Spatial distribution pattern of rural tourism destinations in China and its influencing factors

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ABSTRACT Based on methods of kernel density estimation, standard deviation ellipse and Geographic Detector, we explored the spatial distribution pattern and influencing factors of China's 2495 rural tourism destinations. Results showed that China's rural tourism destinations increased rapidly from 2014 to 2022, but inter-provincial differences expanded, with South China region and the southern part of North China region gradually becoming areas with relatively abundant rural tourism resources. Central area of Beijing-Tianjin-Hebei district and central area of Yangtze River Delta always had the densest rural tourism destinations, making the spatial pattern showing a circle structure around the core node. Concentration trend of rural tourism destinations along the northeast-southwest axis was gradually obvious, and the gravity center showed a slow westward trend. Double superior rural tourism destinations were also mainly distributed in South China and North China regions, showing a trend of three pillars with more northerly gravity center. Spatial pattern of China's rural tourism destinations was affected by multiple factors, and the driving structure has transitioned from single-factor weak explanatory power to multi-factor strong synergistic effect.

KEY WORDS China's Beautiful Leisure Villages – China's Key Rural Tourism Villages – spatial distribution pattern – influencing factors

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1. Introduction

Research on the spatial patterns of rural tourism destinations is rooted in the tradition of regional spatial structure theory. Core-periphery theory provides a foundational explanatory framework for understanding spatial imbalances in the development of rural tourism destinations. This theory, together with growth pole theory and cumulative causation theory, jointly explains why rural tourism destinations exhibit spatial distribution characteristics such as being around cities or adjacent to scenic areas (Zhou, Deng 2024). Distance decay theory, on the other hand, explains the spatial agglomeration patterns of rural tourism destinations from the perspective of travel costs, and directly gave rise to the formation of the recreational belt around metropolis theory. These theories provide sufficient theoretical support for scholars studying the spatial patterns of rural tourism destinations.

Scholars started to study the spatial pattern and distribution law of rural tourism destinations early, mainly focusing on the spatial structure characteristics and driving factors of rural tourism destinations (Pearce 1999; Nepal 2005; Pulina, Dettori, Paba 2006; Li, Qin 2008; Baležentis et al. 2012), the spatial evolution characteristics (Christaller 1964), and the relationship between rural tourism activities and geospatial structure (Nilsson 2002). They payed attention to the application of theories and models, and commonly addressed the development of rural tourism and its impact on rural areas, with discussions conducted through case studies of typical examples (Iorio, Corsale 2010; Kim, Jamal 2015). For example, Sang-Hyun Lee (Lee et al. 2012) discussed the spatial centrality of 43 villages in South Jeolla Province, South Korea, and its value to integrated tourism management based on centrality theory. Barkauskas (Barkauskas, Barkauskienė, Jasinskas 2015) analyzed the influencing factors of rural tourism in Lithuania from the perspective of macro environment. However, previous studies mainly adopted qualitative methods with relatively simple analysis means and tools.

In the later period, characteristic towns emerged in Spain, France, America and other countries, evaluation systems of rural tourism destinations in China obtained continuous innovation such as China's Beautiful Leisure Villages, China's Key Rural Tourism Villages, China Rural Tourism Maker Demonstration Bases, China Important Agricultural Cultural Heritages and provincial rural tourism characteristic villages, making the spatial distribution of rural tourism destinations become a hot proposition by scholars, especially Chinese scholars. Research methods were increasingly rich and complex and tended to be quantitative, such as geographical concentration index(Xu et al. 2021), Gini coefficient (Lei, Liu 2021), geographical linkage rate (Jiao et al. 2018), spatial variation indicator (Zhang et al. 2019), nearest point index (Ma, Zhang, Huang 2023), global Moran's I index and LISA cluster maps (Sarrión-Gavilán, Benítez-Márquez, Mora-Rangel 2015), kernel density estimation (Schivo et al. 2019), standard deviation ellipse (Zhu et al. 2023), geographic detector (Qi et al. 2022), Ripley's K function (Yang, Zhu 2023) and so on. Spatial patterns of multi-scale rural tourism destinations have been analyzed, including municipal, provincial, watershed, and national levels. In addition, further studies have been made on potential and accessibility of rural tourism destinations (González-Ramiro et al. 2016), influencing factors of spatial structure characteristics(Mitchell, Shannon 2018) and spatial optimization (Bian, Chen, Zeng 2022; Xie et al. 2022).

However, existing studies primarily take single official list as their research subject and focus solely on China's Beautiful Leisure Villages, China's Key Rural Tourism Villages, or single categories such as traditional villages, star-rated rural tourism sites or forest villages, which suffer from certain sample selection biases. Most studies employ cross-sectional data for analysis, placing villages selected in different years on the same temporal cross-section, thereby neglecting the dynamic evolutionary process of the spatial patterns of rural tourism destinations. In fact, the selection time spans of various batches of lists are considerably long, and differences in selection timing may lead to chronological misalignment in spatial pattern analysis. The study by Zhou et al. (Zhou, Deng 2024) is one of the few representative efforts that attempt to integrate multiple data sources. This research consolidated multiple inventories, including farm stays, homestays, National Demonstration Sites for Leisure Agriculture and Rural Tourism, China's Beautiful Leisure Villages, and China's Key Rural Tourism Villages, revealing the regional distribution patterns of rural tourism destinations as characterized by low mountains, proximity to water, adjacency to roads, surrounding cities, attachment to scenic spots, and multi-variability, marking a breakthrough in data coverage. Nevertheless, its spatial analysis remains primarily focused on static pattern descriptions, failing to fully incorporate the temporal dimension into spatial econometric models, and the considerable heterogeneity of data sources may lead to uneven data quality.

China initiated the selection of China's Beautiful Leisure Villages in 2014 and China's Key Rural Tourism Villages in 2019. By the end of 2022, a total of 1,659 villages had been designated as China's Beautiful Leisure Villages, while 1,366 villages had been listed as China's Key Rural Tourism Villages, reflecting China's abundant rural tourism resources. In 2019, rural tourism received 3.09 billion visits, playing a significant role in promoting rural revitalization and common prosperity. In-depth exploration of the spatio-temporal evolution characteristics and formation mechanisms of China's rural tourism destinations, along with efforts to promote the rational utilization and scientific layout of resources, can provide theoretical support and practical application for improving the quality of rural tourism supply, upgrading consumption, aiding in poverty alleviation, and boosting rural revitalization (Yang et al. 2021). This study integrates two

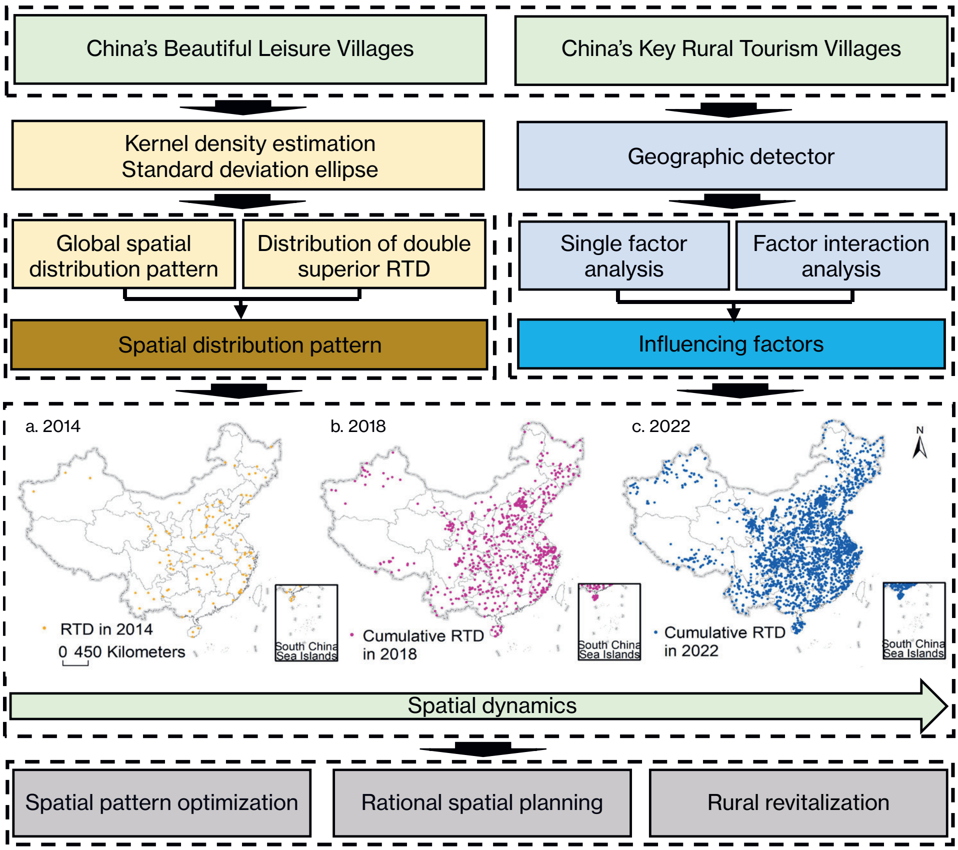

Fig. 1 – Contribution roadmap of this study. RTD – rural tourism destinations.

evaluation systems, namely China's Beautiful Leisure Villages and China's Key Rural Tourism Villages, to more comprehensively depict the spatial pattern of rural tourism destinations in China and further analyzes the influencing factors, aiming to support rational spatial planning, enhance the demonstrative role of key villages and towns, provide scientific basis for local government planning and spatial decision-making (Molinaro, Corrado, Scorza 2025), and promote high-quality development of rural tourism. The contribution roadmap of our study is shown as Figure 1.

