Spatial heterogeneity and determinants of recreational vehicle and tent campsites in China: Insights from the OPGD model

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ABSTRACT The resurgence of camping tourism has integrated the pursuit of high-quality tourism development into the broader framework of Chinese-style modernization. This study constructs a dataset of campsite locations across 337 cities in China to analyze the spatial distribution of recreational vehicle and tent campsites. Using entropy weighting and the Optimal Parameters-based Geographical Detector model, it examines the driving factors. Key findings include the following: (1) Campsites cluster mostly on the eastern side of the Heihe-Tengchong line. Recreational vehicle campsites show a "multi center-clustered" pattern, while tent campsites exhibit shared clustering with recreational vehicle sites and a distinct "belted contiguous areas" pattern. (2) Government and policy heavily influence recreational vehicle campsites, whereas social and demographic factors are crucial for tent campsites. Shared location factors include proximity to city centers, roads, scenic areas, water bodies, and low-light-pollution zones. (3) Interaction effects analysis reveals that multifactor interactions, particularly in the government and policy environment, significantly impact campsite distributions.

KEY WORDS recreational vehicle campsites – tent campsites – spatial distribution characteristics – the OPGD model – China

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1. Introduction

In the last few years, the leisure and tourism industry has been strategically aligned with the principles of Chinese-style modernization, focusing on high-quality growth. Among these initiatives, camping tourism has emerged as a significant new leisure sector, boosting economic growth and consumer spending. Although scholarly interest in camping tourism began early, research in this area remains limited and fragmented. An examination of the literature available in the Web of Science database reveals a concentration on themes such as tourist perspectives on campsite selection and experiences (Mikulić et al. 2017), the nexus between campsites and environmental safety(Almeida et al. 2017; Del Moretto, Branca, Colla 2018), the integration of campsites into landscapes (Martín, Martínez, Gordon 2022), the equilibrium between camping activities and biodiversity preservation (Colléony, Geisler, Shwartz 2021), the effects of tourism policies on land utilization for camping (Chen, Tu, Tung 2022), and the development of pricing strategies for campsites (Garcia, Sanchez, Marchante 2011). Despite these advances, international research distinctly lacks focus on the spatial differentiation of campsites and the factors influencing this differentiation. In China, studies on camping tourism primarily stem from practical experiences and policy-driven initiatives. While domestic scholars are beginning to address the spatial aspects of camping sites (Li et al. 2017; Li et al. 2023), issues remain in traditional analysis methods, campsite classification, and the selection of relevant influencing factors. As emphasized by Mikulić et al. (2017), despite camping tourism's growing prominence within the overall tourism industry, it has been relatively overlooked by tourism and hospitality research. Even recent studies (Li et al. 2023) have underscored the need to deepen classification research and explore the spatial distribution patterns and driving mechanisms of different types of campsites, which serves as a primary motivation for this study.

In fact, the evolution of campsites in China presents significant variances when compared to regions where the camping industry is more mature, such as the United States and Europe. These differences stem from diverse economic levels, population densities, and sector-specific regulatory frameworks, such as road and parking regulations for recreational vehicles. Obviously, this sector's growth is tightly intertwined with the country's natural resources, socio-economic conditions, and policy landscape. Investigating the intrinsic mechanisms influencing the spatial layout of campsites in China, and identifying patterns through domestic camping practices to formulate theories of camping industry development, are crucial. Such theories could guide and optimize the spatial layout of campsites, addressing the critical needs for sustainable development and current business practices.

To bridge these gaps, this study applies the "exclusivity" principle in categorizing Chinese campsites into recreational vehicle campsites and tent campsites.

Employing Python and POIKIT software, this study gathers the point of interest data for these campsites, analyzing their spatial distribution using Average Nearest Neighbor, Gini coefficient, and Kernel Density Estimation techniques. Additionally, the study employs the Entropy Weighting Method and Optimal Parameters-based Geographical Detector to unveil, at the prefectural city scale, the explanatory power and interactive effects of six major categories of influencing factors and twenty-five secondary indicators on the spatial differentiation of these two types of campsites. These insights offer local governments and campsite managers crucial information for the development, construction, and optimization of campsites, contributing to the sustainable and robust growth of the camping industry. Furthermore, this research may serve as a reference for the development of camping tourism and leisure industry in other countries or regions with environments akin to those of China.

2. Methods and Materials

2.1. Research methods

2.1.1. Average nearest neighbor

Propelled by the advancements of Clark and Evans (1954) and Pinder, Shimada, Gregory (1979), Nearest Neighbor Analysis has gradually evolved into a spatial analysis method particularly utilized in human geography and urban geography. The Nearest Neighbor Index effectively reflects the spatial distribution characteristics of point features. The core idea is that the spatial distribution of point features can be categorized into three types: clustered, uniform, and random. The formula is:

$$\overline{r_E} = \frac{1}{2}\sqrt{n/A} \tag{1}$$

$$NNI = \frac{\overline{r_i}}{\overline{r_E}} \tag{2}$$

In the Formulas, *NNI* is the nearest-neighbor index, that is, the ratio of the average to the theoretical nearest-neighbor distance, reflecting the spatial distribution characteristics of homestay points; Here, n denotes the number of campsites in the study area, A is the area of the study region, $\overline{r_E}$ represents the theoretical nearest neighbor distance for the spatial distribution of campsites within the study area, $\overline{r_i}$ is the average distance from each campsite to its nearest neighboring spatial point. When the Nearest Neighbor Index NNI = 1, it indicates that the campsites within the national scope are randomly distributed. When NNI > 1, it suggests that the campsites are uniformly distributed, and when NNI < 1, it indicates that the campsites are clustered. The smaller the value of NNI, the stronger the degree of clustering.

2.1.2. Gini coefficient and geographic concentration index

Nearest Neighbor Analysis can reveal the spatial distribution characteristics of campsites as point features on a national scale. To understand the spatial distribution of campsites at the provincial level, it is necessary to utilize the Gini coefficient and geographical concentration index for further analysis. As a tool for measuring the equilibrium of point features in geographical space, the Gini coefficient typically uses the Lorenz Curve method for calculation, with the formula as follows:

$$S = \frac{\sum_{i=1}^{n} Y_i - 50(n+1)}{100n - 50(n+1)} \tag{3}$$

In the formula, S represents the Gini coefficient, Y_i is the cumulative percentage up to the i province; and is n the number of provinces. The value of S ranges between [0, 1], where a higher value indicates a more uneven distribution of campsites within the region. When $S = 0$, it signifies that the campsites are evenly distributed across all areas; when $S = 1$, it indicates that the campsites are concentrated in a single area.

The Geographical Concentration Index (G) represents the degree of concentration of the study object's distribution and is primarily used to explore the concentration level of campsite distributions across the country. The formula is as follows:

$$G = 100\sqrt{\sum_{i=1}^{n} \left(\frac{X_i}{T}\right)^2} \tag{4}$$

In the formula: X_i represents the number of campsites in the i province of China; T is the total number of campsites nationwide; n denotes the number of provinces in the country (including municipalities directly under the central government and autonomous regions). The higher the value of G, the higher the degree of concentration. Assume $G = G_0$, when the campsites are distributed evenly across the country. If $G > G_0$, it indicates that campsites are concentrated in distribution; conversely, if $G < G_0$, the distribution is more dispersed.

2.1.3. Kernel density estimation

Kernel density analysis is used to calculate the density of point or line feature measurements within a specified neighborhood range, utilizing the spatial attributes of data samples to study spatial distribution characteristics. This method can better demonstrate the concentration of spatial distribution of accommodations. The kernel density is calculated as follows:

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \tag{5}$$

In the formula, $\hat{f}(x)$ represents the estimated density value at point x, which is the weighted sum of all sample points x_i according to the kernel function K and the bandwidth h. Here, n is the number of sample points, h is the bandwidth, used to control the smoothness of the estimate; d is the dimensionality of the data; x_i is the i point in the sample; and K is the kernel function, which assigns weights to each sample point.

2.1.4. The entropy method

The Entropy Method is a quantitative statistical technique used to objectively determine the weight or significance of various indicators in multi-criteria decision-making or evaluation. This method is particularly useful in scenarios where subjective weighting may introduce bias, as it relies entirely on the inherent variability of the data. The weights of different indicators are determined based on their degree of dispersion: the smaller the entropy value, the greater the dispersion, and consequently, the greater the influence of the indicator on the comprehensive evaluation. Indicators with higher dispersion are assigned higher weights to reflect their significance.

