Spatio-Temporal Evolution Characteristics and Spatial Differences in Urban Tourism Network Attention in China: Based on the Baidu Index

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Abstract: There is a long-term equilibrium relationship between urban tourism network attention (UTNA) and the volume of tourism. Understanding the spatio-temporal patterns of UTNA before and after the COVID-19 pandemic has important implications for destination management. On the basis of the Baidu index, this study collected the tourism network attention of 337 prefecture-level cities in China from 2018 to 2021 through data mining and analyzed the spatio-temporal evolution characteristics and regional differences in UTNA in China by using the seasonal concentration index, the Zipf model and the Dagum Gini coefficient. The results show that, firstly, the UTNA decreased significantly during the study period, with significant seasonal variability and spatial unevenness; April, July, August and October comprise the high season, while January, February, November and December comprise the low season. Secondly, in terms of regional heterogeneity, the seasonal differences in UTNA are generally greater in the northeast regions than in the central, and western regions, and are the smallest in the eastern regions. Thirdly, the UTNA shows a strong rank-scale characteristic, indicating that Beijing, Chongqing, Shanghai, Guangzhou, Xi’an, and others that are rich in tourism resources are the main high-value cities, and “core-edge” characteristics gradually formed around these municipalities and capital cities. Lastly, of the four regions, the northeast regions had the largest intraregional and inter-regional differences. From the perspective of the contribution to regional difference sources $G_{nh}>G_{t}>G_{w}$, inter-regional disparities are the main reasons for the overall differences. Accordingly, policy suggestions are proposed to further promote the sustainable development of tourism destinations.

Keywords: urban tourism network attention (UTNA); spatio-temporal evolution; regional differences; Dagum Gini coefficient; COVID-19 pandemic

1. Introduction

Tourism is a pillar industry with strong economic contributions and a high degree of marketability [1]. In the last five years, the value of the tourism industry in China has been worth around 4% of GDP, according to calculations by the Chinese National Bureau of Statistics [2]. Playing a key role in expanding consumption, boosting the economy, and driving employment and other aspects of economic and social development, tourism has become an indispensable part of people’s well-being [3–5]. Against the background of the steady development of the overall situation of the Chinese national economy, the tourism industry has also gradually entered the stage of high-quality development, showing long-term improvements [6]. However, due to the influence of the economic development level, resource distribution and the regional transportation infrastructure, imbalances in regional tourism development in China have been an ongoing problem [7]. In addition, the tourism industry is very sensitive and vulnerable to meteorological disasters, geological disasters, and infectious diseases. In particular, the COVID-19 pandemic has
generated an unprecedented level of public fear [8], with long-lasting consequences on global economic flows, the travel industry, and each individual [9]. Thus, the travel industry, which relies heavily on passenger volumes, has been hit hard by the restrictions on movement due to the pandemic. During the pandemic, tourists’ willingness to travel and travel habits were affected accordingly, with new changes in tourism demand [10]. Consequently, both challenges and opportunities exist for the development of tourism. In this context, further research into the development of changes in the domestic tourism market is desperately needed.

Cities are both the main carriers of tourism economic growth and the basic sites of tourism activities [11]. By enriching tourism activities, cities increase their exposure, enhance tourist attractions, and facilitate the movement of tourists through cities. In turn, this revitalizes city elements, taps the city’s value, and boosts the city’s economy, which provides further high-quality travel services for tourists. Several studies have shed light on urban tourism development, especially from a resource, economic, and passenger flow perspective. However, most studies have used statistics from traditional sample surveys, lagging behind the rapid growth in tourism [12]. With the continuous development of information technology, network data with large volumes, full dimensions, and high accuracy and continuity have become a hot topic in tourism research. The attention to a tourism network is a direct manifestation of tourists’ demand and behavior regarding the network. As the platform holds the largest information search database in China, Baidu plays an extremely important role in the search for dissemination of UTNA. On this basis, the data in this study were derived from the Baidu index.

Obtaining daily data is an important prerequisite for exploring the spatial and temporal differences in UTNA in Chinese, so we collect the daily Baidu index of 337 prefecture-level cities in China from 2018 to 2021 to measure the attention of their tourism networks. This study divided China’s 337 prefecture-level administrative units into four major regions, then the seasonal concentration index was used to analyze the characteristics of the changes in annual and monthly UTNA over time under the influence of the pandemic. ArcGIS software was used to map the spatial distribution of UTNA in China. After that, the Dagum Gini coefficient was used to decompose the regional differences in UTNA and analyze the sources of regional differences in regional tourism network attention. Our findings can help governments to identify the spatial disequilibrium characteristics of UTNA and explore the adverse effects on tourism and the developing trends of the pandemic.

