Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 7, No. 2, June, 2026

Spatial Distribution of Rural Tourism Villages: A Nearest Neighbor and Kernel Density Analysis

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Received 16 October 2025; Revised 22 April 2026; Accepted 06 May 2026; Published 01 June 2026

Abstract

The research aims to analyze the spatial distribution pattern of characteristic villages for rural tourism in Sichuan Province, in order to optimize the allocation of tourism resources and promote local economic growth. The research adopted the nearest neighbor index and kernel density estimation methods, and analyzed them in combination with the data from 2014 to 2024. The results showed that the nearest neighbor index of Chengdu City was 0.85, and the estimated nuclear density of Aba Prefecture was 0.58, indicating that there were diversity and density differences in the distribution of characteristic villages for rural tourism in different regions. The research reveals the correlation between the spatial distribution of characteristic villages in rural tourism and regional natural resources, cultural characteristics, and tourism development policies. This research makes an innovative stride by applying the nearest neighbor index and kernel density estimation techniques to the spatial distribution analysis of distinctive villages within the realm of rural tourism. It offers a robust scientific foundation for the strategic planning and effective management of rural tourism in Sichuan Province, thereby enhancing the regional case studies within rural tourism research. Moreover, this study holds substantial practical importance in fostering the sustainable development of rural tourism endeavors.

Keywords: Characteristic Villages of Rural Tourism; Spatial Distribution; Nearest Neighbor Index; Kernel Density Estimation.

1. Introduction

Sichuan Province in Southwest China has beautiful natural landscapes and rich cultural heritage. In recent years, following the launch of the national strategy for rural revitalization, rural tourism (RT) has rapidly emerged in Sichuan Province, serving as a key approach to spur regional economic development, encourage the optimization of rural industrial makeup, and improve the quality of life of farmers [1, 2]. As the central pillar for RT advancement, characteristic villages not only carry the protection and inheritance of regional culture and ecological resources but also serve as an important source of income for local residents. However, with the rapid growth of RT, how to scientifically plan and manage the spatial distribution (SD) of these characteristic villages to achieve sustainable development has emerged as a pressing matter requiring immediate attention. Currently, the development of characteristic villages in Sichuan Province presents a diversified trend, with different regions developing RT models with local characteristics based on their respective natural resources and cultural backgrounds [3, 4]. However, due to the lack of more systematic research on the sustainable development model of characteristic villages, areas with rich tourism resources may be overdeveloped, while areas with scarce resources may be left out for a long time [5, 6].

The interaction between socio-economic factors and spatial agglomeration is a key factor influencing the development of RT. Among them, income levels and policy funds constitute the market driving force for the

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https://doi.org/10.28991/HIJ-2026-07-02-08

agglomeration of RT. Villages with better economic development usually have more distinct characteristic industries and mature product systems, which is conducive to the formation of demonstration sites. Policy funds and planning regulation are important factors influencing the spatial agglomeration of RT. The government consciously supports communities with tourism development potential through infrastructure construction, marketing promotion, and investment in tourism projects, making them the core nodes of regional tourism development. Capital and technology tend to flow to regions rich in tourism resources, with concentrated tourism flows and high tourism return rates, in order to enhance the spatial allocation efficiency of capital and generate agglomeration phenomena. Transportation factors are the foundation for the agglomeration and development of RT, and their density reflects the accessibility and convenience of local RT development. Tourism expenditure interacts with disposable income, jointly influencing the demand level, profit level, investment scale, product price, and other aspects of the regional RT market.

Many scholars have studied the spatial pattern of tourism areas. In order to explore the sustainable development of RT characteristic villages in Henan Province, Yunchao et al. [7] proposed an analysis method based on global autocorrelation. Their research findings demonstrated that there were obvious agglomeration characteristics in northern, central, and southern Henan, showing the SD characteristics of "close to mountains, around the city, and along the road". Tao et al. [8] proposed an analytical method based on location entropy and kernel density (KD) to explore the spatial layout and geographic traits of tourist towns within the Wuling Mountain region. They quantitatively analyzed the distribution pattern of 289 tourist attractions and summarized the influencing factors. The findings revealed that tourist towns varied by region in terms of quantity and tourism development, displaying notable geographical clustering patterns overall. This resulted in the formation of several high-density areas alongside numerous smaller settlements, with a clear distribution along transportation networks. Weng et al. [9] introduced an analytical approach incorporating KD analysis, nearest neighbor (NN) distance analysis, spatial autocorrelation analysis, centroid trajectory analysis, and geographical detectors to examine the spatiotemporal distribution patterns of A-grade tourist destinations in China's Chengdu-Chongqing area. Their findings indicated that these tourist attractions were generally clustered, with Chengdu and Chongqing serving as primary hubs and Yibin as a secondary center. Natural landscape attractions were predominantly located in the Yangtze River basin and higher-altitude areas at the region's periphery, showing notable variations in KD distribution. Chengdu and Chongqing, in particular, demonstrated clear advantages in this regard.

Lin et al. [10] used Huangcheng Village as a case study to investigate the distinctive features and underlying mechanisms of how tourism advancement affects the landscape pattern of traditional villages. They analyzed four remote sensing images taken between 1995 and 2020 to assess landscape expansion and pattern transformations, employing geographical detectors to identify influencing factors. The findings revealed that landscape changes were primarily marked by the ongoing encroachment of natural landscapes by non-natural ones, along with continuous expansion through edge and leapfrog growth around tourism resources. Simultaneously, the dominance and connectivity of non-natural landscapes increased, leading to an overall landscape pattern transition from "relatively intact (becoming fragmented) moving towards completeness". Liang et al. [11] analyzed the spatial distribution characteristics and influencing factors of tourism interest point data in Chengdu, Sichuan Province, China, and proposed a comprehensive analysis framework combining spatial autocorrelation, kernel density estimation (KDE), and geographic detector methods. The results showed that the tourism interest points in Chengdu presented significant spatial agglomeration characteristics, mainly concentrated in the city center and its surrounding areas, and there were obvious differences in the spatial distribution of different types of tourism POIs. Among them, transportation conditions, population density, economic development level, and policy support were the main factors influencing the spatial distribution of tourism interest points in Chengdu. Based on the current situation of the spatial distribution characteristics of greenhouse gas emissions at the global, national, and sub-national scales, Crippa et al. [12] proposed a multi-scale spatial distribution analysis method for greenhouse gas emissions based on the EDGAR v8.0 database. The results showed that global greenhouse gas emissions were highly concentrated in space, with the main emission areas concentrated in a few countries and regions, and the spatial distribution characteristics of different emission sources (such as energy, industry, transportation, etc.) varied significantly.

Although existing studies have achieved relatively good results, there are still some deficiencies. Firstly, most of the existing research focuses on specific regions or specific types of RT destinations, lacking systematic studies on this specific region of Sichuan Province. Secondly, most studies only focus on the spatial distribution characteristics at a certain point in time and lack the analysis of the spatial evolution laws within a certain time span. Furthermore, the uneven distribution of characteristic villages for RT may exacerbate the imbalance in regional development, leading to the waste of tourism resources and environmental damage [13, 14]. Based on this, the present study analyzes the distribution pattern of relevant villages in Sichuan Province using the nearest neighbor index (NNI) and KDE. The aim of the study is to propose targeted management strategies and planning suggestions based on the distribution pattern of villages to facilitate the enduring progress of RT. The innovation of this study lies in systematically analyzing the SD characteristics of various types of characteristic villages in RT in the specific region of Sichuan Province, enriching the regional case studies of RT research. Additionally, applying the NNI and KDE methods to the SD analysis of characteristic villages in RT provides a new quantitative tool for spatial planning of RT.