Unlike traditional methods, the Entropy Method primarily derives weights from the informational content of the data, regardless of its linearity. This approach minimizes the influence of subjective biases, significantly enhancing the reliability and credibility of the results (Zou, Yi, Sun 2006). The Entropy Method involves the following key steps: (1) normalize the data; (2) calculate probabilities; (3) calculate entropy values; (4) calculate the degree of diversification; (5) calculate weights; (6) calculate composite scores. In this study, the entropy method is utilized to measure indicators such as Natural Ecology and Environmental Resources (NER), Economic Development level (EDL), Social and Demographic Environment (SDE), Transportation Infrastructure and Location (TIF), Tourism and Cultural Resources (TCR), and Government and Policy Environment (GPE) across Chinese municipalities. This facilitates a nuanced analysis of various factors influencing municipal development.

2.1.5. The optimal parameters-based geographical detector model

The Geographical Detector is a promising approach and a primary tool for detecting and utilizing spatial heterogeneity. Its conceptual foundation lies in leveraging spatial heterogeneity to test the consistency of spatial patterns between dependent and independent variables, thereby measuring explanatory power (q-value). A key advantage of this method is its minimal reliance on assumptions, effectively addressing the limitations of traditional statistical techniques in handling categorical variables. A fundamental prerequisite for spatial analysis using the Geographical Detector is the discretization of continuous spatial data. The traditional Geographical Detector model requires manual discretization of continuous variables, introducing subjectivity and potential inaccuracies.

To address these limitations, Song et al. (2020) proposed the Optimal Parameters-based Geographical Detector (OPGD) model, which enhances the accuracy and effectiveness of spatial analysis. The OPGD model optimizes spatial data discretization by determining the best parameters for methods such as equal intervals, natural breaks, quantiles, geometric intervals, and standard deviations. Additionally, it identifies the optimal number of categories (e.g., 4–8) and spatial scale parameters.

This study employs the OPGD model to detect the driving forces behind RV campsites and tent campsites in China. Based on this, it further explores the interactions of First-Level Indicators and Second-Level Indicators to test the changes in the impact of different influencing factors on the dependent variables (numbers of RV and tent campsites) after interactions. Specifically, it reassesses whether the explanatory power of interactions on the dependent variables is weakened or strengthened after different influencing factors interact. This method offers certain advantages over traditional regression analysis (Wang, Xu 2017).

2.2. Index selection

The investigations into the factors influencing the layout of tourist attractions and other nascent tourism models also offer valuable insights applicable to camping tourism and campsite layout (Zhang et al. 2023, Zuo et al. 2021). In addition, the insights of campsite business managers are essential for understanding the spatial differentiation of campsites. This study collaborates closely with representatives from the primary campsite types in China – TO JOURNEY CO., LTD and LEHERO CAMP, focusing on recreational vehicle and tent campsites respectively – to refine and analyze research indicators. It uses six primary and twenty-five secondary indicators across prefecture-level cities. For details on these indicators, see Table 1.

2.3. Data collection

This study employed a Python web scraping program complemented by POIKit 2.0.2 software for campsites data. To ensure data accuracy, we conducted a thorough cleaning and deduplication process. A subset of the data was cross-verified with information from Dianping.com, China's largest review website. Additionally, we validated our findings against lists of national-level 5C and 4C recreational vehicle campsites from 2021 to 2023.

Following the expectations of Li et al. (2023), we classified the data into recreational vehicle campsites and tent campsites. Recreational vehicle campsites are defined as professional campsites that either provide specialized parking for recreational vehicles, offer recreational vehicle accommodation services, or both. Tent campsites are identified as those offering services such as tent accommodation, rentals, or cabin stays without recreational vehicle facilities. The distinctions between these categories are marked, not only in services but also in the scale of operations and land use. Finally, the study accurately identified and performed sample checks on campsite names, resulting in a comprehensive database of 5,054 validated records, including 578 recreational vehicle campsites and 4,476 tent campsites. These records underpin our analysis of the spatial distribution of campsites in China.

Additionally, the majority of data on all influencing factors were sourced from socio-economic statistical bulletins and public databases maintained by Chinese government agencies at various levels. For detailed information on the data sources, please refer to Table 1.

3. Spatial distribution characteristics of campsites in China

3.1. Macro-pattern of recreational vehicle and tent campsites

ArcGIS 10.8 (ESRI, Inc., Redlands, CA, USA) is employed as the primary analytical tool in this study. The distribution map of campsites in China reveals significant clustering, particularly on the eastern side of the Heihe-Tengchong Line (see Figure 1). As per the academic conventions for regional division in China, the country is segmented into seven major regions: Northeast China, East China, North China, Central China, South China, Southwest China, and Northwest China. Statistical analysis indicates that East China has the highest concentration of campsites, followed by South China and Southwest China, with Northeast China recording the lowest (see Table 2). Nearest Neighbor Index (NNI) analysis (Formulas (1) and (2)) shows an average actual nearest neighbor distance ($\overline{r_1}$) of 8.99 km, compared to a theoretical expected nearest neighbor distance ($\overline{r_E}$) of 29.82 km, resulting in an NNI of $0.3015 < 1$, confirming the spatial clustering of campsites nationally.

Further detailed analysis using the NNI to assess the spatial distribution types of recreational vehicle and tent campsites in China finds the average actual nearest

Table 1 – Selection and description of hypothesis-influencing variables

Primary indicators	Secondary indicators	Unit	Sources and Description of Indicators
Natural Ecology and Environmental Resources (NER)	AQI	NA	Air Quality Index (average of 2020–2022): This indicator is sourced from the Chinese Air Quality Online Monitoring Analysis Platform, compiled from daily statistical data into annual statistics.
	DGAQ	days	Number of Days with Good Air Quality in 2022: According to the Technical Regulation on Ambient Air Quality Index (HJ 633-2012), an AQI below 100 qualifies as good.
	SH	Hours	Sunshine Hours in 2022. The indicator is sourced from the Statistical Yearbooks of China and various provinces and cities (2022).
	RD	days	Rainy Days in 2022. The data is sourced from the National Centers for Environmental Information (NCEI). This dataset counts the number of days with rainfall exceeding 10 mm.
	CTD	days	Comfortable Temperature Days in 2022. The data is sourced from the National Centers for Environmental Information (NCEI). According to the standards set by the China Meteorological Administration, the external ambient temperature range of 18–25 degrees Celsius is considered comfortable for humans.
	RDR	km/km^2	River Density within the Region. The data is sourced from the National Geomatics Center of China. The formula used is the total length of rivers within the region divided by the administrative area of the region.
Economic Development Level (EDL)	PCGDP	Yuan	PCGDP: Per Capita Gross Domestic Product; PCDI: Per Capita Disposable Income; PCCE: Per Capita Consumer Expenditure; ENGEL: Engel Coefficient, a measure of the proportion of household income spent on food. Sourced from the "Statistical Bulletin of National Economic and Social Development" (2022).
	PCDI	Yuan	
	PCCE	10K Yuan per person	
	ENGEL	NA	
	VIIRS-NLI	NA	VIIRS Nighttime Light. The data is captured by the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (SNPP) satellite.
Social and Demographic Environment (SDE)	PCPGS	m^2	Per capita park green space area. Sourced from the "China Urban Construction Statistical Yearbook" (2022).
	HCL	person	Human Capital Level. The data is sourced from the "China Urban Statistical Yearbook" and the "Statistical Bulletin of National Economic and Social Development" published by various prefectural-level cities.
	PDA	Persons per km^2	Population Density. The calculation formula is the ratio of the resident population in the area to the administrative area of the region. The data on resident population comes from the "Statistical Bulletin of National Economic and Social Development" published by various cities in 2022.