The design of this study incorporates three aspects of innovations. Firstly, It integrates two official selection systems, namely China's Beautiful Leisure Villages and China's Key Rural Tourism Villages, and constructs a more complete rural tourism destinations sample through deduplication, which compensates for the coverage limitations of a single selection system and ensures consistency in data sources. Secondly, it covers the time span from 2014 to 2022 and incorporates multiple batches of selection villages, laying the foundation for subsequently introducing a temporal dimension to analyze the spatial evolution characteristics of China's rural tourism destinations. Thirdly, our research integrates spatial data analysis with spatial econometric models to systematically examine the spatial dependence characteristics and driving factors of the spatial pattern of China's rural tourism destinations, thereby providing a scientific basis for rational spatial planning of rural tourism destinations.

2. Materials and methods

2.1. Data sources and processing

Nine batches of China's Beautiful Leisure Villages and four batches of China's Key Rural Tourism Villages during 2014 to 2022 were obtained from official website of the Ministry of Agriculture and Rural Affairs of the People's Republic of China as basic data, among which rural tourism destinations in Xinjiang Production and Construction Corps were not included in Xinjiang Uygur Autonomous Region. A total of 2,495 rural tourism destinations were sorted out by excluding the repeated rural tourism destinations in the list of China's Beautiful Leisure Villages and the list of China's Key Rural Tourism Villages, and the statistical years of repeated rural tourism destinations were the years of their first inclusion in either of the two lists. Then we obtained the latitude and longitude coordinates of 2495 rural tourism destinations from the website of Baidu Map Coordinate Pickup System as the initial data for the following studies.

Other data required in our study were mainly from the regional statistical bulletins on national economic and social development, statistical yearbooks, and official websites of the cultural and tourism departments. rural tourism destinations of Taiwan, Hong Kong and Macao were not included in the evaluation systems, so our research areas were other 31 regions in China, excluding Taiwan, Hong Kong and Macao.

2.2. Methods

2.2.1. Kernel density estimation

Kernel density estimation is used to analyze the distribution density of rural tourism destinations. Density field surface is constructed by calculating the densities around the elements of rural tourism destinations, and transformation of the elements from discrete to continuous fields is realized through smooth gradient surfaces (Gao et al. 2023). The higher the kernel density value, the denser the distribution of rural tourism destinations, and vice versa. The formula for calculating kernel density (Zheng, Tian, Yang 2021) is:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x-x_i}{h}\right)$$

Where: $f(x)$ represents the estimated kernel density of rural tourism destinations, n is the number of sample points of rural tourism destinations, h is bandwidth, k is kernel function, $(x-x_i)$ is the distance from rural tourism destination valuation point x to sample point x_i.

2.2.2. Standard deviation ellipse

Standard deviation ellipse was first put forward by Lefever in 1926 (Lefever 1926), used to analyze the distribution direction, dispersion and center of geographical elements through ellipse's main parameters such as center coordinates, macro axis, branchy axis, oblateness and azimuth angle. Center coordinates of the standard deviation ellipse represent gravity center of rural tourism destinations, and macro axis and branchy axis indicate the degree of dispersion in X and Y axes. The longer the macro axis and the shorter the branchy axis, the larger the oblateness and more obvious the clustering trend. Azimuth angle represents its main trend direction.

2.2.3. Geographic detector

Geographic detector is used to reveal the interpretation ability of various influencing factors on the spatial differentiation of geographical elements, and is a new statistical method to study spatial differentiation (Wang, Xu 2017). Interpretation ability of each factor is reflected by q value, whose value ranges from 0 to 1. The closer q value is to 1, the stronger the influence of the factor on the spatial differentiation of rural tourism destinations. The closer q value is to 0, the weaker the influence of the factor. Its calculation formula is:

$$q = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{k} n_i\sigma_i^2$$

Where: k is layer number of influencing factor X_i, n is the number of samples, i is from 1 to k, σ_i^2 and σ^2 are rural tourism destinations number variances of layer i and the whole study area respectively.

3. Results

3.1. Spatial distribution pattern

As obvious from Figure 2, the number of China's Beautiful Leisure Villages was relatively stable over the years. 98 villages were first selected in 2014, about 148 villages were selected each year from 2015 to 2018, and about 250 villages were included each year from 2019 to 2022. The number of China's Key Rural Tourism Villages fluctuated greatly over the years. 314 villages were first evaluated in 2019, and 663 villages were selected in 2020, far exceeding the number of selected China's Beautiful Leisure Villages the same year. However, the number of selected China's Key Rural Tourism Villages dropped rapidly since 2021, with only 194 and 195 villages included each year.

The primary reason for the above-mentioned characteristics of the interannual changes in China's rural tourism destinations lies in the restrictions on selection quotas and adjustments to selection criteria imposed by the Chinese government for the two sets of rural tourism destination systems, as shown in Table 1. From 2014 to 2022, both the selection processes for China's Beautiful Leisure Villages and China's Key Rural Tourism Villages exhibited a shift from provincial quotas to national-level coordination, indicating a transition from local self-nomination to nationwide merit-based selection. The quota for China's Beautiful Leisure Villages generally showed an upward trend, increasing from 165 villages to 201 villages, and eventually stabilizing at around 250 villages. This is broadly consistent with

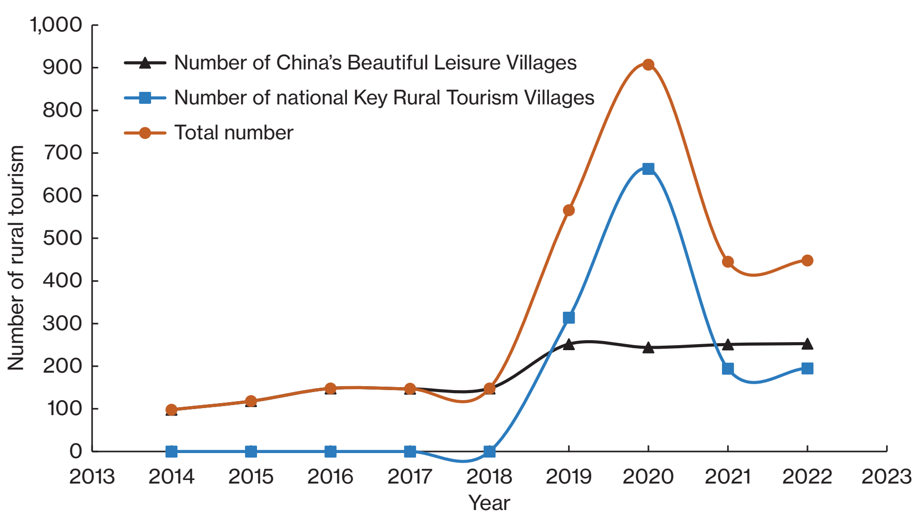

Fig. 2 – Time series change diagram of the number of rural tourism destinations in China

Table 1 – Selection criteria and quota adjustments for China's Beautiful Leisure Villages and China's Key Rural Tourism Villages