2. Material and Methods

2.1. Data Sources and Preprocessing

Situated in the southwestern part of China, Sichuan Province is well-known for its abundant and varied natural scenery and deep-rooted cultural traditions, establishing it as a key originator of RT in the nation. In recent times, as the rural revitalization strategy has been thoroughly implemented, RT in Sichuan has thrived, emerging as a significant force in propelling local economic development, facilitating the restructuring of rural industries, and enhancing the living standards of rural residents [15, 16]. The geographical location of Sichuan Province is depicted in Figure 1.

Figure 1. The geographical location of Sichuan, China

When exploring the SD pattern of characteristic villages for RT in Sichuan Province, China, the accuracy and completeness of data serve as the foundation for ensuring reliable analysis results. The study first conducted a detailed review of data sources and scientifically and reasonably processed the collected data to ensure that subsequent analysis accurately reflects the SD characteristics of characteristic villages for RT. The data sources in the study mainly include the Sichuan Provincial Department of Culture and Tourism, the culture and tourism bureaus of various cities (prefectures), the Sichuan Provincial Geographic Information Public Service Platform, field research, questionnaire surveys, and publicly available online data. The relevant schematic is presented in Figure 2.

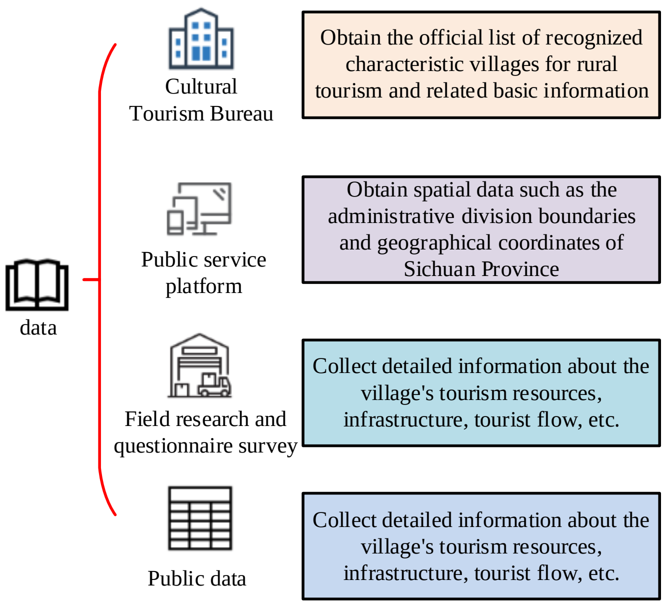


Figure 2. Data sources of RT in Sichuan Province, China

In Figure 2, the Cultural Tourism Bureau primarily obtains official lists of designated RT villages and related basic information, including village names, counties (cities and districts) where they are located, and types of RT projects.

The public service platform mainly acquires spatial data such as administrative boundaries and geographic coordinates of Sichuan Province, China. Field research and questionnaire surveys involve visiting some RT villages to collect detailed information on tourism resources, infrastructure, and tourist traffic [17, 18]. Additionally, questionnaire surveys are used to understand the attitudes and needs of local residents towards the development of RT. Finally, based on publicly available data from the internet, data such as tourist evaluations and travel guides are collected from channels such as travel websites and social media platforms to supplement and enrich the tourism resource information of RT villages. To guarantee the precision and usability of the data, the collected data underwent preprocessing. Firstly, duplicate data and obviously erroneous data records were removed. For example, for the geographic coordinate data of RT villages, outliers with latitude and longitude exceeding the geographical range of Sichuan Province were eliminated [19, 20]. The relevant mathematical expression is presented in Equation 1.

$$O=\begin{cases}1 & if \quad \lambda\notin[\lambda_{\min},\lambda_{\max}] \quad or \quad \phi\notin[\phi_{\min},\phi_{\max}]\\ 0 & Otherwise\end{cases} \tag{1}$$

In Equation 1, O represents the judgment of outliers, and λ and ϕ represent the longitude and latitude, $[\lambda_{min}, \lambda_{max}]$ and $[\phi_{min}, \phi_{max}]$ denote the longitude and latitude range of Sichuan Province. After data cleaning, data from different sources are uniformly converted into a format that can be used for geographic information system analysis. Additionally, data from different sources are integrated to form a complete database of characteristic RT villages. For some missing data, the average value of similar villages is used for filling [21, 22]. Taking the missing tourist flow as an example, the relevant mathematical expression is presented in Equation 2.

$$V_{miss}=\frac{1}{n}\sum_{i=1}^{n}V_i \tag{2}$$

In Equation 2, V_{miss} represents the missing tourist flow, V_i represents the tourist flow of similar villages, and n is the number of similar villages. To eliminate the dimensional influence between different indicators, the study normalized indicators such as tourist flow and tourism revenue, with the relevant mathematical expression shown in Equation 3.

$$V_{\text{Normalization}}=\frac{V-V_{\min}}{V_{\max}-V_{\min}} \tag{3}$$

In Equation 3, $V_{Normalization}$ represents the normalized data, V represents the original value, and V_{min} and V_{max}, respectively represent the minimum and maximum values of the indicator among all RT characteristic villages. For the administrative boundary and geographic coordinate data of Sichuan Province, projection transformation and coordinate correction were conducted [23]. Specifically, the geographic coordinates were converted from the WGS-84 coordinate system to the CGCS2000 coordinate system to adapt to the data standards of the Sichuan Provincial Geographic Information Public Service Platform [24, 25]. The relevant mathematical expression is presented in Equation 4.

$$(\lambda^{\sim},\phi^{\sim})=(\lambda+\Delta\lambda,\phi+\Delta\phi) \tag{4}$$

In Equation 4, $(\lambda^{\sim},\phi^{\sim})$ represents the geographic coordinates in the CGCS2000 coordinate system, $\Delta\lambda$ and $\Delta\phi$ represent the translation amounts during the coordinate system transformation process. Finally, there may be some extreme values in various tourism indicators. The study first detects outliers using the Z-score method and then processes them through the median replacement method. The relevant mathematical expression is presented in Equation 5.

$$V_{correction}=\begin{cases}M & if \quad |Z|\succ Q\\ V & Otherwise\end{cases} \tag{5}$$

In Equation 5, $V_{correction}$ represents the corrected data, M represents the median, Z represents the value after Z-score adjustment, and Q represents the preset threshold. Through the aforementioned data preprocessing steps, the study can guarantee the precision and completeness of the data, thereby offering a solid data basis for subsequent NNI and KD analysis.

2.2. NNI Analysis Method

After processing the data on RT in Sichuan Province, the study introduced the NNI, which is a broadly applied method for analyzing the SD pattern of point features. It determines whether the SD of point features is random, uniform, or clustered by calculating the distance between each point and its NN [26, 27]. The relevant mathematical expression is presented in Equation 6.

$$\begin{cases}NI=\dfrac{\bar{d}}{d_e}\\ d_e=\dfrac{1}{2\sqrt{\dfrac{n}{A}}}\end{cases} \tag{6}$$

In Equation 6, NI represents the NNI, $\overline{d}$ represents the observed average NN distance, which is the average distance between all points and their NNs; d_e represents the expected average NN distance under a completely random distribution, n is the number of points, and A is the area of the study region. For the NNI NI, when $NI < 1$, it indicates that the SD of point features is clustered; when $NI = 1$, it indicates that the SD of point features is random; when $NI > 1$, it indicates that the SD of point features is uniform. Specifically, the average NN distance $\overline{d}$ is first calculated. For each RT characteristic village i, the distance d_{ij} to its NN village j is calculated, and then the average $\overline{d}$ of all distances is calculated. The relevant mathematical expression is presented in Equation 7.

$$\overline{d} = \frac{1}{n}\sum_{i=1}^{n} d_{ij} \tag{7}$$

After obtaining the average NN distance, d_e is calculated grounded in the study area A and the number of points n, using Equation 6. Meanwhile, the observed average NN distance $\overline{d}$ is compared with the expected average NN distance d_e to calculate the NNI NI. Based on the above NNI analysis method, the study further utilizes the statistical characteristics of the NNI to evaluate the SD pattern of characteristic villages in Sichuan Province. Based on this research, a statistical distribution diagram of NN distance is introduced, which can visually reflect the distribution characteristics of the data and determine whether its SD significantly deviates from random distribution [28, 29]. The NN graph shows the relationship between the critical value of the NNI and the *p*-value at a given significance level. By comparing the actually calculated NNI with these critical values, the study can determine whether the SD of RT characteristic villages is random, clustered, or dispersed. The illustrative diagram of the average NN distance is presented in Figure 3.