	AGR	NA	Aging Ratio. This indicator measures the proportion of the population aged 60 and older relative to the total urban registered population for the year. The data is sourced from China's Seventh National Population Census.
	MVS	10k unit	Motor Vehicles Stocks. The data is sourced from the "Statistical Bulletin of National Economic and Social Development" (2022).
Transportation Infrastructure and Location (TIF)	RND	Km/100 km²	RND: National and provincial roads Density; EXD: Highway Density. The data is sourced from the "Statistical Bulletin of National Economic and Social Development" issued by various prefectural-level cities for the year 2022 and was obtained through subsequent calculations.
	EXD	Km/100 km²	
	ADNMC	Km	Average Distance from Campsites to Nearest city Center.
Tourism and Cultural Resources (TCR)	ASS	unit	A-level scenic spot. The data is sourced from the official websites of national and provincial cultural and tourism departments, as well as from government data resource networks.
	TCV	unit	Number of Traditional Chinese Villages. Such villages are designated by the Ministry of Housing and Urban-Rural Development of China.
	NHCVT	unit	Number of National Historical and Cultural Villages and Towns. Which are designated by the Ministry of Housing and Urban-Rural Development and the National Cultural Heritage Administration.
	CRE	unit	Camping Related Enterprises. Which are identified and compiled from www.qcc.com.
	NHAM	unit	Number of Hotel Accommodation Merchants. Data for hotel accommodations (the point of interest data) from Amap is collected using Python web scraping software.
Government and Policy Environment (GPE)	DBI	NA	Doing Business Index. The data from: Zhang Sanbao; Zhang Zhixue (correspondent); Huang Minxue, 2023, "Evaluation of Doing Business in Chinese Cities", https://doi.org/10.18170/DVN/9NJDWE, Peking University Open Research Data Platform, V2. And, Zhang Sanbao; Zhang Zhixue (Communication), 2022, "Business Environment Assessment of Chinese Provinces", Peking University Open Research Data Platform, V3.
	LGPB	NA	Local General Public Budget. It is used as a measure to reflect various government subsidies to enterprises, as well as government investments in industries such as culture, tourism, and sports. The data is sourced from the "Statistical Bulletin of National Economic and Social Development" (2022).

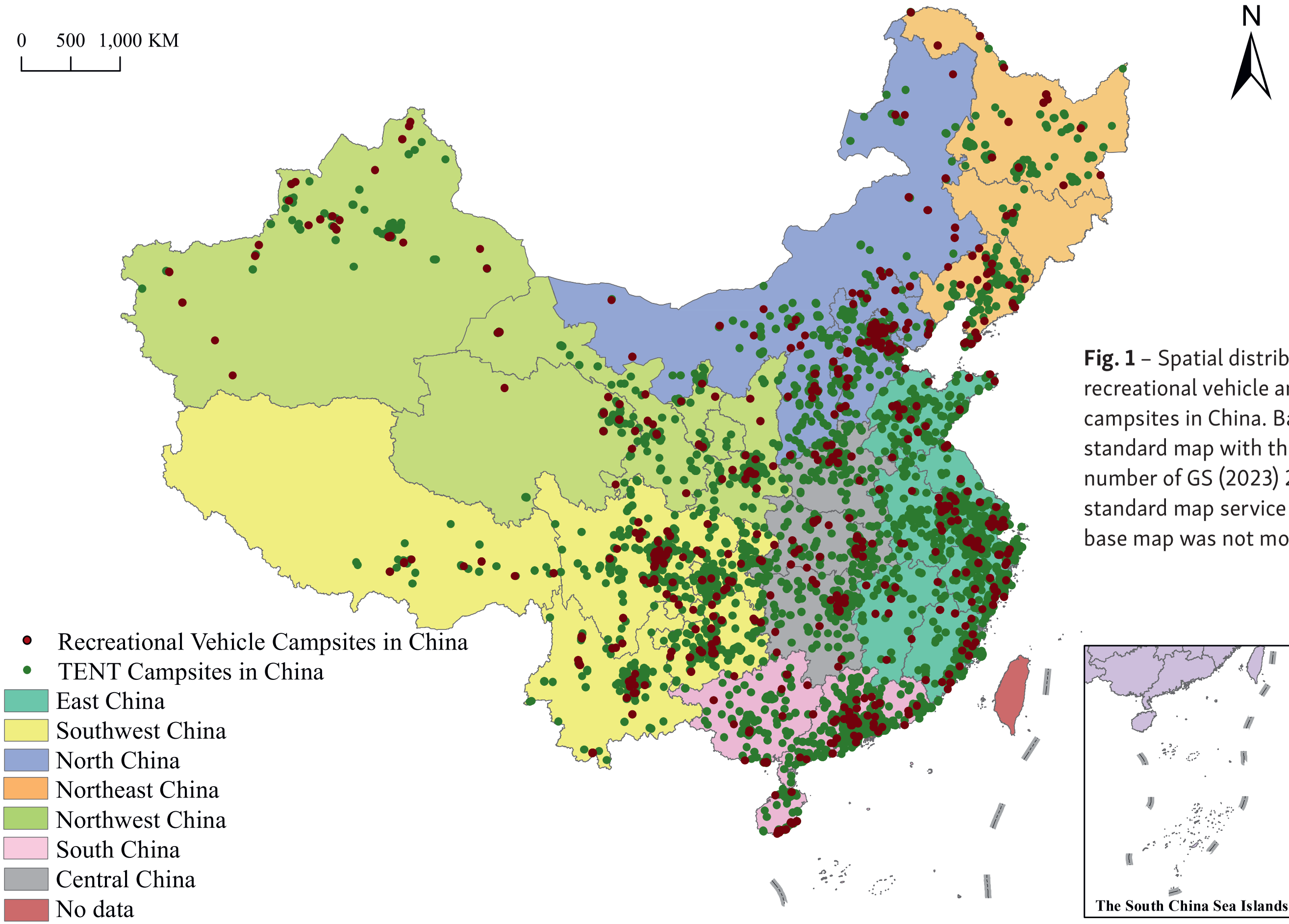


Fig. 1 – Spatial distribution of recreational vehicle and tent campsites in China. Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.

Table 2 – Seven major Geographic Regions of China and the Spatial Distribution of Campsites

Major Geographic Regions of China	List of Province	Total Number of Campsites	Include		NNA (nearest neighbor analysis)			
			Recreational vehicle Campsites	Tent Campsites	Observed Mean Distance (km)	Expected Mean Distance (km)	Nearest Neighbor Ratio	Spatial Distribution Patterns
Northwest China	Heilongjiang/Jilin/Liaoning	298	44	254	12.934	37.566	0.3443	Agglomeration
East China	Shandong/Jiangsu/Shanghai/ Zhejiang/Anhui/Jiangxi/Fujian	1,224	127	1,097	7.104	15.303	0.4642	Agglomeration
North China	Hebei/Beijing/Tianjin/Shanxi/ Neimenggu	596	96	500	11.291	32.289	0.3497	Agglomeration
Central China	Henan/Hubei/Hunan	542	54	488	10.656	18.845	0.5655	Agglomeration
South China	Guangdong/Guangxi/Hainan	957	70	887	6.167	15.016	0.4107	Agglomeration
Southwest China	Sichuan/Yunnan/Guizhou/ Chongqing/Xizang	956	117	839	9.071	26.023	0.3486	Agglomeration
Northwest China	Xinjiang/Ningxia/Qinghai/ Shaanxi/Gansu	481	70	411	13.173	50.211	0.2624	Agglomeration

Notes: The point of interest data of campsites does not include Hong Kong, Macao and Taiwan.

neighbor distance for recreational vehicle campsites ($\overline{r_1}$) to be 36.87 km, while the theoretical expected nearest neighbor distance ($\overline{r_E}$) is 83.82 km, yielding an NNI of 0.4399 < 1. For tent campsites, the average actual nearest neighbor distance $\overline{r_1}$ is 9.37 km, with a theoretical expected nearest neighbor distance $\overline{r_E}$ is 31.81 km, resulting in an NNI of 0.2946 < 1. These results indicate a pronounced clustered distribution pattern for both types of campsites. Additionally, errors in the Nearest Neighbor Index are validated through a Voronoi diagram (Voronoi diagram CV), revealing a coefficient of variation for recreational vehicle campsites at 243.01% and for tent campsites at 612.09%, both substantially exceeding the clustering threshold of 64%. This underscores the strong clustering characteristics of both recreational vehicle and tent campsites in China, suggesting significant potential for centralized and clustered development within the camping sector.