Selection system	Selection year	Selection criteria	Selection quatos	Available quotas / count	Actual applications / count
China's Beautiful Leisure Villages	2014	Diverse industrial functions, unique village scenery, positive cultural ethos	Each province: maximum 5 villages Municipalities with independent planning status: maximum 2 villages	165	98
	2015	Same as 2014	same as 2014	165	118
	2016	Beautiful ecological environment, diverse industrial functions, unique village scenery, positive cultural ethos	Each province: maximum 6 villages Municipalities with independent planning status: maximum 3 villages	201	148
	2017	Same as 2016	Same as 2016	201	147
	2018	Strong organizational leadership, notable industrial advantages, solid economic foundation, beautiful ecological environment, diverse industrial formats, well-developed service facilities, sound folk customs, prominent brand effects	Same as 2016	201	148
	2019	Notable distinctive advantages, well-developed service facilities, sound folk customs, prominent brand effects	Each province: maximum 8 villages Municipalities with independent planning status: maximum 3 villages	263	252
	2020	Same as 2019	According to the quota allocation table	245	244
	2021	Same as 2019	According to the quota allocation table	254	251
	2022	Distinct industrial advantages, well-developed service facilities, sound folk customs, prominent brand effects	According to the quota allocation table	256	253

Selection system	Selection year	Selection criteria	Selection quatos	Available quotas / count	Actual applications / count
China's Key Rural Tourism Villages	2019	Rich cultural and tourism resources; sound protection of natural ecology and traditional culture; well-developed rural homestays; mature tourism product systems with high quality; well-established infrastructure and public services; and notable employment-driven income generation effects	Each province: maximum 15 villages	465	314
	2020	Rich and rationally developed cultural and tourism resources; sound inheritance, protection, transformation, and development of rural culture; mature tourism product systems with high quality; well-regulated homestay development with distinctive themes; beautiful and livable ecological environment; well-established infrastructure and public services; sound and rational institutional mechanisms with efficient operations; and notable benefits in driving entrepreneurship, employment, and socio-economic development	Each province: maximum 25 villages Each of the first 71 National All-for-One Tourism Demonstration Areas: up to 2 additional recommended villages	917	663
	2021	Same as 2020	According to the quota allocation table	200	194
	2022	Same as 2020	According to the quota allocation table	200	195

the interannual variation trend of China's Beautiful Leisure Villages. From 2019 to 2020, the quota for China's Key Rural Tourism Villages surged sharply from 465 villages to 917 villages, and then plummeted to 200 villages per year in 2021 and 2022, which consequently led to an extreme peak in the interannual variation of China's Key Rural Tourism Villages and rural tourism destinations in 2020.

From 2014 to 2022, the selection criteria for China's Beautiful Leisure Villages evolved from three dimensions to eight dimensions, and eventually stabilized at four dimensions. The functional positioning of China's Beautiful Leisure Villages shifted from traditional sightseeing to leisure living and industrial integration, the governance requirements transitioned from soft advocacy to institutional constraints and negative lists, and the policy orientation shifted from scale expansion to quality improvement and standardized management. From 2019 to 2022, the selection criteria for China's Key Rural Tourism Villages increased from six dimensions to eight dimensions and remained stable. The evaluation standards deliberately aligned rural tourism with the Five Revitalizations of rural revitalization, and the functional expectations for China's Key Rural Tourism Villages were comprehensively upgraded from a singular tourism demonstration model to a comprehensive rural revitalization benchmark. Although the selection criteria for both systems of rural tourism destinations are mostly qualitative, with only a very few quantitative indicators appearing in the 2018 selection criteria for China's Beautiful Leisure Villages, the connotation of the evaluation standards has shown a trend of continuous deepening, with progressively higher requirements imposed on villages applying for designation. This has constrained the interannual expansion trend of China's rural tourism destinations to a certain extent.

3.1.1. Spatial distribution of global rural tourism destinations

3.1.1.1. Inter-provincial spatial differentiation

According to the data processing method mentioned above, repeated villages were eliminated to obtain the cumulative number of rural tourism destinations in 31 regions in 2014, 2018 and 2022, and the natural break point classification method of ArcGIS10.8 was used to symbolize them. As can be seen in Figure 3, in 2014, the number of rural tourism destinations in different regions ranged from 0 to 6 with a small gap, most regions (67.7%) had 3 or 4 rural tourism destinations. Fujian topped the list with 6 rural tourism destinations, Shandong and Zhejiang come second, both with 5 rural tourism destinations. Heilongjiang, Anhui, Jiangxi, Qinghai, Ningxia and Tianjin had only 1 or 2 rural tourism destinations respectively, and no villages in Tibet had been selected. In 2018, the number of rural tourism destinations in Zhejiang, Fujian and Shandong remained in the top three, rising to 34, 33 and 30 respectively. 13 regions such as Jiangsu, Henan, Guangxi,

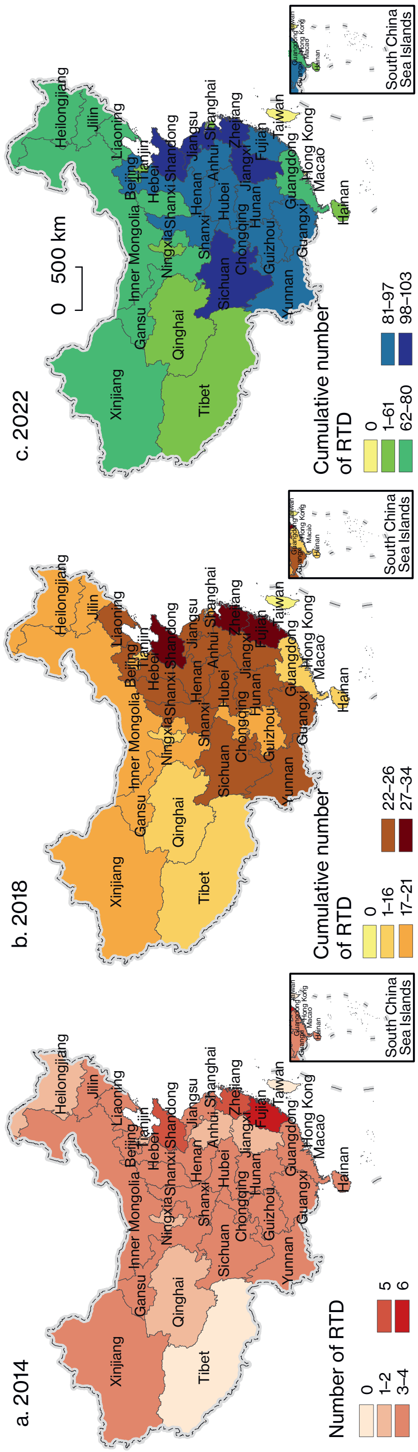

Fig. 3 – Inter-provincial spatial differentiation of rural tourism destinations in China. RTD – rural tourism destination.

Sichuan and Yunnan followed, with 22 to 26 rural tourism destinations. Tibet had the fewest rural tourism destinations, with only 13. In 2022, the number of rural tourism destinations in Zhejiang, Shandong, Sichuan, Jiangsu and Jiangxi had exceeded 98, making them the five regions with the largest number of rural tourism destinations in China. Sichuan replaced Fujian and ranked one of the top three. Tianjin, Ningxia, Hainan, Shanghai, Tibet and Qinghai had fewer rural tourism destinations, and the least of which was Tianjin, who had only 45 rural tourism destinations.

On the whole, the number of rural tourism destinations in all regions continued to increase, providing residents with more rural leisure tourism options, but regional gap in the number of rural tourism destinations widened, with the maximum range increasing from 6 in 2014 to 58 in 2022. According to the four major geographical divisions in China, South China region and North China region gradually become regions with relatively rich rural tourism resources, while Northwest China region and Qinghai-Tibet region were in a relatively inferior position.

3.1.1.2. Kernel density analysis

Spatial kernel density analysis was carried out on point feature set of rural tourism destinations in 2014, 2018 and 2022 respectively by using kernel density estimation tool in ArcGIS10.8 and taking 200 kilometers as search radius. When the travel time exceeds 152 minutes, there is a 100% chance that happiness becomes worse (Erinne 2022), and the average speed of long-distance self-driving travel ranges from 70 to 90 km/h, thus a distance of 200 km can be considered a reasonable spatial interaction range when examining the spatial distribution of rural tourism destinations at the national scale. This range will smooth out local details at the municipal or county level, thereby revealing large-scale spatial hotspot areas.

As can be seen from Figure 4, In 2014, the distribution of rural tourism destinations was scattered and most parts of China had low density of rural tourism destinations, with kernel density value less than 0.355 rural tourism destinations / 10,000 km². Only in the scattered small lamellar areas such as Beijing-Tianjin-western Hebei-eastern Shanxi-northern Henan, southern Jiangsu-southeastern Anhui-eastern Zhejiang-eastern Fujian, eastern Sichuan-western Chongqing, eastern Qinghai, southwest Gansu, southern Ningxia, southwest Guizhou, northeast Hunan, southwest Hainan, and central Shandong, rural tourism destinations were slightly dense, but there were still less than 1.2 rural tourism destinations / 10,000 km².