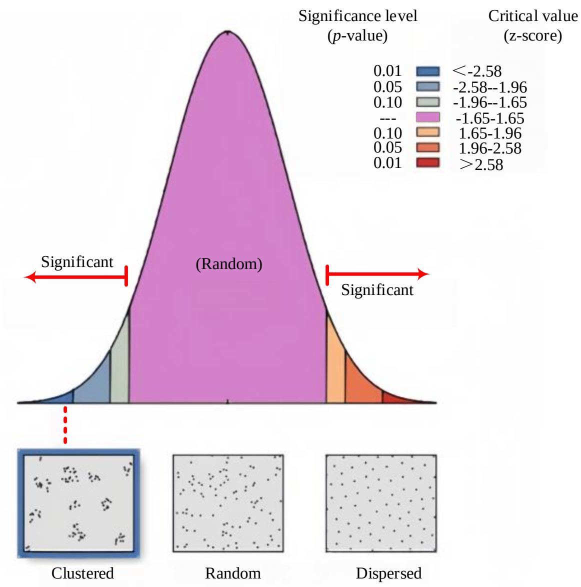


Figure 3. Average NN map of Sichuan Province

The average NN distance distribution shown in Figure 3 is a normal distribution curve, representing the expected distribution of the NNI under the assumption of a completely random distribution. The shaded areas on both sides of the curve indicate the critical Z-score values at different significance levels (*p*-values). When the Z-score falls below -2.58 or exceeds 2.58, the corresponding *p*-value is less than 0.01, suggesting that the SD significantly deviates from the random distribution at the 1% significance level. If the Z-score lies within the ranges of -2.58 to -1.96 or 1.96 to 2.58, the associated p-value falls between 0.01 and 0.05, indicating that the SD significantly deviates from the random distribution at the 5% significance level. If the Z-score falls within the ranges of -1.96 to 1.65 or 1.65 to 1.96, the corresponding p-value is situated between 0.05 and 0.10, indicating that the SD may deviate from the random distribution at the 10% significance level. In addition, among the three typical SD patterns, point features in a clustered distribution are spatially aggregated, resulting in smaller NN distances; point features in a random distribution are evenly distributed in space, and the NN distances conform to the expected values of the random distribution. Point features in a dispersed distribution are spatially scattered, resulting in larger NN distances.

By comparing the NNI obtained through actual calculations with the critical Z-score value in the graph, we can determine the SD pattern of characteristic RT villages in Sichuan Province. For example, if the Z-score value corresponding to the calculated NNI falls in the blue area on the left (Z-score < -2.58), it can be considered that the SD of characteristic RT villages is significantly clustered at a significance level of 1%.

2.3. KD Analysis Method

After analyzing the SD pattern of characteristic villages in RT in Sichuan Province based on the NNI, the study introduced the KD analysis method to acquire a more thorough comprehension of the SD density and clustering trend of these characteristic villages. KD analysis can provide a continuous density estimation, which helps reveal the SD details of the data, thus complementing the results of the NNI analysis. The schematic diagram of the living and residential KD based on rural areas in Sichuan Province is presented in Figure 4.

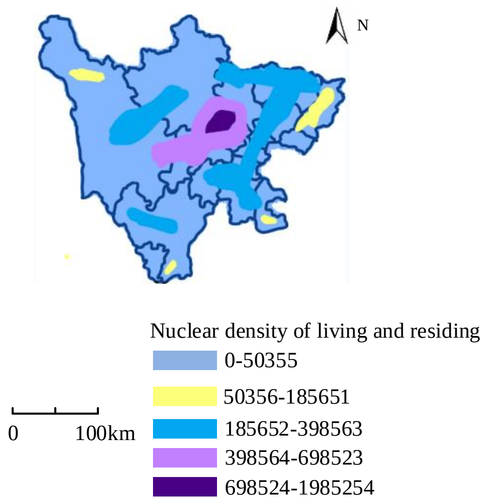


Figure 4. Schematic diagram of the density of living and residential nuclei in Sichuan Province

In Figure 4, the fundamental idea of KDE is to approximate the true probability density function using a set of kernel functions. For a given set of data points $\{x_1, x_2, \cdots, x_n\}$, the KDE is presented in Equation 8.

$$\tilde{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) \tag{8}$$

In Equation 8, $K_{\square}$ represents a kernel function with width □. In the multidimensional data such as the geographical coordinates of RT characteristic villages in Sichuan Province, it is often necessary to use multidimensional KDE. Based on Equation 6 for estimating multidimensional KD, the two-dimensional representation of $K_{\square}$ is presented in Equation 9.

$$K_h(u) = \frac{1}{2\pi h^2} e^{-\frac{|u|^2}{2h^2}} \tag{9}$$

The choice of kernel function exerts a notable influence on the results of KDE. Common kernel functions include Gaussian kernel, uniform kernel, and triangular kernel. In this study, the Gaussian kernel function is selected, and the relevant mathematical expression is presented in Equation 10.

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \tag{10}$$

In Equation 10, u is the difference between the estimated point and each point in the dataset. In KDE, bandwidth □ is one of the key parameters, which controls the degree of smoothing. The selection of bandwidth is usually determined through cross-validation, Siverman's rule, and Scott's rule [30, 31]. In this study, Siverman's rule is adopted, and the relevant mathematical expression is presented in Equation 11.

$$h_{Silverman} = 0.9 \times n^{-\frac{1}{5}} \min(\sigma, IQR / 1.34) \tag{11}$$

In Equation 10, IQR represents the interquartile range of the data. In geostatistics, the estimation of KD is commonly used for spatial data analysis. For spatial point patterns, KDE can explain the clustering trend of points [32, 33]. The calculation of spatial KDE can be based on Equation 12.

$$\tilde{f}(s) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{h^2} K\left(\frac{\| s - s_i \|}{h}\right) \tag{12}$$

In Equation 12, s and s_i represent spatial location points, $||s - s_i||$ indicates the Euclidean distance between two points. Furthermore, KDE can be combined with local spatial autocorrelation indicators to assess the local patterns of SD. The relevant mathematical expression is presented in Equation 13.

$$I_i = \frac{W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})^2} \tag{13}$$

In Equation 13, I_i is the local spatial autocorrelation index, W_{ij} is the spatial weight matrix, x_i and x_j are the data points, and $\bar{x}$ is the mean value of the data points. For the smoothing function in KDE, the study introduces the Akaike information criterion to select the optimal smoothing function, with the relevant mathematical expression shown in Equation 14.

$$A_i = -2In(\tilde{L}) + 2r \tag{14}$$

In Equation 14, $\tilde{L}$ represents the max value of the likelihood function, and r denotes the number of model parameters. Finally, KDE can be used to identify local patterns in Sichuan's RT data, such as local maxima and minima. The identification of local maxima can be achieved by calculating the first derivative of the KDE and finding its zero point, with the relevant mathematical expression shown in Equation 15.

$$\frac{\partial \tilde{f}(s)}{\partial s} = 0 \tag{15}$$

By solving Equation 15 and finding the local maximum point of the KDE, we can map it to the aggregation area of characteristic RT villages in Sichuan Province. For the definitions of high-density and low-density regions, the study employed the quantile method. The specific research will use the upper quartile (75th percentile) of the density values obtained by KDE as the threshold for high-density regions, and the lower quartile (25th percentile) as the threshold for low-density regions. This method enables the study to delineate density regions in accordance with the inherent distribution characteristics of the data, rather than resorting to arbitrary or predetermined thresholds. The final analysis process for the SD pattern of characteristic RT villages in Sichuan Province is presented in Figure 5.