3.2. Provincial spatial distribution equilibrium of recreational vehicle and tent campsites

The Gini coefficients (S values) for recreational vehicle campsites and tent campsites in China, calculated using Formula (3), are 0.3158 and 0.3898, respectively. Both values fall within the range of 0 to 1. According to the Lorenz curve (see Figure 2), more than 40% of recreational vehicle campsites are concentrated in

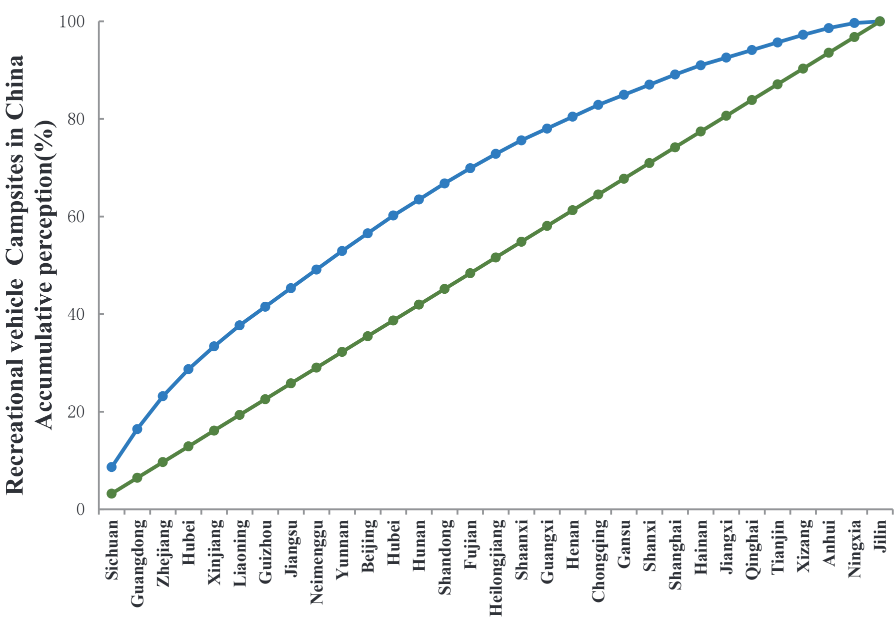


Fig. 2 – The Lorenz curve of distribution of campsites in China

the provinces of Sichuan, Guangdong, Zhejiang, Hebei, Xinjiang, Liaoning, and Guizhou. For tent campsites, the provinces of Guangdong, Zhejiang, Sichuan, Jiangsu, and Hubei collectively account for 42% of the total, confirming the uneven spatial distribution of campsites across types.

Furthermore, the geographical concentration index (G, Formula (4)) for recreational vehicle campsites nationwide is calculated at 20.76, surpassing the baseline value (G_0) of 17.96, thus indicating $G > G_0$. This result suggests a high level of concentration and centralized distribution of recreational vehicle campsites at the provincial scale. Similarly, the geographical concentration index for tent campsites is 23.92, also exceeding the baseline ($G_0 = 17.96$), which signifies $G > G_0$ and confirms a concentrated distribution pattern at the provincial scale for tent campsites as well.

3.3. Spatial distribution density analysis

Using the point of interest data of campsites, the distribution density of the two primary types of campsites in China was analyzed using the kernel density analysis method in ArcGIS 10.8 software. As depicted in Figure 3, both recreational vehicle and tent campsites demonstrate a notably uneven spatial distribution, characterized by a “multi center-radiation cluster” pattern. Recreational vehicle campsites, in particular, are distributed in a “multi center-clustered” pattern. Spatially, this distribution is organized around “four primary cores and one smaller typical density center”. The “four primary density cores” include: (1) Greater Bay Area: Centered around Guangdong; (2) East China Radiation Cluster: Encompassing Jiangsu, Zhejiang, and Shanghai; (3) Southwestern Cluster: Centered around Sichuan and Chongqing within the Yunnan-Guizhou-Sichuan area; (4) North China Strip Cluster: This cluster is strategically centered around Beijing and Tianjin. Referred to as the “one small,” this emerging fifth center in Hubei is gaining prominence, poised to become a significant density center for campsite distribution.

However, tent campsites are more commonly found in “belted contiguous areas”, indicating a linear spread along economic and geographic corridors: (1) Yangtze River Economic Belt: spans from Sichuan Province to Shanghai, tracing the Yangtze River; (2) North-Central Economic Corridor: extends from the Beijing-Tianjin area through Shandong, Henan, and Shaanxi. Additionally, Yunnan and Liaoning are noted for developing radiation clusters centered around their provincial capitals.

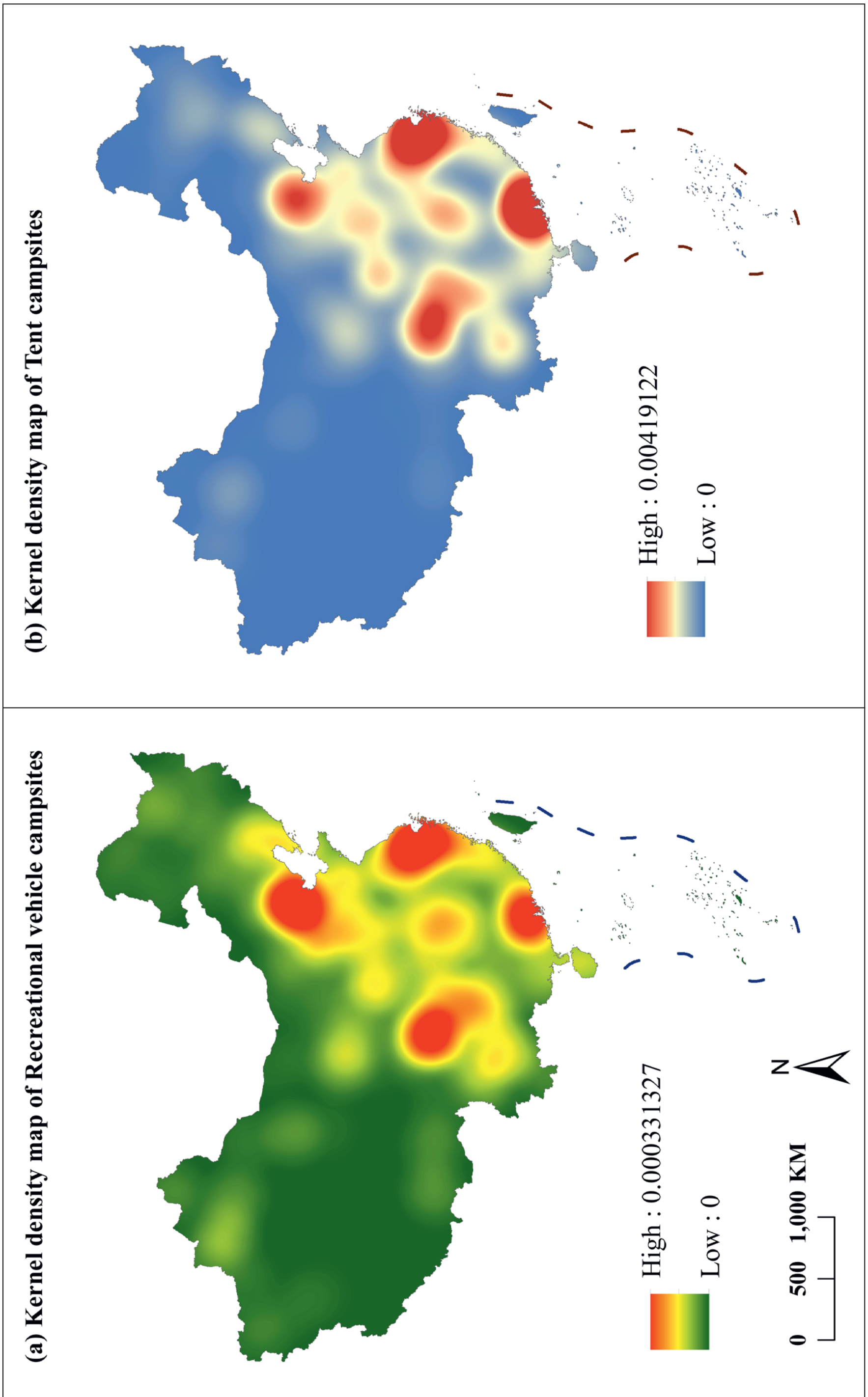


Fig. 3 – Kernel density map of recreational vehicle and tent campsites in China. Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.

4. Determinants influencing the spatial heterogeneity of campsites distribution in China

4.1. Detecting factors of the spatial distribution of recreational vehicle and tent campsites

To further elucidate the impact of each factor, the study conducted single-factor detections, analyzing the explanatory power of secondary indicators detailed in Table 3.

4.1.1. Natural ecology and environmental resources

Natural and ecological resources are commonly recognized as pivotal for the development and spatial arrangement of tourist attractions. Notably, Li et al. (2023) emphasized that these resources also play a crucial role in shaping the fundamental spatial layout of campsites in China. As a prominent form of sustainable tourism, the siting of campsites is expected to be closely integrated with these natural elements. Contrary to this prevailing view, findings from the Optimal Parameters-based Geographical Detector suggest a divergent trend. The Natural Ecology and Environmental Resource Endowment (NER) indicator shows surprisingly low explanatory power for recreational vehicle campsites at 0.0726**, positioning it second to last among the six primary categories assessed. For tent campsites, it ranks even lower, with an overall q-value of 0.1305***, challenging the widely held belief of campsite distribution at the prefecture level in China.