In 2018, the kernel density values of rural tourism destinations in large contiguous areas of North China and South China region were mostly higher than 0.355 rural tourism destinations / 10,000 km², among which Beijing-Tianjin district and Taihu Lake Basin were the densest areas of rural tourism destinations,

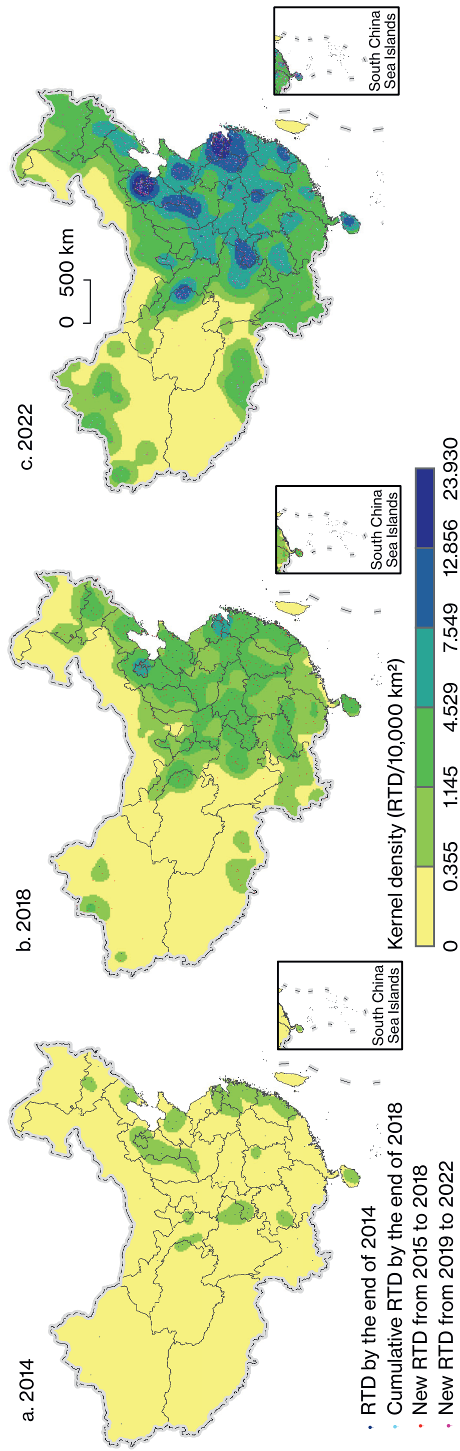

Fig. 4 – Kernel density evolution of rural tourism destinations in China under a 200 km bandwidth

with kernel density values ranging from 4.529 rural tourism destinations / 10,000 km² to 7.549 rural tourism destinations / 10,000 km², forming two core nodes. Five radial continuous areas around the low-density area formed by southwest Henan and central-northern Hubei, and several scattered areas including Hainan, Guangxi-Guizhou-Yunnan border, central-southern Liaoning, central-northern Jilin, northern Ningxia, central-southern Guangxi were the sub-dense areas, with 1.145 to 4.529 rural tourism destinations / 10,000 km². rural tourism destinations were scattered in most of Northwest China region and Qinghai-Tibet region, and the kernel density values were still lower than 0.355 rural tourism destinations / 10,000 km², only in the border between Inner Mongolia and its neighboring provinces, the northwestern and western Xinjiang, the eastern border between Qinghai and Gansu, and the southern part of Tibet, there existed small areas with denser rural tourism destinations.

In 2022, areas with kernel density values higher than 0.355 rural tourism destinations / 10,000 km² further expanded, and the kernel density values of rural tourism destinations in the vast contiguous areas of North China and South China region were generally higher than 1.145 rural tourism destinations / 10,000 km². Large continuous areas along the triangular boundary line formed by the core nodes of Beijing, Chongqing and Shanghai city, and scattered small areas such as southern Jilin-northern Liaoning, northern Ningxia, central-western Guizhou, northeastern Guangxi, central Guangdong and central-eastern Hainan possessed concentrated distribution of rural tourism destinations, with kernel density higher than 4.529 rural tourism destinations / 10,000 km². Among them, Beijing-Tianjin district and Taihu Lake Basin were still areas with the highest density of rural tourism destinations in China, who had more than 12 rural tourism destinations / 10,000 km² on average, and the maximum kernel density value up to 23.929 rural tourism destinations / 10,000 km² as shown in Figure 4. Center of Beijing-Tianjin-Hebei district, center of Yangtze River Delta, central Shandong, Shanxi-Hebei-Henan border, Gansu-eastern Qinghai border, Sichuan-Chongqing border, Jiangxi-eastern Hunan border, southeast Fujian and central Hainan were sub-dense areas of rural tourism destinations, with an average of 7.549 to 12.856 rural tourism destinations / 10,000 km². The kernel density of rural tourism destinations in the Northwest China region and Qinghai-Tibet region such as the border between Inner Mongolia and its neighboring provinces, western and northern Xinjiang, and central-southern Tibet were also higher than 1.145 rural tourism destinations / 10,000 km², and some areas can even reach 4.529 rural tourism destinations / 10,000 km².

To examine the stability of hot spots of rural tourism destinations in China, and travel time tolerance varies across individuals, this study also conducted kernel density estimation using bandwidths of 100 km, 150 km, and 250 km respectively. Due to space limitations, only the kernel density map with a bandwidth of 100 km

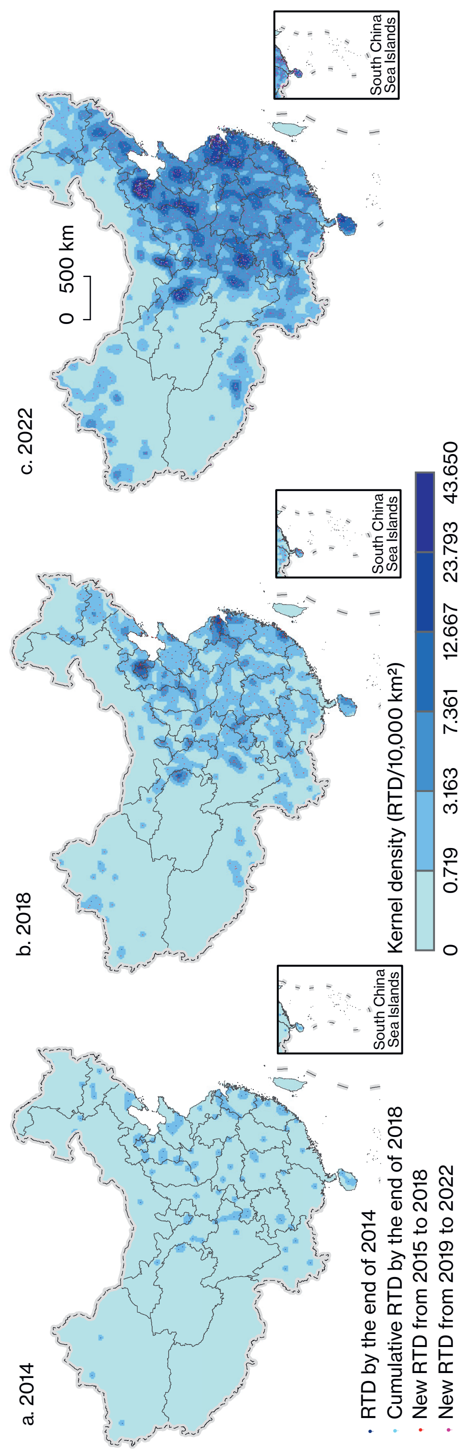

Fig. 5 – Kernel density evolution of rural tourism destinations in China under 100 km bandwidth

is presented in this article, see Figure 5. As shown in the figure, the kernel density distribution at a bandwidth of 100 km is more refined, capable of revealing local hot spots and presenting scattered points and small clusters. However, the hot spot areas of China's rural tourism destinations across different years remain consistent with those under the 200 km bandwidth. The kernel density distributions of China's rural tourism destinations at the unshown bandwidths of 150 km and 250 km exhibit similar characteristics. Specifically, the larger the bandwidth, the more the small-scale details are smoothed out, while the contiguous distribution pattern at the macro scale becomes more prominently highlighted, thus better revealing the overall macroscopic pattern. Conversely, the smaller the bandwidth, the more clearly the relatively dense local areas can be distinguished, though the overall pattern appears more fragmented and richer in detail. Nevertheless, the hot spot areas of China's rural tourism destinations remain stable across all four different bandwidths.

