attractions of different grades and regional spatial vitality in Xinjiang, revealing the complex interaction characteristics between the utilization of attraction resources and vitality. The study finds that tourist attractions in Xinjiang exhibit significant grade differences and spatial agglomeration effects. In particular, AAAAA attractions are primarily concentrated in Urumqi and its surrounding areas, while AAAA attractions are more dispersed, and AAA attractions have a broader distribution, making it difficult to form effective agglomeration effects. The spatial vitality of Xinjiang demonstrates notable imbalances, with Urumqi and its surrounding areas showing the highest vitality, characterized by active tourist flows and frequent tourism activities. The northern and central regions follow, displaying relatively stable spatial vitality. In contrast, remote areas such as southern and eastern Xinjiang, despite having some tourism resources, experience lower overall vitality levels due to inconvenient transportation and inadequate infrastructure, leading to weaker tourist mobility and a lack of vitality.

There are notable discrepancies in the matching of tourist attractions across various grades and the regional spatial vitality in Xinjiang. In particular, the matching degree of AAAAA attractions with spatial vitality is relatively high, as the areas where these attractions are located often possess good infrastructure and transportation conditions, resulting in concentrated tourist flows. The matching degree of AAAA attractions exhibits regional variability; while some areas show good matching, certain regions in northern Xinjiang demonstrate a lower degree of matching, reflecting regional differences in resource utilization efficiency. In contrast, AAA attractions display a clear mismatch between resources and vitality in remote areas. Although these attractions are widely distributed, they fail to effectively stimulate regional vitality, indicating that insufficient infrastructure and transportation conditions significantly limit the enhancement of their vitality.

This study offers important practical references for revealing the development potential of tourism resources and boosting vitality in Xinjiang. Additionally, the study findings can assist policymakers in formulating more targeted strategies for tourism resource development and infrastructure improvement. Future research should investigate the dynamic changes between tourist attractions and spatial vitality by incorporating more socioeconomic factors and long-term time series data, particularly across different seasonal and policy contexts.

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