2. Literature Review

As humans advance into the era of information, increasing numbers of tourists are using the internet to obtain tourism information and make travel plans. Tourist network attention is the intuitive manifestation of tourist demand and behavior within the network. Since the 1990s, the gradual application of online information systems in various fields of tourism has aroused academic interest in the field of website information flow and tourism flow. Therefore, researchers have taken to studying the design of tourism websites and the behavior of tourist networks [13–16] and certain research results have been achieved. Users have become more dependent on tourism network information with the rise of various travel websites, and research into various kinds of travel search data has increased rapidly. Many scholars use search query data to model tourism demand through multiple models such as the dynamic linear model [17], the FOA-BP method [18] and KELM models [19] to improve the predictive accuracy. The results have shown that there is a strong correlation between tourist network attention and the changes in passenger flow, both spatially and temporally.

Compared with foreign studies, research on tourism network attention in China has covered multiple spatial and temporal scales from provincial to regional and national. Currently, an increasing number of scholars have portrayed the spatial and temporal evolution of the network attention of different types of tourist attractions and have theoretically elaborated on the reasons for their geographical differences [20,21]. Scholars have
mainly focused on the temporal evolution of tourism network attention for different types of tourist attractions. Some scholars have found that attention to tourist attractions is characterized by a typical seasonal pattern [22], which acts as a harbinger of the visitors [23]. Later, many scholars investigated the spatial distribution of 5A—level tourist attractions and their degree of network attention [24]. A few scholars discussed the distribution patterns of the network attention of classic red tourism scenic spots in China and their dynamic mechanism [25]. Some scholars used the seasonal concentration index to study the temporal structural characteristics of tourism flows in China [26]. However, the subjects of the previous studies were diverse in certain aspects, while ignoring urban tourism. It is vital to pay attention to regional differences in UTNA because of its variety across many regions in some countries, especially in those with many cities such as China. With the rapid expansion of urban tourism in China, regional differences have become an important element in the study of spatial non-equilibrium in urban tourism. A few scholars found that the tourism demand of residents of different cities was characterized by extremely complex and diverse spatial variations [27]. Some scholars found that the regional network's attention to tourist satisfaction has remarkable differences [28,29].

Although the studies mentioned above obtained some key information on UTNA, there are at least three aspects that should be improved. First, the COVID-19 pandemic has become an exogenous factor that cannot be ignored, as it has affected the development of the tourism industry, and the regional differences in the impact of COVID-19 on tourism need further empirical testing. Second, the regional differences in tourism network attention have been neglected, and we cannot identify the key factors inducing the differences and provide more information for policymakers. The Dagum Gini ratio developed by Dagum can be used to obtain the true differences in UTNA among regions and can also find the source of the difference [30]. This study conducted an empirical analysis of the regional differences in UTNA according to the division of the four major regions in China. We not only focused on the differences in and contribution sources of UTNA but also expanded the research perspective to evaluate the internal structure. Third, many studies have examined UTNA from the perspective of a nation, a specific province, or a specific region. However, few studies have focused on cities. Therefore, focusing on the operation patterns and spatial distribution of urban tourism network concerns and extending the research field of tourism activities to the city level can deepen the urban tourism research system and also provide an academic reference for the formulation of balanced development strategies for urban tourism from the perspective of demand.

3. Materials and Methods
3.1. Sample Datasets

In this study, the samples of our study were 337 prefecture-level cities in China (excluding the Hong Kong Special Administrative Region, the Macao Special Administrative Region, and Taiwan), which covered almost all prefecture-level cities. The selection of China was due to its worldwide importance as a recipient of tourists, and the accessibility and convenience of the study data.

From 2018 to 2021, China’s total national tourism revenue was CNY5.97 trillion, CNY6.63 trillion, CNY2.23 trillion, and CNY2.92 trillion (USD0.902 trillion, USD0.961 trillion, USD0.323 trillion, and USD0.453 trillion) and the total tourist arrivals were 5.6802 billion, 6.1513 billion, 2.879 billion and 3.246 billion [31], respectively, for each year, although this was affected by the general environment of the pandemic. In 2020 and 2021, the total tourism revenue and total trips were reduced, but China ranked second after the United States among the top 20 countries in the global tourism economy [32,33], and China is an important part of the development of world tourism. This case study is typically representative and has great practical significance. The Baidu index data contain rich information and are an excellent and sufficiently representative resource for measuring UTNA [34,35].
The Baidu index is a statistical measure of keywords that calculates the search frequency of each keyword as a web search weighted sum. The index reflects the attention of web users to specific areas [36]. Therefore, we needed to choose the most relevant keyword within the search queries. According to some existing articles [37,38], we used direct keyword selection and keyword selection scope to determine the search keywords [39] and took the following steps to select the keywords.

First, we took the 337 cities studied as the basic scope, combined with the general characteristics of tourists’ search behavior for tourism information. We established the first batch of search keywords through the direct lexical method of “city + tourism”, and obtained 337 keywords included in the Baidu index.

Second, high-quality scenic spots are important for fostering the attraction of tourist destinations [40]. The 5A and 4A scenic spots, which are evaluated, examined, and approved by the Ministry of Culture and Tourism and the Provincial Department of Culture and Tourism, are the two highest levels of tourist attractions in China. They are the key tourism products of tourist destinations for the source market with high levels of tourist attraction that have become an important object of tourism research. According to statistics obtained from the Ministry of Culture and Tourism of the People’s Republic of China, there were 4466 5A and 4A scenic areas at the end of December 2021. In line with this, the search keywords used in this study were based on the commonly used names of scenic spots. Finally, we obtained 1206 keywords included in the Baidu index.