On the whole, the density of rural tourism destinations in China remained increasing from 2014 to 2022, forming a circle structure around the core node. Higher density areas expanded rapidly from the eastern coast and northwest to Inner Mongolia boundary and Sichuan-Tibet-Qinghai-Xinjiang border. Beijing-Tianjin-Hebei district and Yangtze River Delta always had the greatest concentration of rural tourism destinations in China. This aligns with the core–periphery theory and distance decay theory in explaining the imbalanced spatial distribution of rural tourism destinations in China. Hot spot areas with high density, such as the Yangtze River Delta and Beijing-Tianjin-Hebei district, are core regions that benefit from large and affluent tourist markets and convenient transport, resulting in dense distributions of rural tourism destinations. As high-speed rail and private car ownership expand, tourism demand spreads along transport corridors, generating new rural tourism destinations clusters in previously low-density areas, this diffusion effect gradually brings peripheral areas into the core's sphere of influence.

3.1.1.3. Standard deviation ellipse analysis

Dispersion and directionality of rural tourism destinations in 2014, 2018 and 2022 were analyzed respectively by using Directional Distribution (SDE) Tool in ArcGIS10.8, and results can be seen in Figure 6 and Table 2. The first level standard deviation was selected for the size of the ellipse, covering about 68% of China's rural tourism destinations.

Spatial distribution pattern of rural tourism destinations in China was relatively stable during 2014 to 2022, but there existed important changes. Branchy axis of the standard deviation ellipse shortened gradually from 1,025.253 km in 2014 to 1,016.535 km in 2022, indicating that the centripetal force of the spatial

Table 2 – Related eigenvalues of standard deviation ellipses

Year	Longitude of gravity center (°)	Latitude of gravity center (°)	Macro axis (km)	Branchy axis (km)	Azimuth (°)	Oblateness (%)
2014	112.992	33.134	1,127.036	1,025.253	31.287	9.031
2018	112.683	33.438	1,144.298	1,021.854	51.465	10.700
2022	112.085	33.233	1,150.841	1,016.535	51.007	11.670

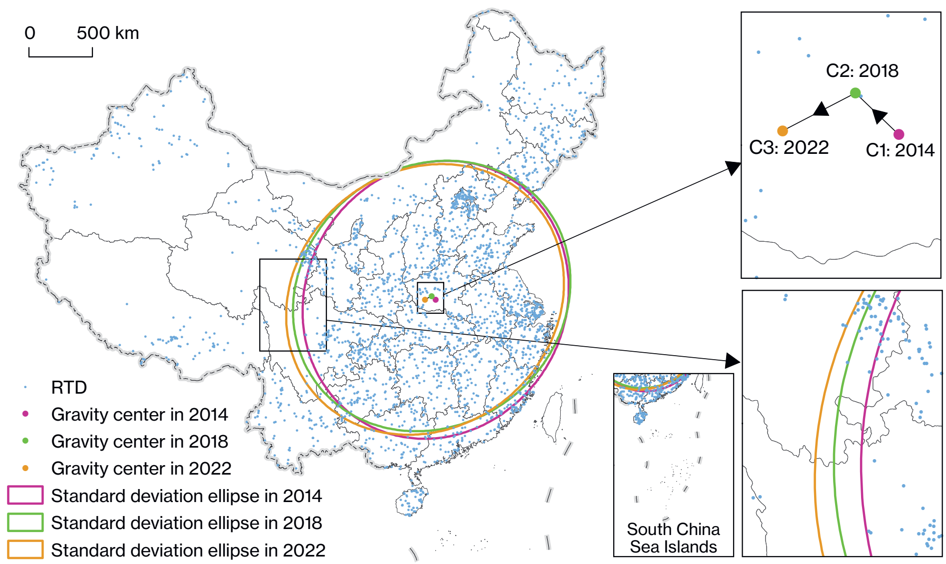

Fig. 6 – Standard deviation ellipse and gravity center migration of rural tourism destinations in China

distribution of rural tourism destinations enhanced. Macro axis of the ellipse lengthened and oblateness of the ellipse enlarged gradually, indicating that the spatial distribution of rural tourism destinations tended to be directional and show a clustering trend along the macro axis. However, the absolute oblateness value and the degree of ellipse flatness were small, which indicated that the spatial agglomeration range of China's rural tourism destinations was not large. In 2014, ellipse azimuth was north by east 31.287°, and it remained about north by east 51° in 2018 and 2022, indicating that the spatial agglomeration direction of rural tourism destinations in China was always southwest to northeast. Gravity center of the standard deviation ellipse was located in Sheqi County of Nanyang City in 2014, moved northwest to Nanzhao County of Nanyang City in 2018, and moved southwest to Zhenping County of Nanyang City in 2022, indicating that the gravity center of China's rural tourism destinations in presented a slow westward migration trend.

3.1.2. Spatial distribution of double superior rural tourism destinations

Honorary title of tourism destinations can significantly improve their popularity and reputation, and tourism destinations with multiple honorary titles can form a siphon effect on surrounding areas. In our study, villages on the list of both China's Beautiful Leisure Villages and China's Key Rural Tourism Villages were collectively referred to as double superior rural tourism destinations, showing their quality superiority compared with other rural tourism destinations selected on one list only. By the end of 2022, China has 530 double superior rural tourism destinations, accounting for 21.24% of the total number of rural tourism destinations. Same methods were used to visualize the spatial distribution, density and direction of double superior rural tourism destinations, see Figure 7.

Double superior rural tourism destinations were mainly concentrated in South China region and North China region, among which Beijing-Tianjin-Hebei district and Yangtze River Delta had 42 and 91 double superior rural tourism destinations respectively, accounting for 25.09% of the total number of double superior

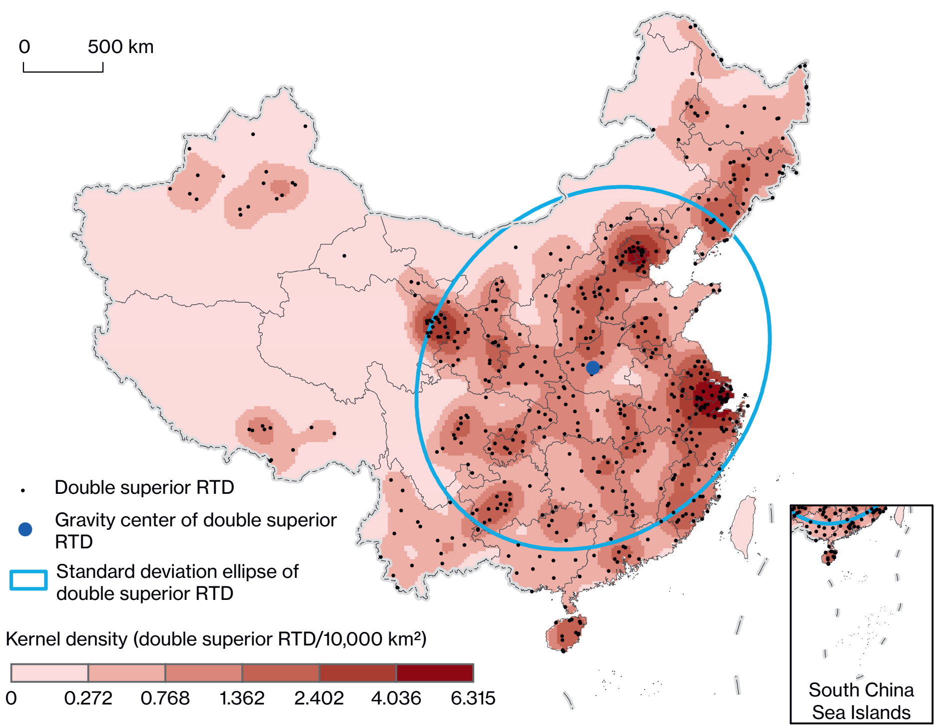

Fig. 7 – Kernel density distribution, standard deviation ellipse and gravity center of double superior rural tourism destinations

rural tourism destinations together. There were very few double superior rural tourism destinations in most areas of Northwest China region and Qinghai-Tibet region, with fairly scattered distribution. Beijing-Tianjin district and Taihu Lake Basin were the densest areas of double superior rural tourism destinations in China, with kernel density values higher than 4.036 rural tourism destinations / 10,000 km². There existed 2.402 to 4.036 double superior rural tourism destinations per 10,000 km² in the central area of Beijing-Tianjin-Hebei district, the central area of Yangtze River Delta, and Gansu-eastern Qinghai border, they were the sub-dense areas and presented a trend of tripartite confrontation. The number of double superior rural tourism destinations in Inner Mongolia, western Gansu, northern Xinjiang and the large areas of Sichuan-Tibet-Qinghai-Xinjiang border was very small, with an average of less than 0.272 double superior rural tourism destinations per 10,000 km².