Further investigation into secondary indicators related to NER reveals more nuanced insights: (1) River Density within the Region (RDR) exhibits the highest relative explanatory power within this category, followed by the number of days with good air quality (DGAQ) and sunshine hours (SH). These three secondary indicators significantly delineate the spatial distribution of both recreational vehicle and tent campsites. This underscores the pronounced riparian distribution characteristics of campsite distribution, suggesting that tourists prefer locations with excellent air quality and abundant sunlight; (2) the number of comfortable temperature days (CTD) exhibits only minimal explanatory power regarding the distribution of tent campsites. Moreover, the Air Quality Index (AQI) and the number of rainy days (RD) appear to have negligible effects on the spatial layout of campsites across China. This analysis underscores the complexity and nuance involved in understanding the spatial distribution of recreational vehicle and tent campsites.

To investigate the pronounced characteristic of "riparian distribution" in campsite locations, we conducted an overlay analysis of the point of interest locations of recreational vehicle and tent campsites with water systems and lakes

Table 3 – The OPGD model of main influencing factors of spatial heterogeneity of recreational vehicle and tent campsites in China

First-level Indicators	Second-level Indicators	Var	Weights	VIF	Recreational vehicle campsites				Tent campsites			
					Symbol	Discretization Method	q value	q value	Symbol	Discretization Method	q value	q value
NER	AQI	X1	0.184	4.83	Positive	Natural (6)	*0.0237*	*0.0726***	Positive	Geometric (7)	0.0255	0.1305***
	DGAQ	X2	0.03	5.10	Positive	Quantile (6)	0.0348**		Positive	Quantile (6)	0.0383**	
	SH	X3	0.221	2.68	Positive	Sd (8)	0.0725***		Positive	Natural (8)	0.0526**	
	RD	X4	0.164	2.87	Negative	Sd (6)	*0.0094*		Negative	Equal (8)	0.0323	
	CTD	X5	0.082	1.44	Positive	Quantile (8)	*0.0213*		Positive	Quantile (8)	0.0451**	
	RDR	X6	0.319	3.37	Positive	Geometric (5)	0.1528***		Positive	Geometric (5)	0.2337***	
EDL	PCGDP	X7	0.317	3.78	Positive	Equal (7)	0.1512***	0.2378***	Positive	Equal (7)	0.1851***	0.3506***
	PCDI	X8	0.287	9.03	Positive	Equal (6)	0.2813***		Positive	Equal (8)	0.4046***	
	PCCE	X9	0.319	1.37	Positive	Sd (6)	0.1697***		Positive	Sd (6)	0.2659***	
	Engel	X10	0.061	1.57	Negative	Geometric (5)	0.1679***		Negative	Geometric (5)	0.1382***	
	VIIRS-NLI	X11	0.016	9.83	Negative	Sd (8)	0.3275***		Negative	Geometric (8)	0.4649***	
SDE	PCPGS	X12	0.029	1.12	Positive	Quantile (8)	*0.0172*	*0.442****	Positive	Quantile (8)	0.0331	0.6477***
	HCL	X13	0.448	3.41	Positive	Natural (7)	0.4875***		Positive	Natural (8)	0.5715***	
	PDA	X14	0.307	8.04	Positive	Sd (7)	0.1812***		Positive	Sd (5)	0.3101***	
	AGR	X15	0.014	2.35	Negative	Geometric (5)	0.1801***		Negative	Geometric (5)	0.1306***	
	MVS	X16	0.203	7.05	Positive	Equal (7)	0.5528***		Positive	Equal (7)	0.7211***	
TIF	RND	X17	0.436	2.94	Positive	Quantile (7)	0.0528**	0.0699**	Positive	Quantile (7)	0.0689**	0.1749***
	EXD	X18	0.564	2.76	Positive	Natural (8)	0.1578***		Positive	Natural (8)	0.2662***	
TCR	ASS	X19	0.068	2.73	Positive	Natural(8)	0.3282***	0.3958***	Positive	Natural (8)	0.4019***	0.5633***
	TCV	X20	0.299	2.14	Positive	Sd (8)	*0.0224*		Positive	Sd (8)	0.0681*	
	NHCVT	X21	0.277	2.05	Positive	Sd (5)	0.1145***		Positive	Sd (5)	0.1015***	
	CRE	X22	0.351	3.68	Positive	Quantile (4)	0.3344***		Positive	Quantile (4)	0.5514***	
	NHAM	X23	0.005	5.42	Negative	Equal (7)	0.5308***		Positive	Equal (7)	0.7785***	
GPE	DBI	X24	0.089	1.77	Positive	Equal (8)	0.1961***	0.4389***	Positive	Equal (8)	0.3053***	0.5966***
	LGPB	X25	0.911	5.47	Positive	Natural (6)	0.5347***		Positive	Natural (7)	0.6643***	

across the four major typical clustered areas, as depicted in Figure 4. This analysis revealed that the majority of campsites are strategically located along rivers and lakes, affirming their preference for water proximity. Further analysis, inspired by insights from firm managers, involved an overlay of campsite locations with elevation terrain within these key areas, shown in Figure 5. The results indicated that most campsites, whether recreational vehicle or tent, are predominantly situated in plain areas, although a notable number are also found along low mountain ranges and valley terrains. This preference for specific elevation terrains is more distinct in the spatial distribution of recreational vehicle campsites, whereas tent campsites exhibit a more dispersed distribution pattern in terms of elevation terrain.

4.1.2. Economic development level

Economic development level (EDL) significantly influences the spatial distribution of campsites in China, exhibiting explanatory powers of 0.2378 for recreational vehicle campsites and 0.3506 for tent campsites, both of which pass the 1% significance level test. As China transitions into a phase of high-quality economic growth, camping tourism has emerged as a regional adaptation to this new economic paradigm, aiming to foster high-quality regional development. Indeed, the tourism industry, being a comprehensive economic sector, has traditionally been a catalyst for local economic growth. Particularly for newer forms of tourism such as camping, the unique consumption patterns associated with it can generate higher tourism revenues compared to conventional urban tourism.

In refining the secondary indicators for EDL, following enterprise feedback, we have introduced the Engel coefficient and the nighttime light index (VIIRS-NLI) as negative factors for the first time. Despite these secondary indicators initially showed limited importance in the entropy method analysis, geographical detector analysis revealed their significant explanatory power for both recreational vehicle and tent campsites. Notably, VIIRS-NLI emerged as having the highest explanatory power within its primary indicator category, with q-values of 0.3275^{***} and 0.4649^{***} (Table 3).

4.1.3. Social and demographic environment

The social and demographic environment (SDE) plays a pivotal role in shaping the spatial heterogeneity of recreational vehicle and tent campsites in China, as evidenced by q-values of 0.442^{***} and 0.6477^{***} respectively. These results affirm the market potential effect associated with the locational context of the Heihe-Tengchong Line (Li et al. 2019). Using the OPGD model, our analysis reveals that motor vehicle stocks (MVS), a secondary indicator of SDE, markedly affect