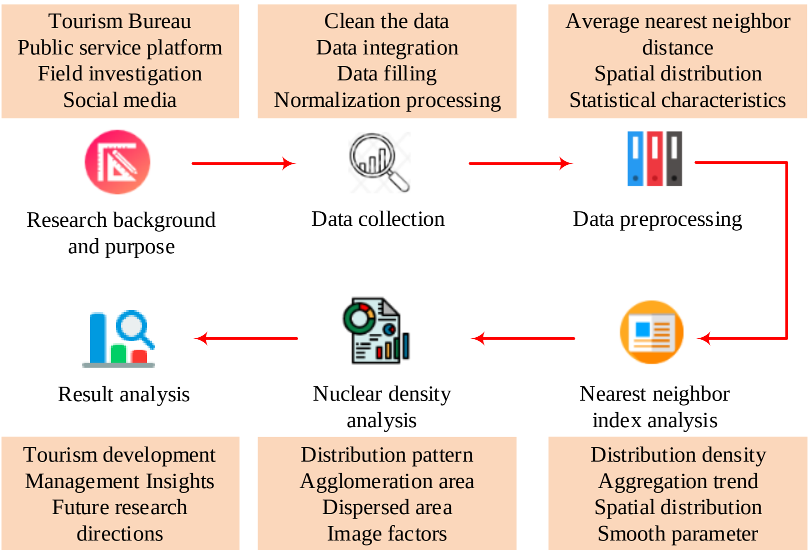


Figure 5. The analysis process of the SD pattern of characteristic villages for RT in Sichuan Province

In Figure 5, relevant tourism data is first obtained through various methods such as the tourism bureau, public service platforms, questionnaire surveys, and social media. Subsequently, data preprocessing is completed through data cleaning, data integration, missing value imputation, and normalization. Then, the distance between each RT characteristic village and its NNing village is calculated to obtain the average NN distance. At the same time, utilizing the statistical characteristics of the NNI, the SD pattern is evaluated through statistical distribution maps. Next, the KDE method is employed to provide the SD density of data points. Combined with local spatial autocorrelation indicators, the local pattern of SD is assessed. Finally, based on the results of data analysis, the distribution pattern of characteristic villages in Sichuan Province is analyzed; meanwhile, agglomeration and dispersion areas, as well as possible influencing factors, are identified.

3. Results

3.1. Analysis of Quantitative Results of SD Patterns

The study initially employed the NNI to evaluate and categorize the distribution patterns across various regions. By calculating and comparing the NNI values of different cities, it revealed the agglomeration, randomness, or uniformity of the distribution of characteristic villages for RT in various areas. The comparison of the NNI for each city in Sichuan Province is presented in Table 1.

Table 1. Comparison of the NNI among various districts and cities in Sichuan Province

City	NNI	City	NNI
Chengdu	0.85	Nanchong	1.22
Zigong	1.05	Meishan	0.87
Panzhihua	0.92	Yibin	1.15
Luzhou	0.78	Guangan	0.98
Deyang	1.18	Dazhou	1.07
Mianyang	0.95	Yaan	0.76
Guangyuan	1.03	Bazhong	1.04
Suining	0.89	Ziyang	0.90
Neijiang	1.01	Aba Prefecture	0.68
Leshan	0.64	Ganzi Prefecture	1.20
Liangshan Prefecture	0.82	-	-

In Table 1, the nearest neighbor indices of different cities varied significantly, reflecting the obvious differences in the spatial distribution patterns of characteristic villages for RT in Sichuan Province. The NNI value of Chengdu City was less than 1, indicating that the spatial distribution of its characteristic villages for RT showed an agglomeration pattern. This might be related to the fact that Chengdu, as the capital city of Sichuan Province, boasts abundant tourism resources, a well-developed transportation network and a relatively high appeal in the tourism market. The NNI value of Leshan City was significantly lower than 1, indicating that the spatial distribution of its characteristic villages for RT was highly concentrated. Leshan City, with famous scenic spots such as the Leshan Giant Buddha as its core, has formed an agglomeration area of multiple characteristic villages for RT. The NNI value of Ganzi Prefecture was greater than 1, indicating that the spatial distribution of its characteristic villages for RT showed a uniform pattern. This might be related to the vast territory and extensive distribution of natural landscapes in Ganzi Prefecture. The characteristic villages of RT in Ganzi Prefecture were mostly distributed in different natural landscape areas, such as Kangding and Daocheng Yading. The distance between these areas was relatively far, resulting in a relatively uniform overall distribution. The NNI value of Nanchong City was also greater than 1, showing the characteristic of uniform distribution. The characteristic villages of RT in Nanchong City were relatively scattered, which may be related to the geographical environment and the distribution of tourism resources of the city. The characteristic villages of RT in Nanchong City mainly focused on agricultural sightseeing and rural leisure, and were distributed in different towns and villages, forming a relatively even distribution pattern. The study then compared the average NN distance and its difference from the expected average NN distance for each city in Sichuan Province, with the results shown in Figure 6.

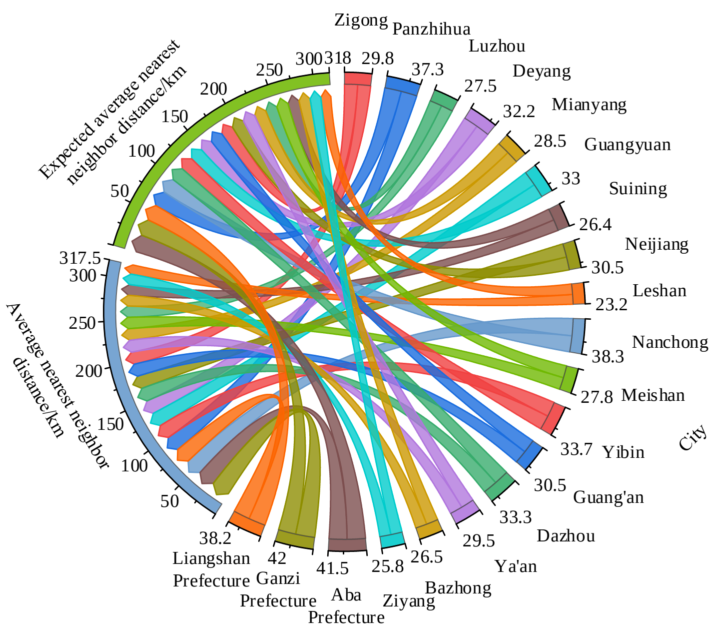
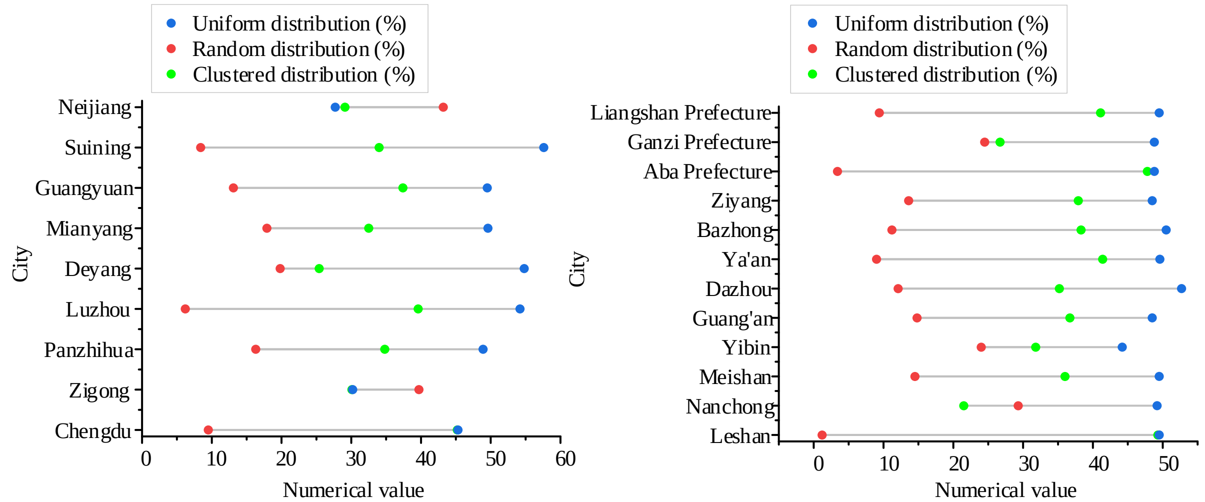