Standard deviation ellipse of double superior rural tourism destinations was 1,215.918 km on the macro axis and 1,024.277 km on the branchy axis, and the oblateness value was 15.761%, which was greater than any of the oblateness values of global ellipses from 2014 to 2022, indicating that spatial distribution of double superior rural tourism destinations showed more obvious directionality. The gravity center's coordinates were 112.864°E and 33.780°N, located in Lushan County of Pingdingshan City, which was more northerly than the gravity center of all rural tourism destinations. On the whole, double superior rural tourism destinations presented more obvious trend of aggregation distribution in the direction of north by east 40.892°.

3.2. Influencing factors of spatial distribution pattern

Based on the relevant studies (Xie, Zhou, Liu 2022; Li et al. 2023), we took the number of rural tourism destinations in 31 regions of China as the dependent variable (Y), and preliminarily selected 14 subfactors from four aspects as the independent variables (X) to construct the geographic detector model. The natural endowment aspect includes five specific indicators such as regional area and average elevation, the development foundation aspect includes four specific indicators such as the number of township-level administrative units and average income of rural residents, the source market aspect includes four specific indicators such as urban population and total tourism revenue, and the transportation accessibility aspect includes one specific indicator, namely highway density.

To identify which factors truly and independently influence the spatial distribution of rural tourism destinations in China, this study took 2022 data as an example and employed an exploratory regression model to eliminate redundant factors with severe multicollinearity, thereby making the model more reliable.

The exploratory regression model in ArcGIS 10.8 was run to obtain the variance inflation factor for each influencing factor. Factors with the variance inflation factor values higher than 7.5 would be eliminated. The average income of rural residents indicator and the average consumption expenditure of urban residents indicator exhibited multicollinearity, with the variance inflation factor values of 11.90 and 11.24 respectively, therefore, the average income of rural residents, which had the higher variance inflation factor value, was eliminated. The tourist arrivals indicator and tourism revenue indicator also showed multicollinearity, with the variance inflation factor values of 11.16 and 16.17 respectively, thus, the tourism revenue indicator, which had the larger variance inflation factor value, was eliminated. The exploratory regression model was run again after removing these two redundant indicators, and the variance inflation factor values of the remaining 12 influencing factors were all below 7.5, constituting the influencing factor system for rural tourism destinations in China, see Table 3.

In order to examine whether each influencing factor exhibits spatial agglomeration on its own, move from spatial structure verification toward spatial attribution interpretation, and systematically reveal the mechanisms of these influencing factors and enhance the credibility of causal inference, this study conducted global spatial autocorrelation analysis (Moran's I) for each influencing factor. The results were shown in Table 4.

In 2014, 2018 and 2022, global Moran's I values of X_1, X_2, X_3, X_4, X_5 and X_{12} were greater than 0, with $p < 0.01$, passing the significance test at the 1% level. This indicates that these six indicators exhibit significant positive spatial autocorrelation within the study area, meaning that regions with higher values tend to be adjacent to each other, and regions with lower values also tend to cluster together, displaying an overall pronounced spatial agglomeration pattern rather than a random distribution. Among them, X_2, X_3, and X_4 had the highest global Moran's I values and z-scores, indicating the strongest degree of spatial clustering.

Global Moran's I values of X_8, X_9, X_{10} and X_{11} were greater than 0, with $0.05 < p < 0.1$, reaching a marginally significant status. These four indicators exhibit a certain degree of positive spatial autocorrelation, showing an overall trend of spatial clustering.

The p-values of X_6 and X_7 were mostly above 0.2, indicating that the 31 provinces do not exhibit spatial clustering characteristics for these two indicators, but instead display a random distribution pattern.

Quantile method and natural breaks (Jenks) method were applied to convert the continuous data of 12 independent variables of 2014, 2018 and 2022 into category data successively, and the values of each independent variable were divided into 4–7 categories according to their optimal classification. For example, the indicator values of X_1 and X_2 in 2022 were classified into 6 and 4 categories respectively under the quantile method. The cut-points for X_1 were 71,728, 145,369, 176,167,

Table 3 – Influencing factor system

Influencing factors	Specific indicators	Unit	Indicator description	Data source
Natural endowment	Regional area (X_1)	km²	Reflects the spatial base for regional development	China Statistical Yearbook
	Average elevation (X_2)	–	Characterizes topographic and geomorphic features	China 1 km Topographic Relief Dataset
	Average annual temperature (X_3)	°C	Measures regional climate comfort, represented by the annual average temperature of the provincial capital city	China Statistical Yearbook
	Water resource abundance (X_4)	m³/km²	Reflects regional water resource endowment, derived by dividing total regional water resources by regional area	China Statistical Yearbook
	Forest coverage rate (X_5)	%	Characterizes regional ecological environment quality and the proportion of green space	China Statistical Yearbook
Development foundation	Number of township-level administrative units (X_6)	count	Characterizes the spatial distribution density of grassroots administrative organizations, obtained by summing the number of towns and townships in each region	China Statistical Yearbook
	Average output value of agriculture, forestry, animal husbandry, and fishery (X_7)	CNY	Measures agricultural production efficiency and the agricultural economic base, derived by dividing the total output value of agriculture, forestry, animal husbandry, and fishery in each region by the rural population	China Statistical Yearbook
	Abundance of tourism resources (X_8)	count	Reflects the suction effect of well-known scenic spots on surrounding scenic spots, represented by AAAAA tourist attractions in each region	Official announcements from the Ministry of Culture and Tourism of the People's Republic of China
Source market	Urban population (X_9)	10,000 persons	Measures the scale of the potential tourist source market	China Statistical Yearbook
	Average consumption expenditure of urban residents (X_{10})	CNY	Reflects the consumption demand and consumption activity level of urban residents	China Statistical Yearbook
	Tourist arrivals (X_{11})	10,000 arrivals	Characterizes the overall tourism market heat and attractiveness of the region	Statistical bulletins on national economic and social development
Transportation accessibility	Highway density (X_{12})	km/km²	Measures the accessibility of rural tourism destinations, derived by dividing regional highway mileage by regional area	China Statistical Yearbook

Table 4 – Global spatial autocorrelation results of each influencing factor

Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
p-value (2014)	0.005	0.001	0.001	0.001	0.001	0.359	0.052	0.023	0.046	0.052	0.009	0.002
z-value (2014)	3.446	7.291	6.194	7.835	5.316	−0.422	1.771	2.378	1.915	1.841	2.991	4.310
Moran's I (2014)	0.234	0.544	0.495	0.690	0.409	−0.061	0.107	0.161	0.125	0.113	0.224	0.357
p-value (2018)	0.005	0.001	0.001	0.001	0.001	0.259	0.356	0.016	0.049	0.092	0.006	0.002
z-value (2018)	3.446	7.291	6.274	7.140	5.348	−0.663	−0.450	2.573	1.834	1.447	3.577	4.213
Moran's I (2018)	0.234	0.544	0.505	0.600	0.415	−0.076	−0.071	0.183	0.119	0.082	0.264	0.346
p-value (2022)	0.005	0.001	0.001	0.001	0.001	0.337	0.410	0.030	0.060	0.028	0.088	0.002
z-value (2022)	3.446	7.291	6.349	7.466	5.348	−0.515	−0.314	2.162	1.759	2.226	1.350	4.232
Moran's I (2022)	0.234	0.544	0.510	0.620	0.415	−0.072	−0.061	0.153	0.111	0.154	0.067	0.342

207,667, and 481,671 km², and those for X_2 were 0.2273, 0.3920, 0.6519, 1.2979 and 2.3682. The indicator values of X_1 and X_2 in 2022 were classified into 5 and 6 categories respectively under the natural breaks (Jenks) method. The cut-points for X_1 were 66,400, 148,000, 236,700 and 721,000 km², and those for X_2 were 0.0982, 0.4523, 1.0217, 1.6173 and 3.5292. Then single factor detection and factor interaction detection results were obtained respectively by running the software of GeoDetector.

3.2.1. Single factor analysis

Single factor detection is used to evaluate the interpretation degree of independent variable to the spatial differentiation of dependent variable. The closer the *q* value of each independent variable is to 1, the greater the influence of the independent variable on the spatial differentiation of rural tourism destinations. The *p* value represents the significance index, and the closer the *p* value is to 0, the more significant the relationship between independent variable and dependent variable. Single factor detection results in 2014, 2018 and 2022 by natural breaks (Jenks) method were shown in Table 5.