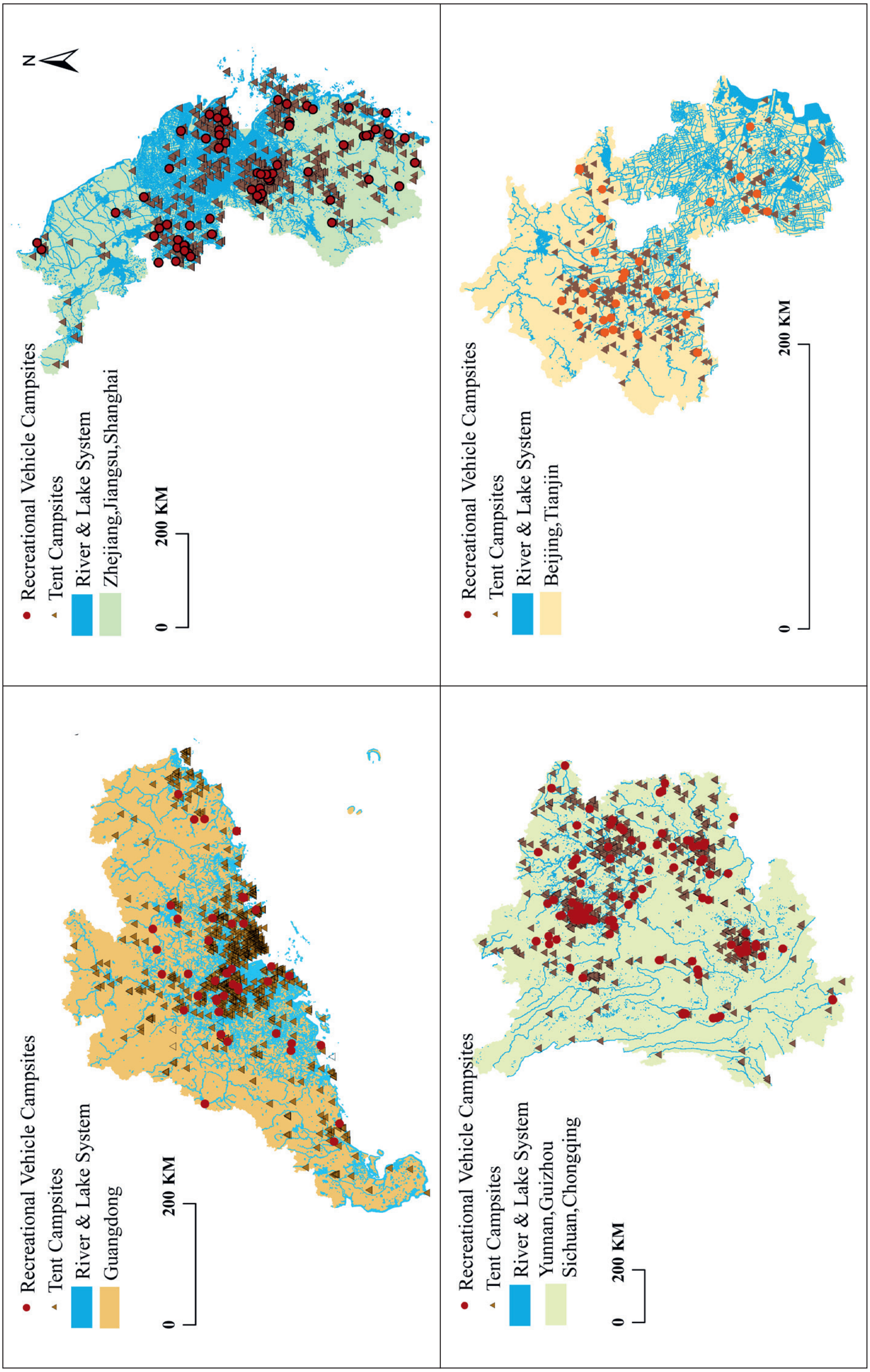


Fig. 4 – The campsites are stacked with rivers and lakes in the key area

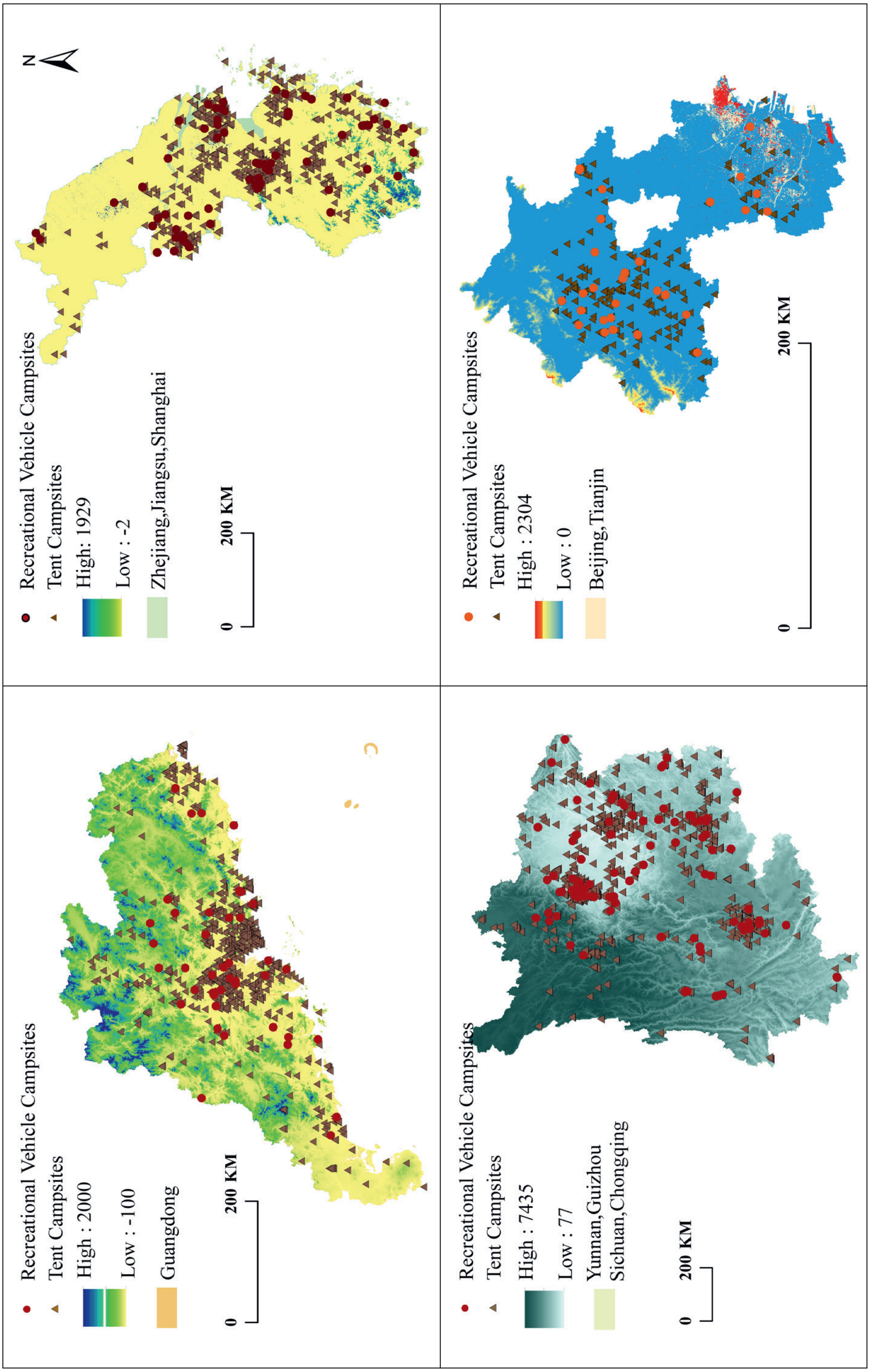


Fig. 5 – The overlay analysis of campsites with terrain in key area

Table 4 – Campsites and the social and demographic environment within the key cities in China

	Recreational Vehicle Campsites Quantity Ranking	Tent Campsites Quantity Ranking	(a) HCL Ranking	(b) PDA Ranking	(c) MVS Ranking
1	Beijing (a, b, c)	Chongqing (a, c)	Guangzhou	Shenzhen	Beijing
2	Chengdu (a, c)	Beijing (a, b, c)	Zhengzhou	Dongguan	Chengdu
3	Hangzhou	Chengdu (a, c)	Wuhan	Shanghai	Chongqing
4	Chongqing (a, c)	Shenzhen (b, c)	Chongqing	Xiamen	Xi-an
5	Shanghai (b, c)	Huizhou	Chengdu	Guangzhou	Suzhou
6	Dalian	Kunming	Beijing	Shantou	Shanghai
7	Nanjing (a)	Hangzhou	Xi-an	Foshan	Zhengzhou
8	Tianjin	Shanghai (b, c)	Nanjing	Zhongshan	Wuhan
9	Kunming	Guangzhou (a, b)	Changsha	Zhengzhou	Shenzhen
10	Wenzhou	Xi-an (a, c)	Nanchang	Wuxi	Dongguan

the distribution of both recreational vehicle and tent campsites across various prefecture-level cities. This correlation underscores the critical role of vehicle accessibility in enhancing camping activity, linking personal vehicle ownership directly to the potential for campsite development. Furthermore, the Human Capital Level (HCL) within SDE is identified as a vital determinant, with well-developed campsites typically clustered in areas characterized by higher human capital. Population Density (PDA) profoundly also influences the spatial differentiation of campsites, areas with higher population densities present larger potential customer bases, thereby boosting the development prospects for campsites in these regions (refer to Table 4 for detailed data for the key cities in China).

Incorporating insights from enterprise managers, the Aging Ratio (AGR) within the population is recognized as a significant negative factor. Regions with a higher AGR show diminished potential for campsite development. This demographic factor has proven to have substantial explanatory power in defining the distribution patterns of both recreational vehicle and tent campsites.