To ensure the reliability of the study, the credibility of the data was further verified. The data during the study period were correlated with the domestic tourism sample survey statistics released by the Ministry of Culture and Tourism for person correlation analysis, and the absolute value of Pearson’s correlation coefficient, R, determined the degree of correlation between the independent and dependent variables, resulting in an R-value of 0.969, indicating that the study is credible.

3.2. Methodology

3.2.1. Seasonal Concentration Index

The seasonal concentration index is one of the classic methods used to analyze the temporal distribution of research objects [41]. It was originally used to analyze the temporal concentration distribution of tourist traffic [21] and now is often used to analyze the temporal concentration distribution of tourist network attention. In this study, the seasonal concentration index was used to reflect the temporal concentration of UTNA. The formula is given below:

\[
S = \sqrt{\sum_{m=1}^{12} (x_m - 8.333)^2 / 12}
\]

where \(X_m\) is the proportion of the UTNA in each month within that of in the whole year. If the value of \(S\) approaches zero, the time distribution in UTNA is relatively uniform, with few differences among months. Increasing values of \(S\) show that the time difference in UTNA is greater.

3.2.2. Zipf Model

The Zipf model is a common indicator used to describe the relationship between urban population size and urban ranking. In recent years, the Zipf model has also been widely used in the field of tourism [42]. In this study, the Zipf model parameter values were used to analyze the relationship between tourism network attention and the rank order of Chinese cities. Our hypothesis was as follows:

\[
\ln P_i = \ln P_1 - q \ln R_i (R_i = 1,2, ..., n)
\]
where $P_i$ is the tourism network attention of a city with the rank order $R_i$. $R_1$ is the maximum tourism network attention among all cities and $q$ is the concentration index. The tourism scale distribution can be divided into three categories on the basis of the $q$ value: decentralized and balanced ($q \leq 0.85$), concentrated ($0.85 < q < 1.2$) and top-ranked ($q \geq 1.2$). When $q = 1$, the urban system is in the natural state of the optimal distribution of the concentration type.

3.2.3. Dagum Gini Coefficient

Dagum [30] proposed a method to decompose the Gini coefficient by subgroups, which effectively solved the problem of crossover between samples and the inability to reveal the source of overall differences, and compensated for the shortcomings of the traditional Gini coefficient and the Theil index.

We used the Dagum Gini coefficient method described by Dagum to decompose the regional differences in UTNA. The Dagum Gini coefficient is defined as:

$$G = \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{r=1}^{n_j} \sum_{s=1}^{n_h} |y_{jr} - y_{hs}|}{2n^2 \mu}$$  (3)

where $G$ is the total Gini coefficient, which measures the total difference in UTNA among cities; $k$ is the number of regions, which included the eastern, northeastern, central and western regions in this study. The four regions are classified according to the National Bureau of Statistics classification criteria [37]. The eastern regions include Beijing, Tianjin, Hebei, Hainan, Guangdong, Guangxi, Fujian, Zhejiang, Shanghai, Jiangsu and Shandong, for a total of 88 cities in 11 provinces. The central regions include Shanxi, Inner Mongolia, Anhui, Jiangxi, Henan, Hubei and Hunan, for a total of 83 cities in seven provinces. The western regions include Sichuan, Chongqing, Yunnan, Guizhou, Tibet, Shaanxi, Gansu, Ningxia, Qinghai and Xinjiang, for a total of 130 cities in 10 provinces. The northeast regions include Liaoning, Jilin and Heilongjiang, for a total of 36 cities in three provinces. Moreover, $y_{jr}$ and $(y_{hr})$ represent the UTNA of cities in the $j$-th and $h$-th region, respectively, where $j=1,2, \ldots, k$ and $h=1,2, \ldots, k$; $\mu$ is the average UTNA of all cities; $n$ is the number of all cities; and $n_j$ and $n_h$ represent the number of cities in the $j$-th and the $h$-th region, respectively.

Similar to the method of Dagum, the total Gini ratio can be decomposed into three parts: the intraregional gap ($G_w$), the inter-regional gap ($G_{nb}$) and transvariation intensity ($G_t$). The three parts satisfy the following:

$$G = G_w + G_{nb} + G_t$$  (4)

The specific decomposition formula is as follows:

$$G_w = \sum_{j=1}^{k} \sum_{s=1}^{n_j} |y_{jr} - \bar{y}_j| s_j$$  (5)

We measured the contribution of the differences in UTNA within a region to the total Gini coefficient $G$ as:

$$G_{nb} = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh}$$  (6)

We measured the net contribution of the extended differences in UTNA between regions to the total Gini coefficient $G$ as:
\[
G_t = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh})
\]  

We also measured the contribution of the transvariation intensity between regions to the total Gini coefficient as \( G \). \( p_j = n_j/n \), \( s_j = n_j \mu_j/n \mu \), where \( \mu_j \) and \( \mu_h \) are the average UTNA of the \( j \)-th and the \( h \)-th region, respectively.