Figure 6. Comparison of the differences in the average NN distance

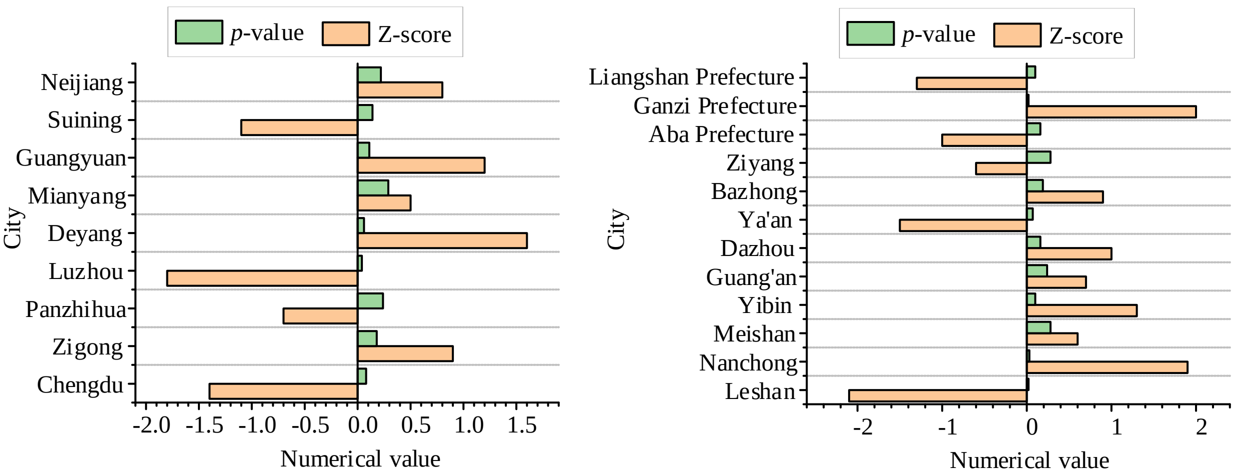
In Figure 6, after calculating the average NN distance of each city in Sichuan Province and the ratio of this distance to the expected average NN distance, the results indicated that for cities where the ratio was less than 1, such as Chengdu (0.87), Luzhou (0.96), and Leshan (0.93), the SD of RT characteristic villages tended to be clustered, meaning that the distance between villages was closer than that in a random distribution. For cities where the ratio was close to 1, such as Zigong (0.99), Mianyang (0.97), and Meishan (0.98), the SD of RT characteristic villages was close to random, meaning that the distance between villages was similar to that in a random distribution. For cities where the ratio was greater than 1, such as Deyang (1.08), Guangyuan (1.06), and Nanchong (1.07), it indicated that the SD of RT characteristic villages tended to be uniform, meaning that the distance between villages was farther than that in a random distribution. The study further compared the proportions of SD types in each city and district of Sichuan Province, and the results are presented in Figure 7.



(a) Comparison of spatial type distribution ratios -1 (b) Comparison of spatial type distribution ratios -2

Figure 7. The proportion of SD types in each urban area of Sichuan Province

Figure 7 presents a comparative analysis of the SD types across various cities and districts in Sichuan. The results indicated that in terms of agglomerative distribution, Leshan City (49.3%) and Aba Prefecture (47.8%) exhibited a higher proportion, suggesting that RT characteristic villages in these regions tended to cluster spatially. This might be attributed to the concentration of local tourism resources, convenient transportation, or policy support. Regarding random distribution, Neijiang City (43.2%) showed a higher proportion, indicating that the SD of RT characteristic villages in this city was relatively random, with no evident trend towards agglomeration or dispersion. This could be related to the city's geographical environment and resource distribution. In terms of uniform distribution, Luzhou City (54.2%) and Nanchong City (49.2%) demonstrated a higher proportion, suggesting that RT characteristic villages in these areas were distributed more uniformly in space. This might be linked to regional planning, land use policies, or the balanced distribution of tourism resources.The significance of the SD was further evaluated through the calculation of Z-score and *p*-value, with the results presented in Figure 8.



(a) Significance comparison-1 (b) Significance comparison-2

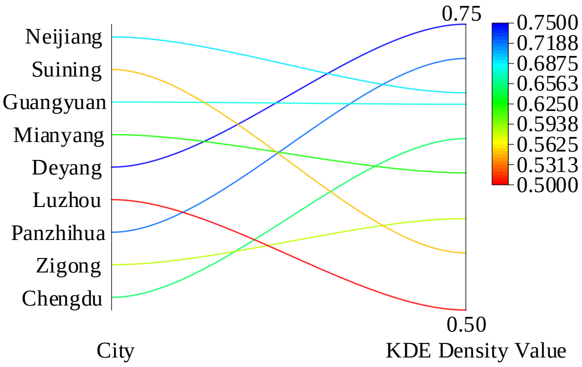
Figure 8. A significant comparison of SD

In Figure 8, the Z-score indicates the degree of deviation from the NNI under the assumption of a random distribution, while the *p* value represents the probability of this deviation being statistically significant. When the *p* value was less than 0.05, it was considered that the SD significantly deviated from the random distribution. In the results, the Z-score of Leshan City was significantly negative, indicating that the spatial distribution of characteristic villages for RT in this city showed obvious agglomeration characteristics. This kind of agglomeration might be related to the distribution of the city's tourism resources. For instance, famous scenic spots like the Leshan Giant Buddha might have attracted the development of tourism in the surrounding areas, forming tourism clusters centered around these attractions.