4.1.4. Transportation infrastructure and location

Analysis conducted using the OPGD model revealed that TIF possesses limited explanatory power for the spatial distribution of recreational vehicle campsites (q-value = 0.0699**) and tent campsites (q-value = 0.1749***). To elucidate the influence of transportation infrastructure on campsite distribution patterns in China, a buffer map of the country's main roads, including highways, national roads, and provincial roads, was generated. This map was overlaid with the vector map of campsites (see Figure 6). The findings indicate that recreational vehicle campsites are significantly aligned along national and provincial roads, though many are not situated directly adjacent to highways. Conversely, tent campsites demonstrate

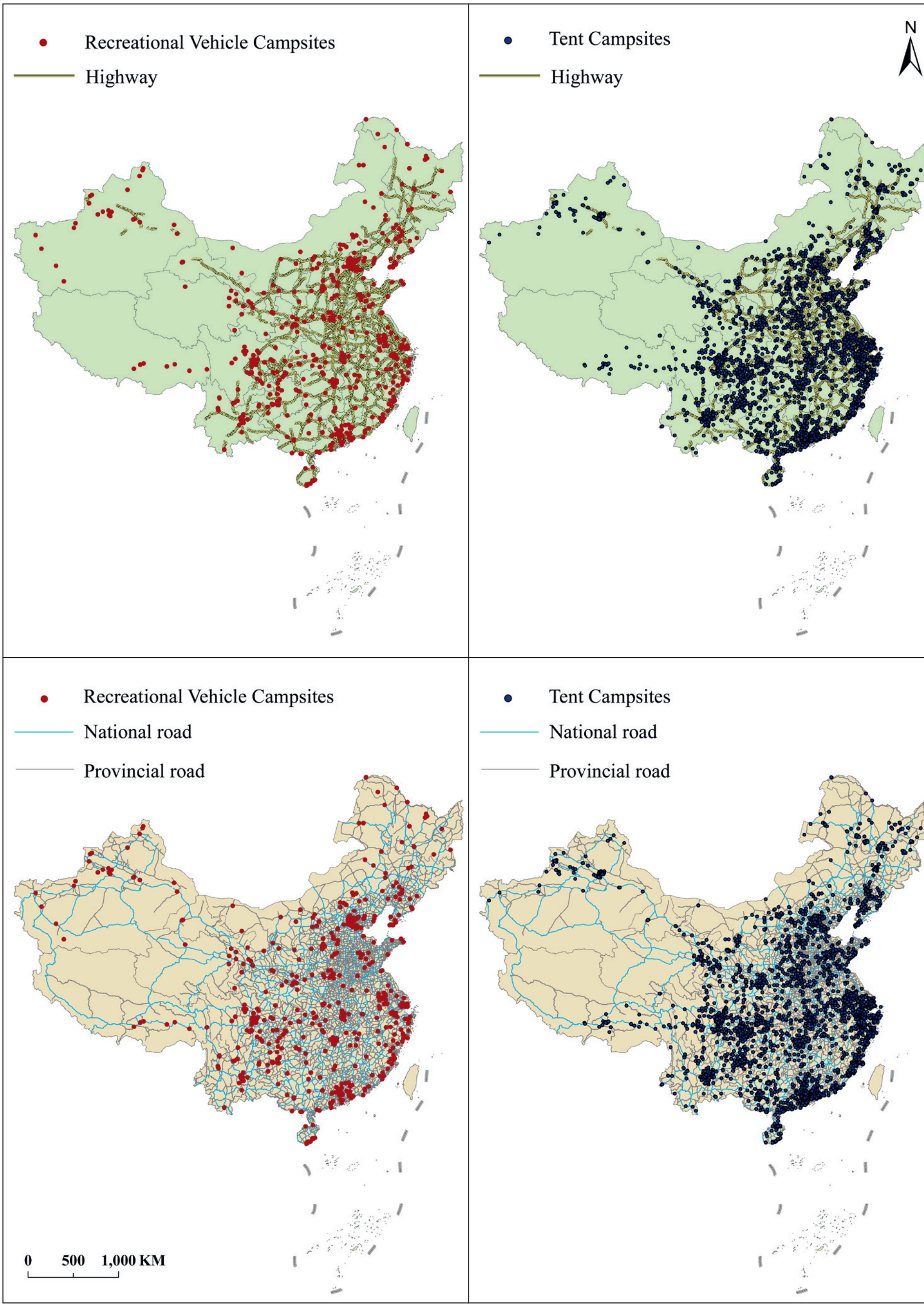
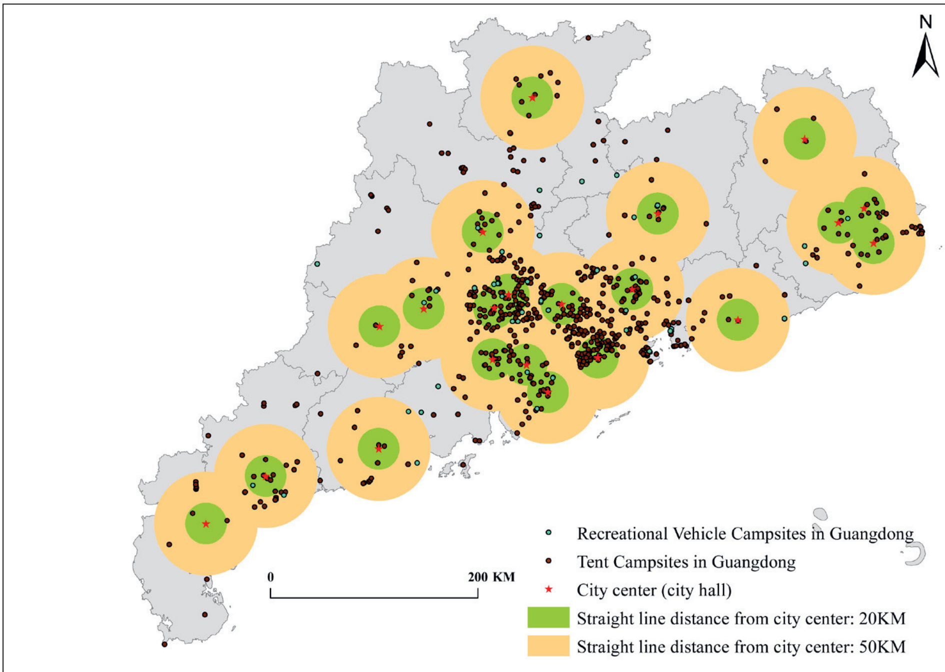


Fig. 6 – The overlay analysis of campsites and road in China. Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.



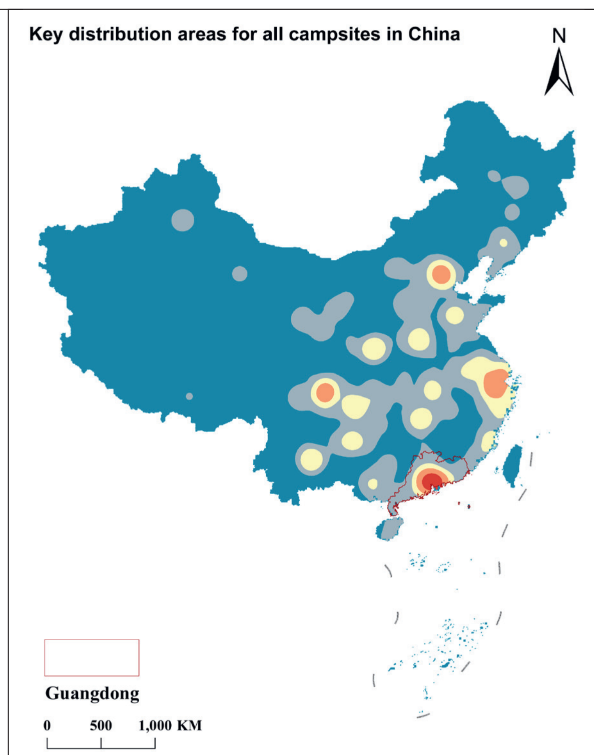


Fig. 7 – The co-occurring spatial relationship between campsites and prefecture-level urban centers in Guangdong Province. Note: Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.

a more pronounced clustering along major roads, particularly at junctions of various transportation routes, where they tend to aggregate more substantially.