In Formula (6), \( D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \) is the relative difference in UTNA between the \( j \)-th and the \( h \)-th region, and the gross UTNA \( d_{jh} \) between the \( j \)-th and the \( h \)-th region, such that \( u_j > u_h \), is:

\[
d_{jh} = \int_0^\infty dF_j(y) \int_0^y (y-x) dF_h(x)
\]

where \( F_j(y) \) and \( F_h(x) \) are the probability density function of the \( j \)-th and the \( h \)-th regions, respectively; \( d_{jh} \) is the weighted average of the UTNA difference \( y_{ji} - y_{hr} \) for all UTNA \( y_{ji} \) of the members belonging to the \( j \)-th region with an UTNA greater than \( y_{hr} \) of the members of the \( h \)-th region, such that \( u_j > u_h \); and \( p_{jh} \) is the first-order moment of transvariation between the \( j \)-th and the \( h \)-th region, such that \( u_j > u_h \), as follows:

\[
p_{jh} = \int_0^\infty dF_h(y) \int_0^y (y-x) dF_j(x)
\]

By definition, \( p_{jh} \) is the weighted average of the difference in UTNA \( y_{ji} - y_{hr} \) and \( u_j > u_h \). The word transvariation indicates the fact that the differences in UTNA considered here have the opposite sign to the difference in the means of their corresponding region.

\( G_{jj} \) is the Gini ratio within a region and \( G_{jh} \) is the Gini ratio between regions:

\[
G_{jj} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}|}{2n_j^2 \mu_j}
\]

\[
G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{n_j n_h (\mu_j + \mu_h)}
\]

4. Results

4.1. Temporal Evolution Characteristics of UTNA

4.1.1. Annual Evolution

To obtain the total Baidu index of each city from 2018 to 2021, the daily search volumes of 337 prefecture-level cities were summed by year (Table 1). It can be seen from Table 1 that the UTNA showed a declining trend from 2018 to 2021: compared with 2018, the percentage of UTNA in 2019, 2020, and 2021 decreased, respectively, by 6.57%, 33.88%, and 33.96%. Before the outbreak of COVID-19, the UTNA was slightly down in 2019 compared with 2018, unlike the rising trend of the tourism demand market. This phenomenon may be attributed to the popularization of online information and the continuous enrichment and development of tourism activities, meaning that as tourists became more familiar with the relevant information about tourist destinations, the demand for learning tourism information through the internet grew weaker. After the outbreak of COVID-19, UTNA decreased sharply, which shows that the outbreak of COVID-19 had a profound impact on the tourism industry. In the context of the outbreak of COVID-19 tourists’ willingness to travel declined sharply, and thus, the inter-annual changes in UTNA have been greatly affected.
The rate of decline in UTNA differed among the eastern, central, western and northeastern regions. The northeast regions and eastern regions were higher than the national average level, while the western region was close to the national average level, and the central region was lower than the national average level, suggesting that the severity of the pandemic varied across different geographic regions and the impact of the pandemic on UTNA also varied across geographic regions. Currently, we are still in the COVID-19 pandemic, so there is a need for a more comprehensive plan to deal with this in different geographic regions.

Table 1. UTNA in different regions in China from 2018 to 2021.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Growth Rate</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nation</td>
<td>Growth rate</td>
<td>33,243,137</td>
<td>31,058,489</td>
<td>21,979,060</td>
<td>21,954,340</td>
</tr>
<tr>
<td>East</td>
<td>Growth rate</td>
<td>15,945,256</td>
<td>14,482,321</td>
<td>10,104,499</td>
<td>10,252,123</td>
</tr>
<tr>
<td>Central</td>
<td>Growth rate</td>
<td>6503.696</td>
<td>6610.595</td>
<td>4664.717</td>
<td>4622.761</td>
</tr>
<tr>
<td>West</td>
<td>Growth rate</td>
<td>9707.182</td>
<td>9032.566</td>
<td>6576.193</td>
<td>6432.636</td>
</tr>
<tr>
<td>Northeast</td>
<td>Growth rate</td>
<td>1087.004</td>
<td>933.007</td>
<td>633.652</td>
<td>646.821</td>
</tr>
</tbody>
</table>

Note: The growth rate was calculated using 2018 as the base period. — indicates no value.

4.1.2. Monthly Evolution

This study further analyzed the UTNA at a monthly scale in order to provide a scientific basis for the formulation of a coordinated development policy for the tourism season. The daily search volumes pertaining to 337 prefecture-level cities were summed by month to obtain the total UTNA for each month from 2018 to 2021 (Figure 1). The monthly change in UTNA in China had the following characteristics. First, there were numerical differences in the UTNA in each month from 2018 to 2021. The fluctuation in the curve for the eastern, central, and western regions is consistent with the national average level. Before the COVID-19 outbreak, the trends for 2018 and 2019 were similar, with an upward trend from January to April, a downward trend from April to June, and alternating fluctuation from June to December. Among the months, the UTNA of August was significantly higher than that of other months of the same year in terms of online attention to Chinese cities, forming the main peak, followed by April, July, and October, while November, December, and January generally had low values. After the COVID-19 outbreak, 2020 and 2021 showed different dynamics of change. In 2020, from February to October, Chinese UTNA showed a fluctuating upward trend, with August and October showing significantly higher UTNA than other months of the same year, and that of February being significantly lower. In 2021, January–April showed an upward trend, and April–December showed a fluctuating downward trend, with April, May and July showing significantly higher online attention to Chinese cities than other months of the same year, and January and December showed significantly lower levels of attention.