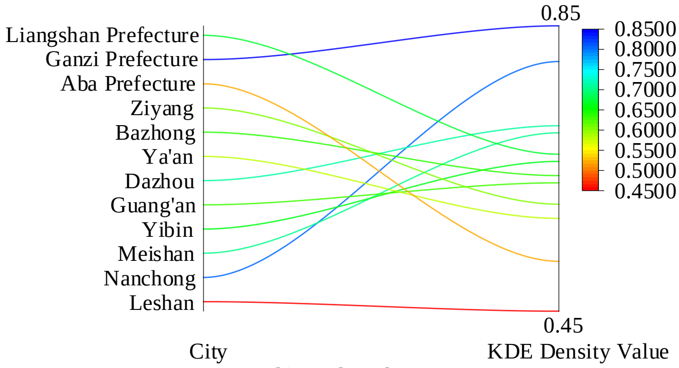
The Z-score of Zigong City and Mianyang City was close to 0, and the *p* value was greater than 0.05, indicating that the spatial distribution of their characteristic villages for RT was close to a random distribution. This might imply that the distribution of tourism resources in these cities was relatively even, or that the tourism development strategies were relatively balanced, without forming obvious tourism clusters or scattered areas. As the capital city of Sichuan Province, the Z-score of Chengdu was negative, which may reflect the agglomeration and development of characteristic villages for RT in its surrounding areas, which was in line with Chengdu's role as a tourism distribution center. The Z-score of Nanchong and Guangyuan cities was positive, which may indicate that the distribution of their characteristic villages for RT was relatively uniform. This might be related to their geographical location, transportation conditions and the distribution of tourism resources.

3.2. Analysis of SD Characteristics of Characteristic Villages for RT in Sichuan Province

After analyzing the distribution patterns of characteristic villages for RT in Sichuan Province, the study further explored the SD characteristics of these villages. Initially, the study compared the KDEs of characteristic villages for RT across various cities in Sichuan Province, with the results presented in Figure 9.



(a) Nuclear density estimation-1



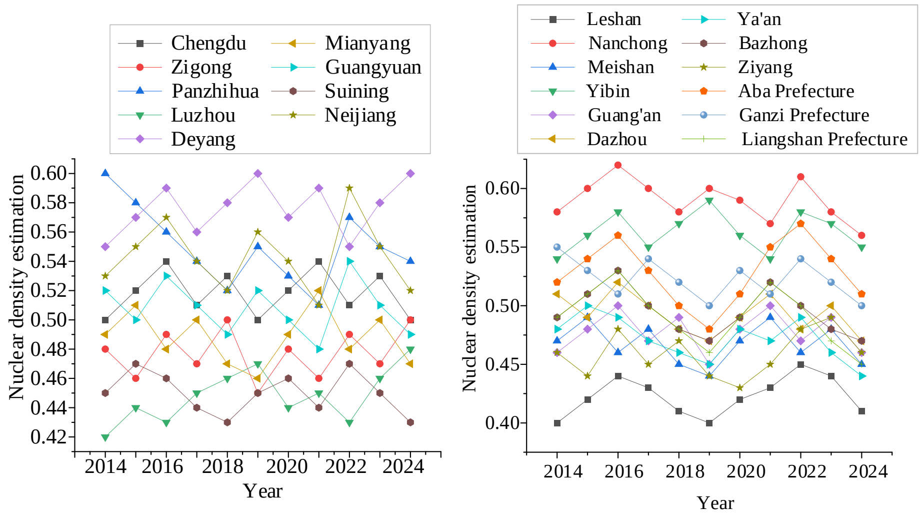
(b) Nuclear density estimation-2

Figure 9. Estimation and comparison of nuclear density of characteristic villages for RT in various cities of Sichuan Province

Figures 9(a) and 9(b) present a comparison of KDEs for various cities and districts in Sichuan Province. The KDE values reflect the relative density of characteristic villages for RT in each city. The results showed that Ganzi Prefecture and Nanchong City had the highest KDE values, at 0.85 and 0.80 respectively, indicating that these areas had a very dense distribution of characteristic villages for RT. This might be due to their abundant tourism resources, good transportation conditions, or successful policies for the development of RT. The KDE values for Chengdu, Deyang, Guangyuan, and Yibin ranged from 0.65 to 0.75, revealing a relatively moderate distribution of characteristic villages for RT in these areas, suggesting a more balanced development of RT.

The estimated nuclear density of Leshan City was the lowest, at 0.45, which was significantly lower than that of Ganzi Prefecture and Nanchong City ($p < 0.05$), indicating a sparser distribution of characteristic villages for RT in this area. This might be due to insufficient development of tourism resources, inconvenient transportation, or inadequate support for RT policies in the region. The study further categorized characteristic villages for RT in Sichuan Province into five major types: historical preservation, characteristic industries, natural scenery, pastoral landscapes, and folk culture, and explored the changes in KDE for each category from 2014 to 2024. Firstly, the changes in KDE values for the historical preservation category are presented in Figure 10.

In Figure 10, the KDE for Chengdu, the capital city of Sichuan Province, fluctuated around 0.50 from 2014 to 2024, indicating that the distribution density of Chengdu's historically preserved RT villages remained relatively stable during this decade. This might imply that the city's RT resources have been continuously protected and moderately developed, attracting a stable flow of tourists. Due to the impact of COVID-19, Chengdu may have been significantly affected by the epidemic, especially in the early 2020, tourism activities may have decreased significantly. However, due to its strong economic foundation and the diversity of its tourism resources, Chengdu may have recovered from the epidemic relatively quickly, maintaining the stability of the nuclear density estimate. With the acceleration of urbanization, Chengdu has attracted a large number of migrant population, which may have increased the demand for RT, thereby helping to maintain or even slightly increase the estimated nuclear density. The KDE for Zigong gradually rose from 0.48 in 2014 to 0.50 in 2024, showing a slight upward trend. This suggested that Zigong has achieved certain success in promoting RT villages and developing tourism resources, gradually attracting more tourists and enhancing the attractiveness of RT. During the epidemic, the city adopted effective tourism promotion measures, and the recovery of tourism demand after the epidemic was relatively rapid.



(a) A comparison of the changes in the kernel density estimates of the historical retention category-1

(b) A comparison of the changes in the kernel density estimates of the historical retention category-2

Figure 10. The estimated nuclear density of historical preservation characteristic villages

At the same time, benefiting from the growth of urban population, these new residents may seek RT as a way of leisure and cultural experience, thereby promoting the development of RT. The KDE for Guangyuan was 0.52 in 2014 but decreased to 0.49 in 2024, indicating a fluctuating downward trend. This suggested that Guangyuan lacked sufficient attraction in its RT villages. The KDE for Leshan started at 0.40 in 2014 and decreased to 0.41 in 2024, remaining relatively low and showing little change. This indicated that Leshan's historically preserved RT villages might not be effectively attracting tourists, and the region needed to strengthen the safeguarding and advancement of tourism resources. During this period, the epidemic may have further suppressed tourism demand and affected the development of RT. Meanwhile, Leshan City needs more measures to attract new residents and tourists in order to enhance the appeal of its RT and the estimated nuclear density. The KDE for Ganzi Prefecture decreased from 0.55 in 2014 to 0.50 in 2024, suggesting that the region achieved some success in the early stages of RT development but may have subsequently experienced a decline in attractiveness due to market saturation, over exploitation of resources, or other external factors. The study further compared the KDEs of characteristic villages in various cities and districts in Sichuan Province, with the results shown in Figure 11.