From the perspective of temporal evolution, the explanatory power of influencing factors on the spatial differentiation of rural tourism destinations in China exhibited a pronounced increasing trend over the study period. In 2014, only X_{11} passed the significance test at the 5% level, while X_2 and X_5 demonstrated marginally significant effects, with p-values falling between 0.05 and 0.1. The remaining factors did not reach statistical significance, suggesting that the independent explanatory capacity of individual driving factors during this period remained generally weak, and that the spatial differentiation pattern of rural tourism destinations in China may have been primarily governed by the synergistic interactions among multiple factors or by latent variables not incorporated into the analytical framework.

In 2018, X_1, X_3, X_4, X_5, X_9 and X_{11} successively manifested explanatory power. Among these, X_1 and X_9 passed the significance test at the 5% level, whereas X_3, X_4, X_5 and X_{11} exhibited marginal significance ($0.05 < p < 0.1$), indicating that the influence of certain factors on the spatial pattern had begun to transition from a latent state to a manifest one.

By 2022, a total of five factors, namely X_1, X_6, X_8, X_9, and X_{11}, all passed the significance test at the 1% level, with q-values exceeding 0.57. This indicates that the core set of driving factors had become increasingly well-defined and stable over time.

This sustained upward trajectory suggests that the spatial differentiation pattern of rural tourism destinations in China intensified markedly between the year of 2014 and 2022, with the effects of various driving factors being progressively unleashed and accumulated. Such a pattern reflects a typical evolutionary process in socio-economic systems, wherein influencing factors gradually shift from a state of ambiguity toward one of clarity and specificity.

It is noteworthy that the q-value of X_8 experienced a substantial surge from 0.504 in 2018 to 0.809 in 2022, representing a relative increase of 60.5% and being the most pronounced enhancement among all examined factors. X_8 emerged as the predominant factor exerting the strongest explanatory power and was capable of independently accounting for over 80% of the spatial variation of rural tourism destinations in China. The q-value of X_1 likewise exhibited a considerable upward

Table 5 – Single factor detection results under natural breaks (Jenks) method

Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
q-value (2014)	0.242	0.385	0.182	0.077	0.294	0.294	0.341	0.361	0.323	0.152	0.400	0.232
p-value (2014)	0.200	0.080	0.421	0.579	0.060	0.672	0.134	0.235	0.137	0.632	0.036	0.156
q-value (2018)	0.508	0.253	0.236	0.260	0.540	0.363	0.293	0.504	0.614	0.186	0.467	0.243
p-value (2018)	0.012	0.348	0.098	0.092	0.059	0.739	0.212	0.196	0.015	0.688	0.052	0.158
q-value (2022)	0.641	0.190	0.310	0.140	0.434	0.614	0.284	0.809	0.710	0.084	0.578	0.439
p-value (2022)	0.000	0.570	0.069	0.403	0.212	0.007	0.219	0.000	0.002	0.931	0.000	0.287

Table 6 – Single factor detection results under Quantile method

Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
q-value (2014)	0.323	0.188	0.192	0.118	0.275	0.246	0.085	0.211	0.306	0.244	0.332	0.285
p-value (2014)	0.094	0.287	0.297	0.417	0.085	0.108	0.547	0.336	0.064	0.212	0.046	0.069
q-value (2018)	0.628	0.284	0.252	0.138	0.389	0.357	0.523	0.398	0.500	0.379	0.497	0.289
p-value (2018)	0.000	0.103	0.167	0.330	0.039	0.030	0.019	0.068	0.004	0.117	0.008	0.076
q-value (2022)	0.614	0.095	0.390	0.228	0.363	0.643	0.370	0.808	0.747	0.119	0.561	0.299
p-value (2022)	0.002	0.455	0.055	0.152	0.030	0.000	0.154	0.000	0.000	0.380	0.000	0.071

trend, ascending from 0.242 to 0.641 over the nine-year period, with an absolute increment of 39.9%. Similarly, the q-value of X_9 increased from 0.323 to 0.710, maintaining a sustained and steady strengthening trajectory throughout the study period.

Overall, X_{11} consistently maintained a high level of explanatory power, whereas X_1, X_3, X_6, X_8, and X_9 all displayed an increasing trajectory in their respective explanatory capacity in the research period. X_2, X_4, and X_5 demonstrated a declining trajectory in their explanatory power, while X_7, X_{10}, and X_{12} had only a marginal impact on the spatial distribution of rural tourism destinations in China.

In order to test the sensitivity of each influencing factor's classification scheme to the geographic detector analysis results, and to enhance the robustness of the importance ranking of these factors, this study supplemented the natural breaks (Jenks) method with the quantile method for a second discretization of each influencing factor, and then repeated the geographic detector computations. The results are presented in the following Table 6.

As can be seen from Table 6, under the quantile method, the explanatory power of factors on the spatial differentiation of rural tourism destinations in China also exhibited a pronounced increasing trend overall, with X_1, X_3, X_6, X_8, X_9 and X_{11} remaining the core driving factors, consistent with the results obtained from the natural breaks (Jenks) method. However, under the quantile method, X_5 demonstrated an increasing trajectory in its explanatory power, passing the significance test at the 5% level in both 2018 and 2022, thereby emerging as one of the core explanatory variables for the spatial differentiation of rural tourism destinations in China. X_{12}, although consistently remaining at a marginally significant level, nonetheless maintained a certain degree of explanatory power for the spatial differentiation of rural tourism destinations in China. X_7 passed the significance test at the 5% level in 2018, but its influence tended to weaken by 2022. X_2, X_4, and

X_{10} exerted only a negligible influence on the spatial distribution of rural tourism destinations in China. X_8 remained the factor with the strongest explanatory power, with q-value of 0.808 in 2022, which further corroborates the applicability of distance decay theory to explaining the spatial agglomeration of rural tourism destinations, namely, the suction effect of well-known scenic spots can drive the development of surrounding scenic areas through tourist flow spillover.

Regional area (X_1) determined the number of administrative villages to a certain extent, which in turn affected the number of rural tourism destinations. Climate suitability was an important factor to be considered in the construction of scenic spots, and average annual temperature (X_3) was directly related to tourists' willingness to visit. Number of township-level administrative units (X_6) represented the cardinal number of rural tourism destinations in each region. The more administrative units, the higher the probability of creating rural tourism destinations. The more the number of AAAAA tourist attractions, the higher the abundance of tourism resources (X_8). Strong radiation effect of well-known scenic spots would attract a large number of tourists, and the total number of tourist arrivals(X_{11}) increased, bringing more tourist flow and tourism income to the surrounding rural tourism destinations, thus forming a virtuous cycle to promote the construction and sustainable development of rural tourism destinations. As a way of interaction between urban and rural areas, most tourists of rural tourism come from cities and towns, and urban population (X_9) directly affected the size of tourist source market. Forests, as tourism landscape resources with ecological and aesthetic value, provided core attractions for rural tourism. Areas with high forest coverage rate (X_5) tended to possess a sound ecological environment, rich biodiversity, and distinctive landscape features, which can satisfy urban residents' demand for a return to nature experience, thereby constituting the resource base for rural tourism development. Most of the participants in rural tourism were self-driving tourists, and highway become the most important transportation infrastructure. Highway density (X_{12}) would directly affect the accessibility of rural tourism destinations and the time cost of tourists.

Elevation and water resources constituted the natural environmental foundation, which commonly exerted their influence in concert with other factors through mediating their respective conditions. In addition, with socioeconomic development and the progressive maturation of the tourism market, anthropogenic factors such as source market size and transportation accessibility have gradually become the dominant forces shaping spatial differentiation, thus leading to the declining trend of explanatory power of average elevation (X_2) and water resource abundance (X_4).

In summary, the core driving factors of the spatial differentiation in China's rural tourism destinations remained highly consistent across the two classification schemes, which indirectly corroborated the reliability of the research findings. Combined with the foregoing analysis of spatial autocorrelation among the 12 influencing factors, the spatial clustering of X_1, X_3,X_5, X_8, X_9, X_{11} and X_{12} has contributed to the spatial clustering of rural tourism destinations in China. In contrast, the spatial clustering of X_2, X_4 and X_{10} did not reinforce the spatial clustering pattern. X_6, though randomly distributed, exhibited a positively skewed normal distribution, which helped explain the spatial clustering of rural tourism destinations. X_7, however, was randomly distributed and bore no meaningful association with the spatial differentiation of rural tourism destinations in China.