The cause is tourism vulnerability and uncertainty regarding the COVID-19 outbreak. Under the impact of the pandemic, residents terminated their travel plans, major attractions were closed, large-scale cultural and entertainment activities were canceled and many tourist destinations were impacted.
Second, according to the calculation results of Equation (1), from 2018 to 2021, the seasonal concentration index of each year was 1.593, 1.659, 1.674, and 1.760, respectively, showing a rising trend (Table 2). The results indicate that there are strong temporal differences in the attention of Chinese urban tourism networks, and the seasonal fluctuations are more obvious. In 2018 and 2019, the seasonal concentration index in the northeastern region was significantly higher than the national level, and this was the most pronounced region in terms of seasonal fluctuations among the four regions, followed by the central, western, and eastern regions, which had relatively minimal seasonal fluctuations. With the largest changes in the growth rates occurring in February, April, July, and September, the overall performance of UTNA is that the normal and low seasons are longer, whereas the peak season is shorter, and the characteristics of the low and peak seasons are obvious.

**Table 2.** The seasonal concentration index of different regions in China from 2018 to 2021.

<table>
<thead>
<tr>
<th>Year</th>
<th>Nation</th>
<th>East</th>
<th>Central</th>
<th>West</th>
<th>Northeast</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>1.593</td>
<td>2.737</td>
<td>1.496</td>
<td>1.615</td>
<td>1.786</td>
</tr>
<tr>
<td>2019</td>
<td>1.659</td>
<td>2.377</td>
<td>1.489</td>
<td>1.728</td>
<td>2.089</td>
</tr>
<tr>
<td>2020</td>
<td>1.674</td>
<td>1.653</td>
<td>1.784</td>
<td>1.692</td>
<td>1.683</td>
</tr>
<tr>
<td>2021</td>
<td>1.760</td>
<td>2.062</td>
<td>1.741</td>
<td>1.867</td>
<td>1.909</td>
</tr>
</tbody>
</table>

### 4.2. Spatial Distribution Characteristics of UTNA

We took the UTNA rankings of 337 prefecture-level cities in 2018 as the horizontal axis and the UTNA over 4 years of each city as the vertical axis, and drew a scatterplot uniformly. The scatterplot was fitted with the help of a logarithmic function, which showed that the fitted values of the curve $R^2$ were 0.681, 0.679, 0.634, and 0.633 from 2018 to 2021 (Figure 2).

On the whole, the UTNA over the years has strong rank-scale characteristics, and there is an obvious hierarchical structure among regional cities. UTNA shows a significant “long tail”. Cities with greater UTNA account for a relatively small proportion, while cities with smaller UTNA account for a larger proportion, highlighting the significant imbalance in UTNA. From the perspective of curve fluctuations, in 2019, the curve fluctuated less, the UTNA in each city changed little and the ranking changed less. However, after
the outbreak of the pandemic, the curve fluctuated more in 2020 and 2021, mainly concentrated in the top 150 cities. The change in the UTNA of the cities was relatively large, indicating that major public health events have a great impact on UTNA, resulting in changes in the original stable demand volume.

Figure 2. Rank-size distribution of the tourism network attention of 337 cities in China from 2018 to 2021.

The results of the Zipf model calculations are shown in Table 3. By comparison, the $q$-values of tourism network attention in Chinese cities during the study period showed an upward trend, indicating that overall, the scale of UTNA was moderately concentrated in large cities, and cities with high tourism network attention still maintained high values under the influence of the pandemic. The mean values of the concentration index in the eastern, central, western, and northeastern regions were 1.055, 0.777, 1.020, and 1.062, respectively. The higher concentration index in the eastern, western, and northeastern regions indicates that the spatial concentration in these three regions was much higher than that in the central region. The central region had the lowest concentration index, indicating that UTNA in the central region was relatively dispersed and balanced. Tourism network attention is influenced by factors such as tourism resource endowments, transportation and travel conditions, tourism motivation and preference, and seasonal changes in destinations. The areas with high values of tourism network suggest that the spatial combination of resource endowments, travel conditions, service facilities, recreation experiences, and other elements are better in these areas.

Table 3. Spatial concentration index of UTNA from 2018 to 2021 (Zipf index).