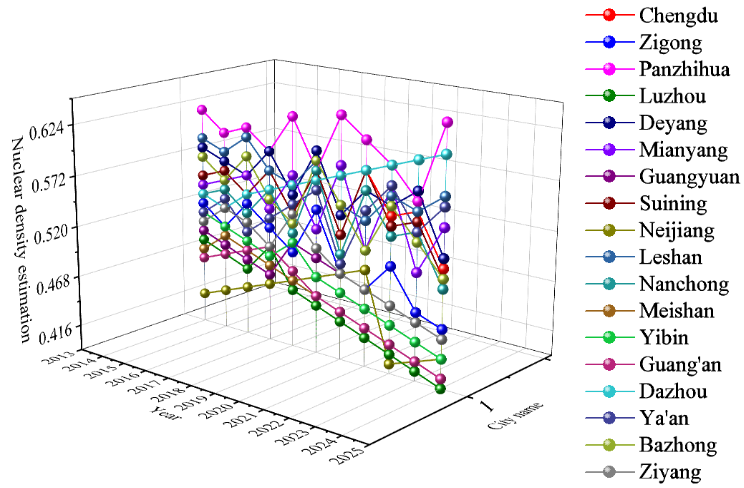
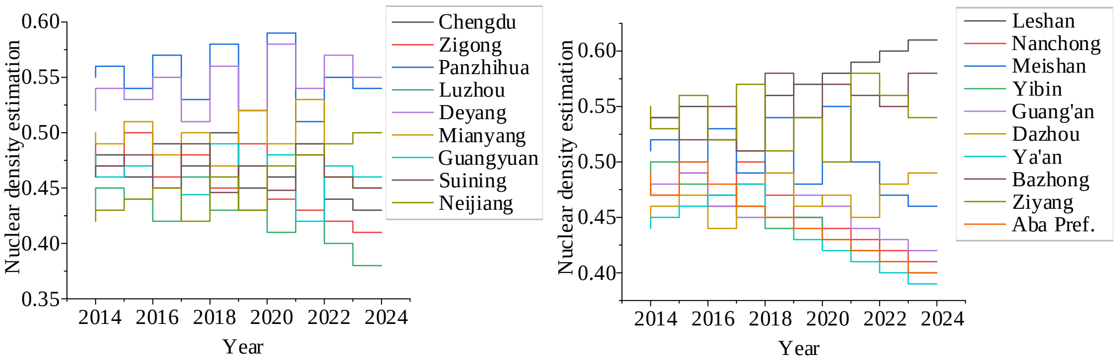


Figure 11. The estimated nuclear density of characteristic villages in the category of characteristic industries

In Figure 11, the estimated KD values for Chengdu fluctuate between 0.51 and 0.59, indicating a relatively stable distribution density of characteristic villages for RT, reflecting the city's sustained attractiveness in the development of characteristic industries. The estimated KD values for Zigong ranged from 0.45 to 0.54, which are generally lower, suggesting that the attractiveness of characteristic villages for RT in the city's characteristic industries needed improvement. The estimated nuclear density of Guangyuan City has significantly increased from 0.50 to between 0.59, showing a significant growth trend ($p < 0.05$), indicating that the city has achieved certain results in the development of characteristic industries. Lastly, the estimated KD values for Leshan remain consistently low, increasing from 0.40 to 0.50 between 2014 and 2024, suggesting that more efforts may be needed to enhance the attractiveness of characteristic villages for RT in the city's characteristic industries. The study further compared the estimated KD values of characteristic villages featuring natural scenery across various cities and districts in Sichuan Province, with the results shown in Figure 12.

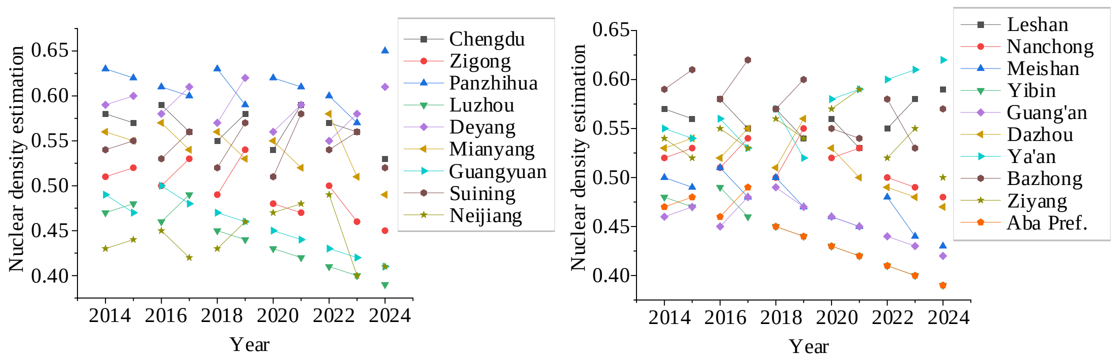


(a) Comparison of estimated nuclear density values of characteristic villages with natural scenery-1

(b) Comparison of estimated nuclear density values of characteristic villages with natural scenery-2

Figure 12. Comparison of estimated nuclear density values of characteristic villages with natural scenery

In Figure 12, the KDE values for Chengdu fluctuate between 0.43 and 0.50, indicating a relatively stable distribution density. This reflected the city's sustained appeal in natural scenery-based RT. The KDE values for Leshan were consistently low, increasing from 0.40 to 0.51, indicating a need for more measures to enhance the attractiveness of its natural scenery-based RT. For Panzhihua, the values have slightly fluctuated from 0.55 in 2014 to 0.54 in 2024, suggesting that the city's appeal in natural scenery-based RT remains stable, possibly due to continuous tourism resource development and protection. For Neijiang, the values have changed slightly from 0.46 in 2014 to 0.45 in 2024, indicating a need for further promotion and development to enhance its popularity. Finally, Aba Prefecture saw a significant increase from 0.53 in 2014 to 0.58 in 2024 ($p < 0.05$), showing an overall upward trend. This indicated that the attractiveness of the prefecture in RT based on natural scenery has increased, which may be attributed to its unique natural scenery and effective development of tourism resources. The study further compared the KDE values of characteristic villages with rural landscapes in various cities and districts in Sichuan, and the results are presented in Figure 13.

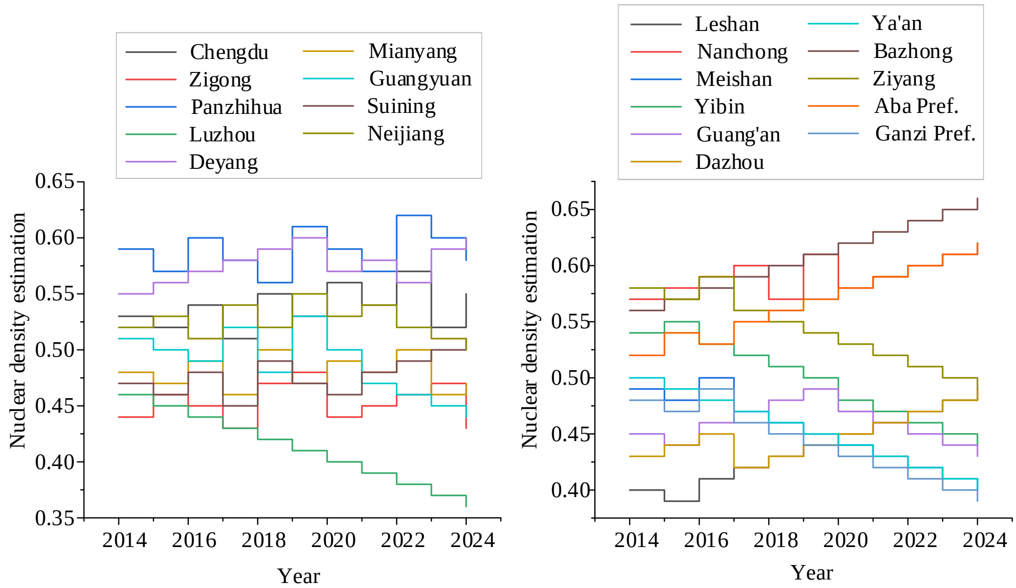


(a) Nuclear density estimation of Rural Landscape Characteristic villages -1

(b) Nuclear density estimation of Rural Landscape Characteristic villages -2

Figure 13. Comparison of estimated nuclear density values of characteristic villages with rural landscapes