3.2.2. Factor interaction analysis

Factor interaction detection is used to assess whether the combined effect of two independent variables increased the explanatory power on the dependent variable. Factor interaction detection was conducted using the GeoDetector for the influencing factors under both the natural breaks (Jenks) method and the quantile method for the year of 2014, 2018, and 2022, generating a total of six factor interaction detection result tables. For the sake of brevity, only the factor interaction detection results for 2022 under both classification schemes are presented as Table 7 and Table 8. As can be seen from Table 7, the combined effect of any two independent variables could significantly enhance the interpretation power on the spatial differentiation of rural tourism destinations in China, among which 90% belonged to two-factor enhancement type and 10% belonged to nonlinear enhancement type. X_3 had the strongest interaction with X_7, with *q* value reaching 0.966. Interaction between X_2 and X_4 was the weakest, with *q* value only 0.421, but it was still stronger than the interpretation force by the two alone.

As can be seen from Table 8, the combined effect of any two independent variables could significantly enhance the interpretation power on the spatial

Table 7 – Factor interaction detection results under natural breaks (Jenks) method

Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	0.641											
X_2	0.844	0.190										
X_3	0.909	0.580	0.310									
X_4	0.827	0.421	0.495	0.140								
X_5	0.819	0.694	0.762	0.585	0.434							
X_6	0.827	0.938	0.925	0.829	0.905	0.614						
X_7	0.848	0.881	0.966	0.766	0.875	0.820	0.284					
X_8	0.932	0.864	0.962	0.949	0.965	0.908	0.915	0.809				
X_9	0.905	0.943	0.958	0.809	0.834	0.914	0.885	0.958	0.710			
X_{10}	0.897	0.509	0.788	0.449	0.824	0.858	0.788	0.931	0.904	0.084		
X_{11}	0.930	0.779	0.890	0.720	0.883	0.880	0.722	0.979	0.861	0.775	0.578	
X_{12}	0.882	0.807	0.786	0.619	0.842	0.900	0.732	0.934	0.849	0.739	0.844	0.439

Table 8 – Factor interaction detection results under Quantile method

Indicators	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	0.614											
X_2	0.784	0.095										
X_3	0.921	0.670	0.390									
X_4	0.942	0.549	0.489	0.228								
X_5	0.798	0.482	0.631	0.603	0.363							
X_6	0.876	0.900	0.923	0.857	0.824	0.643						
X_7	0.923	0.950	0.961	0.880	0.925	0.899	0.370					
X_8	0.942	0.870	0.973	0.958	0.893	0.926	0.950	0.808				
X_9	0.937	0.938	0.973	0.838	0.940	0.947	0.919	0.935	0.747			
X_{10}	0.736	0.386	0.562	0.594	0.523	0.848	0.716	0.889	0.950	0.119		
X_{11}	0.912	0.759	0.802	0.756	0.787	0.836	0.672	0.927	0.934	0.730	0.561	
X_{12}	0.915	0.513	0.606	0.555	0.565	0.910	0.734	0.931	0.862	0.465	0.746	0.299

differentiation of rural tourism destinations in China samely under Quantile method. X_3 had the strongest interaction with X_8 and X_9 alike, with q value reaching 0.973. Interaction between X_{10} and X_{12} was the weakest, with q value only 0.465.

The results of factor interaction detection under the natural breaks (Jenks) and quantile methods for 2014 and 2018 (not shown here) also exhibit characteristics similar to those of 2022. The spatial pattern of China's rural tourism destinations was affected by multiple factors, and the driving structure has experienced a fundamental transition from single-factor weak explanatory power to multi-factor strong synergistic effect. Factors with low influence could significantly enhance their interpretation force when combined with other factors. The interaction of natural factors and social and economic factors formed the imbalance of the spatial distribution of China's rural tourism destinations.

4. Discussion

From the perspective of place-based policy, the designation of various types of rural tourism destination lists constitutes a spatial selection mechanism. The final inclusion in these lists is not a random sample but an outcome of policy-induced preferential selection. Consequently, governmental policy interventions exert a significant influence on the spatial configuration of rural tourism destinations. Given the substantial volume and limited accessibility of data pertaining to non-designated villages, this study does not undertake a comparative analysis of the spatial distribution patterns and determinant factors between designated and non-designated villages. To a certain extent, this may impede the ability to disentangle the natural spatial distribution of rural tourism destinations from the spatial biases inherent in policy evaluation. Nevertheless, it is important to recognize that the spatial distribution of both designated and non-designated villages is not solely dictated by policy intervention, rather, it is the result of a complex interplay of multiple factors, including the physical geographical environment, the abundance of tourism resources, and the scale of urban population. Therefore, focusing exclusively on the designated villages as the research subject remains methodologically justifiable and offers a certain degree of feasibility.

According to current population distribution pattern and distribution of cities of different sizes in China, main source market of rural tourism will remain in the central and eastern regions of China for a long time, and the spatial pattern of rural tourism destinations will not change suddenly. Therefore, government should formulate relevant policies to publicize and promote the specific requirements of China's Beautiful Leisure Villages, China's Key Rural Tourism Villages and other standards, using evaluation as a tool to promote rural construction. Encourage all regions to actively recommend villages that meet the standards, and moderately increase the number of rural tourism destinations in densely populated areas while taking regional balance into account, so as to provide more rural tourism options for tourists. At the same time, establish a periodic acceptance system for China's Beautiful Leisure Villages and China's Key Rural Tourism Villages, strengthen landscape quality management, folk heritage protection and tourism service quality monitoring of selected villages, thus maintaining the sustainability of rural tourism development.

Well-known tourist destinations have a strong siphon effect, and the surrounding rural tourism destinations can realize the secondary distribution of tourism economy to well-known tourism destinations through differentiated product attraction and convenient transportation conditions. Therefore, all regions should pay attention to the construction of AAA level and above tourist attractions, strive to create more high-quality AAAAA and AAAA level scenic spots, and use the radiation driving role of high-level tourist attractions to increase tourist arrivals and income in rural tourism destinations. High-level tourist attractions can also cooperate with the surrounding rural tourism destinations to promote integration construction, create boutique tourism routes, and strive for the integrated development of urban and rural areas.

The key to the development of rural tourism lies in the excellent attractiveness of rural tourism destinations. rural tourism destinations should seriously consider their local characteristics of history, geography, culture and technology to scientifically formulate rural tourism development plans, guide misplaced competition, encourage qualified rural tourism destinations to build rural tourism resorts, and gradually improve the quality of rural landscape. Improve infrastructures such as roads, communications, water and electricity, as well as tourism facilities such as farm houses and homestays. Reasonably add leisure and entertainment facilities with special features to make tours more convenient and interesting, so as to obtain tourist loyalty (Campón-Cerro, Hernández-Mogollón, Alves 2017). Encourage young people to return to their hometowns to start businesses, carry out training on tourism services, strengthen supervision over service quality, and improve the quality and level of rural tourism reception. Attach importance to ecological construction and protect rural natural environment (Li, Ismail, Aminuddin 2024). Strengthen new media marketing and self-media operation and management, steadily improve the visibility and reputation of rural tourism destinations, and pay more attention to "retention" than "flow".

5. Conclusions

By methods of kernel density estimation, standard deviation ellipse and geographic detector, this study revealed spatial differentiation evolution characteristics and influencing factors of rural tourism destinations in China from 2014 to 2022. The conclusions are as follows: (1) The number of rural tourism destinations in all regions increased rapidly, and the difference between 31 regions gradually expanded. South China region and the southern continuous area of North China region gradually become areas with relatively rich rural tourism resources. (2) Inner Mongolia boundary and Sichuan-Tibet-Qinghai-Xinjiang border had always been low-density areas of rural tourism destinations, and other areas possessed increasingly dense distribution, forming a circle structure around the core node. Central areas of Beijing-Tianjin-Hebei district and Yangtze River Delta were always the densest areas of rural tourism destinations. (3) Concentration trend and directionality of China's rural tourism destinations along the southwest to northeast axis was gradually obvious, and their gravity center showed a slow westward trend, but spatial distribution pattern was relatively stable. (4) 530 double superior rural tourism destinations showed similar distribution pattern, but emerged three core code with the densest distribution, including central area of Beijing-Tianjin-Hebei district, central area of Yangtze River Delta, and border area between eastern Qinghai and Gansu, showing a trend of three pillars. The gravity center of double superior rural tourism destinations was more northerly, and showed more obvious trend of aggregation distribution along the direction of north by east 40.892°. (5) Regional area, number of township-level administrative units, abundance of tourism resources, urban population and tourist arrivals were the key factors affecting the spatial differentiation of rural tourism destinations. Average annual temperature, forest coverage rate and highway density were main factors. Combined effect of any two factors could significantly increase the interpretation force, and imbalance of the spatial distribution of rural tourism destinations in China was caused by multiple factors.

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