<table>
<thead>
<tr>
<th>$q$</th>
<th>Nation</th>
<th>East</th>
<th>Central</th>
<th>West</th>
<th>Northeast</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>0.871</td>
<td>0.971</td>
<td>0.713</td>
<td>0.943</td>
<td>0.910</td>
</tr>
<tr>
<td>2019</td>
<td>0.874</td>
<td>1.006</td>
<td>0.723</td>
<td>0.983</td>
<td>0.974</td>
</tr>
<tr>
<td>2020</td>
<td>0.888</td>
<td>1.120</td>
<td>0.828</td>
<td>1.064</td>
<td>1.168</td>
</tr>
<tr>
<td>2021</td>
<td>0.894</td>
<td>1.122</td>
<td>0.843</td>
<td>1.091</td>
<td>1.194</td>
</tr>
</tbody>
</table>

To further visualize the spatial evolution characteristics of UTNA, we used ArcGIS10.16 software to produce a geographic distribution map of UTNA across China from 2018 to 2021 (Figure 3). In line with the practice of Fang and Huang [36], the maps generated in this study were divided into five levels for analysis purposes according to the Jenks method. In 2018, there were 1, 5, 24, 79 and 228 cities with grades from high to low, accounting for 0.30%, 1.48%, 7.12%, 23.44% and 67.66%, respectively. In 2021, there were 1, 7, 37, 92 and 200 cities with grades from high to low, accounting for 0.30%, 2.08%,
10.98%, 27.30%, and 59.35%, respectively. It can be seen that the development speed of cities within the same hierarchical level did not differ much, and the scale level of regional cities shows a “hierarchical progressive” evolution characteristic. Beijing has been in the first tier with the highest UTNA throughout the study period. In 2018, only Chongqing, Xi’an, Guangzhou, Shanghai and Hangzhou belonged to the second tier. In 2021, the cities of Chengdu, and Changsha joined the second tier and an additional 3.86% of cities joined the fourth tier, while 10% fewer cities were in the fifth tier compared with 2018.

It can be seen that most of these cities in the first and second tiers belong to the eastern region of China. Beijing is a typical representative, and only Chengdu and Chongqing belong to the western region, but they all occupy an important position in the Chinese urban system. For example, Beijing, Shanghai, and Guangzhou are the central cities of political and economic development in the country; Chengdu and Chongqing are the national central cities explicitly supported and developed by the Chinese government; and Hangzhou, Nanjing, and Xi’an are the provincial capitals. At the same time, these cities are the strategic core cities of the country’s social and economic development, with convenient transportation, rich tourism resources, relatively complete tourism infrastructure, and a relatively high level of tourism development. Figure 3 shows that the high-value areas of UTNA in China show an island-like distribution pattern; that is, the provincial capital city is the core, and the level of UTNA gradually decreases to the periphery. The high-value cities in the eastern region are mainly concentrated in the Beijing–Tianjin–Hebei area, Shandong Peninsula, the Yangtze River Delta, and the Pearl River Delta urban agglomeration; the central region is mainly concentrated in the Central Plains urban agglomeration, and the western region is mainly concentrated in the Chengdu–Chongqing urban agglomeration.

Figure 3. Spatial distribution of UTNA from 2018 to 2021.

4.3. Overall Differences

4.3.1. Overall Differences

In general, the overall Dagum Gini coefficient of UTNA in China fluctuated between 0.65 and 0.68, peaking at 0.677 in 2019 and falling continuously from 0.661 to 0.658 in 2020 and 2021 (Table 4).
The study results show that the overall regional differences in China exhibited an invert V-shaped fluctuation within the research period. The Gini coefficient values are all high, indicating that there is an imbalance in UTNA in China. Further analysis of regional differences was needed to verify these conclusions.

Table 4. The Dagum Gini coefficient and its decomposition results.

<table>
<thead>
<tr>
<th>Year</th>
<th>Overall</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>0.674</td>
<td>0.661</td>
<td>0.658</td>
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<td></td>
<td>0.687</td>
<td>0.679</td>
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<td></td>
<td>0.682</td>
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<tr>
<td></td>
<td>0.697</td>
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<tr>
<td></td>
<td>0.704</td>
<td></td>
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<tr>
<td>Intra-regional Differences</td>
<td>0.661</td>
<td>0.634</td>
<td>0.633</td>
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<tr>
<td></td>
<td>0.640</td>
<td>0.633</td>
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<td></td>
<td>0.604</td>
<td>0.578</td>
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<td>0.669</td>
<td>0.639</td>
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<td>0.789</td>
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<td>0.699</td>
<td>0.709</td>
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<td>0.790</td>
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<td>0.700</td>
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<td></td>
<td>0.709</td>
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<tr>
<td>Inter-Regional Differences</td>
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<td>0.710</td>
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<td>0.637</td>
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<td>0.645</td>
<td>0.619</td>
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<td></td>
<td>0.623</td>
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<td></td>
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<tr>
<td></td>
<td>0.619</td>
<td></td>
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<tr>
<td>Contribution Rate (%)</td>
<td>27.15%</td>
<td>27.21%</td>
<td>27.59%</td>
<td>27.34%</td>
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<td>39.22%</td>
<td>39.41%</td>
<td>37.50%</td>
<td>38.09%</td>
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<td></td>
<td>33.63%</td>
<td>33.37%</td>
<td>34.91%</td>
<td>34.57%</td>
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</tbody>
</table>

Note: $G_w$ refers to intra-regional differences; $G_{nb}$ refers to inter-regional differences; $G_t$ refers to the intensity of transvariation.