In Figure 13, the KDE for Nanchong City rose from 0.57 in 2014 to 0.59 in 2024, showing slight fluctuations, revealing that the attractiveness of the RT villages with pastoral landscapes in this city remained relatively stable. For Meishan City, the estimate decreased from 0.52 in 2014 to 0.48 in 2024, revealing a slight downward trend. It might require more development of tourism resources and market promotion to enhance its attractiveness. Yibin City's estimated value declined from 0.53 in 2014 to 0.42 in 2024, indicating a downward trajectory, suggesting a weakening of the city's attractiveness in RT with pastoral landscapes. Guang'an City's estimate declined from 0.50 in 2014 to 0.43 in 2024, indicating a significant downward trajectory and the need for certain measures to enhance its attractiveness. Lastly, Aba Prefecture's estimate dropped from 0.59 in 2014 to 0.57 in 2024, with little overall change, suggesting that the attractiveness of RT with pastoral landscapes in this prefecture remains stable. The study concluded by comparing the KDEs of folk culture-style villages in various cities and districts in Sichuan, as presented in Figure 14.



(a) Estimated nuclear density of characteristic villages in the category of folk culture -1

(b) Estimated nuclear density of characteristic villages in the category of folk culture -2

Figure 14. Comparison of estimated nuclear density values of characteristic villages in the category of folk culture

In Figure 14, the KDE values for Chengdu fluctuate between 0.52 and 0.57, indicating a relatively stable distribution density and suggesting that the city's attractiveness in terms of folklore-based RT remained stable. The KDE values for Deyang have increased from 0.55 to 0.60, showing an upward trend and indicating that the city's attractiveness in this area has increased, possibly due to effective tourism resource development and market promotion. The KDE values for Guangyuan ranged from 0.44 to 0.50, indicating a slight downward trend, suggesting that further analysis and measures might be needed to enhance the city's attractiveness. Lastly, the KDE values for Aba Prefecture have increased from 0.58 to 0.66, demonstrating a notable upward trajectory and suggesting that the prefecture's attractiveness in folklore-based RT has significantly enhanced, possibly due to its unique folklore resources and effective tourism promotion.

4. Discussion and Interpretation

To acquire a more profound comprehension of the SD pattern of characteristic villages in RT in Sichuan, especially the SD characteristics of five categories: folk culture, rural landscape, natural scenery, characteristic industries, and historical preservation, this study quantified the distribution pattern and spatial characteristics of characteristic villages in RT in Sichuan Province through the NNI and KDE. The NNI values for Chengdu, Luzhou, Leshan, Ya'an, and Aba Prefecture were less than 1, suggesting that the SD of characteristic villages in RT in these regions exhibited a clustered pattern. The NNI value for Neijiang was close to 1, indicating that the SD of characteristic villages in RT in this region was close to a random pattern. The NNI values for the remaining cities were greater than 1, suggesting that the SD of characteristic villages in RT in these regions exhibited a uniform pattern. Specifically, the NNI value for Chengdu was 0.85, while the NNI value for Aba Prefecture was 0.68, reflecting significant differences in the distribution of characteristic villages in RT among various cities. Currently, Ghasemi [34] focused on 22 districts in Tehran, the capital of Iran, exploring how to enhance the livability of the city through equitable land use allocation. Similar to the research results, Ghasemi [34] also employed NN analysis, combined with standard deviation ellipse analysis and multi-attribute boundary approximate area technology to evaluate SD characteristics. The results indicated that there were differences in service distribution across different districts in Tehran, with the 21st district having the highest livability, while the 10th district faces uneven service distribution. Although the specific circumstances in different regions may vary, some common patterns and mechanisms are similar among different regions. For instance, factors such as the degree of urbanization, policy support, the abundance of natural resources, and cultural characteristics are all of vital importance in the development of RT in different regions. They have significant implications for the planning and management of RT in Sichuan Province and can help decision-makers better understand and respond to the challenges and opportunities in the development of RT.

Through analyzing the KDEs, the study further revealed the distribution density of characteristic villages for RT in geographical space. Among them, Ganzi Prefecture and Nanchong City had the highest KDEs, at 0.85 and 0.80 respectively, suggesting that the distribution of characteristic villages for RT in these areas was very dense. In contrast, Leshan City had the lowest KDE, at 0.45, suggesting that the distribution of characteristic villages for RT in this area is relatively sparse. The research results differed to some extent from those of Wang et al. [35] systematically examined the SD characteristics and contributing elements to intangible cultural heritage in the Yellow River Basin of China through spatial analysis techniques [35]. Specifically, Wang et al. [35] used density-based spatial clustering application noise and KDE methods to construct an analytical framework encompassing natural environment, socio-economic factors, and historical culture. The results showed that different types of intangible cultural heritage in the Yellow River Basin exhibited varying distribution characteristics. However, fluctuations in estimates may occur due to bandwidth adjustment. A smaller bandwidth resulted in estimates closer to data points, leading to greater fluctuations; a larger bandwidth smoothes out estimates, reducing fluctuations, which in turn leads to greater numerical fluctuations in KDEs over time. Additionally, some areas may gradually become new hotspots for activities due to economic development, policy support, etc., while other areas may gradually decline due to resource depletion, policy adjustments, etc., resulting in fluctuations in KDEs.

In summary, the results of NNI and KDE revealed the uneven development of characteristic villages in RT across different regions in Sichuan Province. Due to factors such as natural conditions, cultural resources, and policy support, RT has developed relatively well in some areas, while other areas may require more attention and resource investment to foster the advancement of RT. In addition, machine learning and spatial regression models can serve as powerful tools to complement NNI and KDE. Machine learning models can be used to predict the spatial distribution of characteristic villages for RT. By considering more variables and nonlinear relationships, the accuracy of the prediction can be improved. Spatial regression models can handle complex spatial data, including spatial autoregressive and heterogeneity, which are difficult for NNI and KDE to capture.

5. Conclusion

The study evaluated the SD pattern of characteristic RT villages in Sichuan Province using the NNI and KDE. The results showed that by combining the NNI and KDE values to quantify the SD pattern of characteristic RT villages, this method not only helps identify hotspot areas for RT development but also offers a scholarly foundation for devising tailored tourism development strategies and resource allocation. For example, based on the SD pattern of characteristic RT villages, priority should be given to investing in infrastructure construction in hotspot areas, such as transportation, accommodation, and tourist service centers, to improve convenience and satisfaction for tourists. Additionally, in areas rich in tourism resources, ecological protection measures should be implemented to prevent environmental damage caused by over development, and eco-tourism products should be developed to enhance the sustainability of tourism. Although the research has achieved relatively good results, there are still certain deficiencies. The data on RT in some areas may not be detailed enough or updated in a timely manner, which may affect the accurate analysis of the spatial distribution pattern of characteristic villages in RT in these areas. Meanwhile, the study may not have covered all the characteristic villages of RT in Sichuan Province, especially some remote or newly developed areas, which may have limited the general applicability of the research results. In future research, qualitative research methods such as in-depth interviews and case studies can be combined to complement the deficiencies of quantitative analysis. Additionally, more advanced spatial analysis techniques, such as geoweighted regression and spatial autocorrelation analysis, should be applied to more accurately identify and explain the factors influencing the spatial distribution of characteristic villages in RT.

6. Declarations

6.1. Author Contributions

Conceptualization, L.L., J.L., and B.L.; methodology, L.L., J.L., and B.L.; data curation, L.L., J.L., and B.L.; writing—original draft preparation, L.L.; writing—review and editing, J.L. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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