4.3.2. Intra- and Inter-Regional Differences

In terms of intraregional differences, the difference in the northeastern region fluctuated around 0.7, which is above the national average level, while the other three regions were below the national average level. Intra-regional differences in the northeastern regions generally showed a decreasing trend from 2018 to 2020 but peaked at 0.704 in 2021. Intra-regional differences peaked in 2019 at 0.640, 0.604, and 0.669 in the eastern, central, and western regions, respectively, but declined overall during the study period.

The largest gap was between the northeastern and the eastern regions, followed by the gap between the western and eastern regions, and the smallest gap was between the central and the western regions. In terms of inter-regional trends, the regional differences between the eastern and central regions, between the eastern and western regions, and between the central and western regions gradually narrowed during the study period, while the regional differences between the northeastern and eastern regions, between the northeastern and central regions, and between the northeastern and western regions increased to 0.791, 0.709, and 0.707, respectively, in 2021.

4.3.3. Sources of Variation and Their Contribution

Table 3 summarizes the regional differences in UTNA in China, including the Dagum Gini coefficient within and between regions, as well as the contribution of the overall differences.

In terms of the trend of the evolution of the sources of variation and the contribution of inter-regional differences, the contribution of inter-regional differences was the highest from 2018 to 2021, with an annual average of more than 38% across the four years, and the overall fluctuation was relatively smooth. It is important to note that the contribution of transvariation intensity was second only to that of inter-regional differences and that its evolution was flat over the research period, fluctuating around 34%. We found that the lowest source of variation was the intra-regional differences, fluctuating around 27%. As
can be seen, inter-regional differences were the major source of overall regional differences in China.

5. Conclusions and Recommendations

5.1. Conclusions

On the basis of the Baidu index data, the seasonal concentration index, and the Dagum Gini coefficient, this research analyzed the spatial and temporal evolution of UTNA and the spatial differences of 337 prefecture-level cities in China during 2018–2021, leading to the following conclusions and suggestions.

First, this study of the spatial distribution patterns of UTNA can provide guidance to enhance the resilience of tourism destinations and promote their sustainable development. During the study period, the eastern region had the highest urban tourism network attention, the western region ranked second, the central region ranked third and the northeastern region ranked the lowest. Due to the impact of COVID-19, UTNA experienced different degrees of decline in terms of numbers, with a decline of more than 30% in both 2020 and 2021 compared with 2018. In terms of spatial distribution, there has been spatial variation in the degree of decline in UTNA in China, with an overall characteristic of UTNA being higher in the northeastern and eastern regions, followed by the western region, and the lowest is found in the central region. The northeastern region did not have high UTNA, but it was the most severely hit by the pandemic, with the most severe losses and weaker resilience; the eastern region had the highest UTNA and a high population density, facing a higher level of risk during the pandemic and a relatively strong decline in UTNA, but its market is mature and rich in tourism resources, and it is believed that its recovery will be faster in later stages. The western region has a vast territory and has repeated pandemic outbreaks in several cities, with a relatively high decline in UTNA, but with its rich tourism resources, its recovery will be relatively fast in later stages. The central region, where the degree of impact of the pandemic was smaller, had the highest resilience. The results show that the degree of the impact of the pandemic on the UTNA in different regions varied.

Second, there was a significant decline in UTNA during the study period, but with the consistent seasonality characteristic of three peaks and two valleys. In general, the peaks of UTNA are consistent with the distribution of the national statutory holidays. Specifically, during traditional Chinese festivals such as Labor Day and the Dragon Boat Festival, the climate is relatively comfortable, and the demand for tourism is high. During the Golden Week of the Chinese National Day holiday, the autumn weather is crisp and clean, which attracts many tourists. From July to September, which has high temperatures, and from November to the end of January, with low temperatures, tourism demand is significantly reduced. Under the regulations for pandemic prevention and control of the pandemic, the vast majority of urban and rural residents have conducted their normal leisure activities and tourism consumption at a normal pace, heralding a strong recovery in the domestic tourism market.

Third, the UTNA of China showed significant seasonal differences, with the largest difference in the northeast, followed by the central and western regions, and the lowest in the east. In 2018, 2019, and 2021, the Seasonal Concentration Index was lower than the national average level in the eastern region, while the central, western, and northeastern regions were higher than the national average level. This was reversed in 2020, which was because the uncertainty of the pandemic affected people’s specific travel schedules. The tourism market in the eastern regions is more mature and stable, while the market in the central, western, and northeastern regions is more fragile.

Fourth, the distribution characteristics of UTNA showed clear spatial and temporal continuity, varied substantially across cities, and tended to cluster in space over time. More than 60% of cities showed a low level of tourism network attention, and thus the vast majority of Chinese cities still have more room for growth in tourism network
attention. Only a few cities such as Beijing, Chongqing, Shanghai, and Guangzhou have a high level of tourism network attention, with a significant trend of polarization in the development of tourism in Chinese cities.

Five, the four major regions of China showed significant differences in tourism network attention. In this regard, the northeastern region showed the largest variation, followed by the western and eastern regions, and the central regions had the smallest variation. Differences between the northeastern region and the other three major regions gradually increased over the study period, whereas gaps between the eastern and central regions, between eastern and western regions, and between central and western regions gradually decreased. In conclusion, from the perspective of the contribution of the sources to regional differences \( G_{nb} > G_t > G_w \), inter-regional disparities were the main reasons for the change in the differences. Regional differences were seen in the pandemic risk level and the development of the tourism industry, which also caused the UTNA to have large spatial differences.

5.2. Recommendations

Based on the above research conclusions, to promote high-quality tourism development, this study puts forward the following suggestions:

(1) Enrich Micro-tourism.

The duration and intensity of COVID-19 were beyond expectations. Uncertainty and instability about the pandemic remain. In the context of the regulations for the prevention and control of the pandemic, people’s travel time has become fragmented and the distance traveled is short. With the rise in “micro-tourism” and “micro-vacation” represented by local tours and peripheral tours in nearby areas for a short time with high frequency, as well as the rapid rise in camping and leisure tourism, domestic tourism has developed new growth momentum amidst difficulties. Each region should meet its tourism demand, accelerate its adjustment and continuous transformation of the tourism product structure, and continue the release of market expectations that encourage travel, leisure, and consumption. This will create a market environment that is conducive to medium- and long-distance tourism consumption.

(2) Optimize the Distribution Pattern of Statutory Holiday Time.

This research showed that the urban tourism network mainly focuses on April, August, and October, and the domestic tourism market is characterized by a short peak season and a long low season. China has only two long holidays, the National Day and the Spring Festival, and most others are shorter than three days. This is not enough to support more time-consuming travel, such as long-distance trips and family visits. In the future, consideration could be given to extending the holiday season beyond the existing ones to ensure a Golden Week in each quarter to ease seasonal travel problems.

(3) Cultivate the Metropolitan Tourist Areas.

Cultivating the metropolitan tourism areas is the key point for promoting integrated tourism in urban agglomerations. There is still room to improve the UTNA of most of China. Municipalities and capitals such as Beijing, Shanghai, Guangzhou, and Chongqing are high-value cities, whose tourism demand is strong and whose tourism resources are in good condition. Thus, there is a large gap in the tourism development of different Chinese cities. Areas with high tourism network attention should give full play to their resources and market advantages, and continue to deepen the structural reform of the tourism supply side, to optimize the tourism market, organize and guarantee the system, pay more attention to the promotion of the quality of products and optimization of the product structure, and promote the high-quality development of the tourism industry.

At the same time, the demonstration effect and spillover effect have driven the development of the tourism industry in low-value areas. The low-value areas should
actively adapt to the requirements of developing a high-quality tourism industry, actively explore structural supply side reform of the tourism industry, learn from the experience of high-value areas, strengthen the foundations of local tourism development and gradually reduce the development gap.

(4) Suit Measures to Local Conditions.

First of all, governments should implement different schemes based on the actual situation of each region when formulating tourism development policies. For example, the eastern regions, as leaders in the tourism economy and tourism network attention, show a high level of tourist services and economic development and have strong demand for industrial upgrades and environmental improvement. Thus, governments in these regions should accelerate the modernization of tourism, establish a better leisure and vacation system, and improve the core competitiveness of tourism.

However, the areas in the central and western regions show relatively low levels of tourism network attention and they are also the main destination areas for tourists from the eastern regions. As a result, they are under pressure from the tourism economy to upgrade their brand. The local government should play a leading role in strengthening the integration of tourism resources, developing special tourism, and promoting the upgrading of the tourism brand.

The northeast is the region that receives the least tourism network attention. Despite the cold weather and the fact that snow and ice make up a large portion of the country’s natural resources, the region’s ice features have become well-known brands in recent years due to the many sporting events it hosts. Therefore, the government of northeast China should make great efforts to improve the level of tourism services and develop specialty industries such as ice and snow tourism and ecotourism. On the whole, the state should strengthen its support for the central and northeastern regions in terms of policy support, brand creation, and market docking to further promote coordinated tourism development throughout the region.

6. Limitations

This article has some limitations. Multi-year UTNA data have been collected, but we used the Baidu index as the only data source. This means that our research findings might be less representative than expected. Secondly, to minimize the sampling error, the study constructed the UTNA mostly based on 4A and 5A scenic spots to expand the content of UTNA in terms of keyword selection, but some keywords are not included in the Baidu index. A comprehensive investigation of more information about UTNA is needed in future research. Thirdly, this study explored the regional differences in the tourism network attention of Chinese cities before and after the pandemic, and further exploration of the characteristics and mechanisms of regional differences could be carried out in the future, based on the detection of the causes and effects of the pandemic’s disruption.

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

References