In assessing the location of campsites relative to urban centers, we used the center of the prefectural city government as a benchmark, irrespective of whether campsites are within the same municipal area. Analysis conducted using ArcGIS 10.8, specifically neighborhood analysis-point distance analysis, reveals that nationally, approximately 20% of recreational vehicle campsites are situated within a 20 km straight-line distance from city centers. A more substantial 54% are located within 50 km, and 19.03% are found within 100 km. In contrast, for tent campsites, around 12.2% are within 20 km of city centers, 72.07% within 50 km, and 14.25% within 100 km.

Focusing on Guangdong Province, a notable hub for both recreational vehicle and tent campsites, buffer analysis using circles at 20 km and 50 km distances showed that over 80% of the campsites are positioned within these two ranges. This analysis (illustrated in Figure 7) indicates that both recreational vehicle and tent campsites predominantly exhibit a "near city center" distribution pattern. This proximity suggests a symbiotic relationship between campsites and nearby urban centers, fundamentally shaping their target markets.

4.1.5. Tourism and Cultural Resources

Analysis reveals that the explanatory power (q-value) of tourism and cultural resources for recreational vehicle campsites is 0.3958*** and for tent campsites, it is 0.5633***. Following prior research and recommendations from enterprise managers, metrics such as the number of A-level scenic spots, traditional Chinese villages, national historical and cultural villages and towns, camping related enterprises (non-Campsites) and hotel accommodation merchants were chosen to gauge regional tourism and cultural resources.

Results from the OPGD model indicate that the number of A-level scenic spots holds significant explanatory power for the spatial heterogeneity of both recreational vehicle and tent campsites, with q-values of 0.3282*** and 0.4019***, respectively. National historic and cultural villages and towns also exhibit weak yet significant explanatory power for spatial differentiation among the campsite types (q-values of 0.1145*** and 0.1015***). Conversely, the number of national traditional villages shows no significant impact on recreational vehicle campsite distribution and minimal influence on tent campsite distribution (q = 0.0681*). Upon overlay analysis, notable differences were observed in the distribution of the two types of campsites relative to national traditional villages, particularly for recreational vehicle campsites where the discrepancy is more pronounced.

To more clearly depict the explanatory power of 5A scenic spots, the study generated an overlay map featuring 20 km buffer zones around these attractions

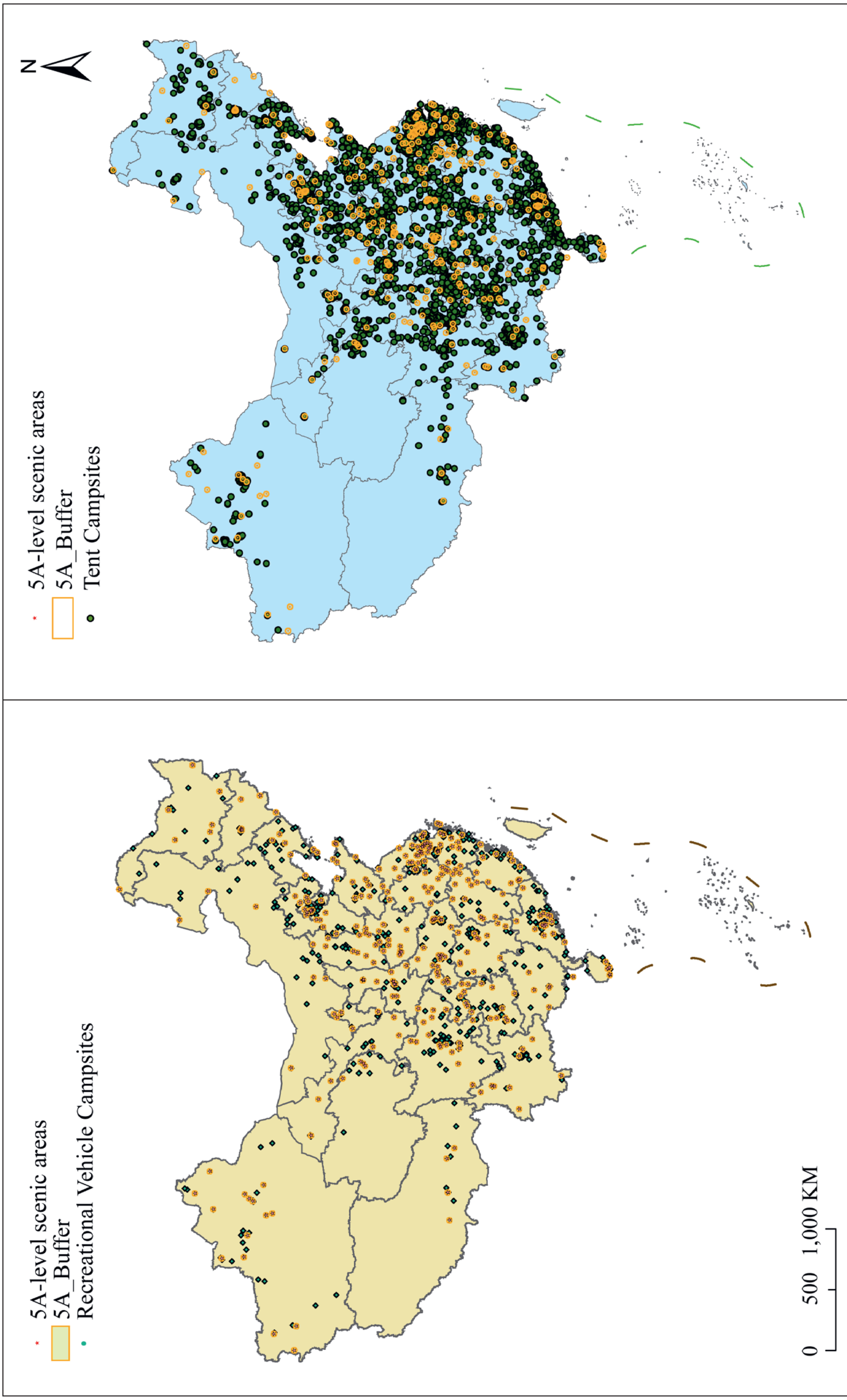


Fig. 8 – The overlay analysis of campsites and 5A-level scenic spots in China. Note: Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.

alongside the campsite locations (see Figure 8). The analysis revealed that approximately 50% of both recreational vehicle and tent campsites are located within these zones, displaying a clear "scenic area-dependent" distribution. Specifically, 298 recreational vehicle campsites are positioned within 20 km of 140 5A scenic spots, comprising 51.56% of all national recreational vehicle campsites. Meanwhile, 2,160 tent campsites fall within these buffer zones of 242 5A scenic spots, accounting for 48.25% of all national tent campsites.

In exploring factors influencing campsite distribution, this study integrates previously overlooked elements, including the presence of campsite-related enterprises (Campgrounds are not included) and hotel accommodations within the region. These firms – encompassing recreational vehicle manufacturing, rental, and camping equipment sales – positively impact the camping tourism industry. The significance of this factor was confirmed through analysis using the OPGD model, demonstrating substantial explanatory power for the spatial differentiation of both recreational vehicle campsites ($q = 0.3344^{***}$) and tent campsites ($q = 0.5514^{***}$). Meanwhile, the analysis employing the entropy method indicated that the weight of the number of hotel accommodations in the region was relatively low, with divergent impacts on recreational vehicle and tent campsites. Subsequent geographical detector analysis revealed a strong influence on the spatial layout, but with opposing effects: negatively affecting recreational vehicle campsites ($q = 0.5308^{***}$) and positively influencing tent campsites ($q = 0.7785^{***}$). A potential explanation is the high cost and limited availability of recreational vehicle accommodations, which may drive tourists towards nearby hotels, adversely affecting the growth of recreational vehicle campsites. For tent campsites, the relationship with hotel accommodations appears more complex, exhibiting both complementary and substitutive dynamics. Proximity to comprehensive hotel services may enhance the attractiveness of tent campsites, providing tourists with alternative lodging options in desirable environments.

4.1.6. Government and policy environment

The results from the OPGD model analysis highlight the government and policy environment as a critical determinant in the spatial distribution of recreational vehicle and tent campsites in China, ranking as the second most influential factor after the SDE. The q-values of 0.4389 for recreational vehicle campsites and 0.5966 for tent campsites, both surpassing the 1% significance level, affirm the substantial role of this factor.

Within the framework of secondary indicators, the Doing Business Index (DBI) demonstrates relatively less explanatory power for the spatial differentiation of recreational vehicle campsites (q-value = 0.1961^{***}) when compared to the impact of local finances (represented by Local General Public Budget, LGPB)

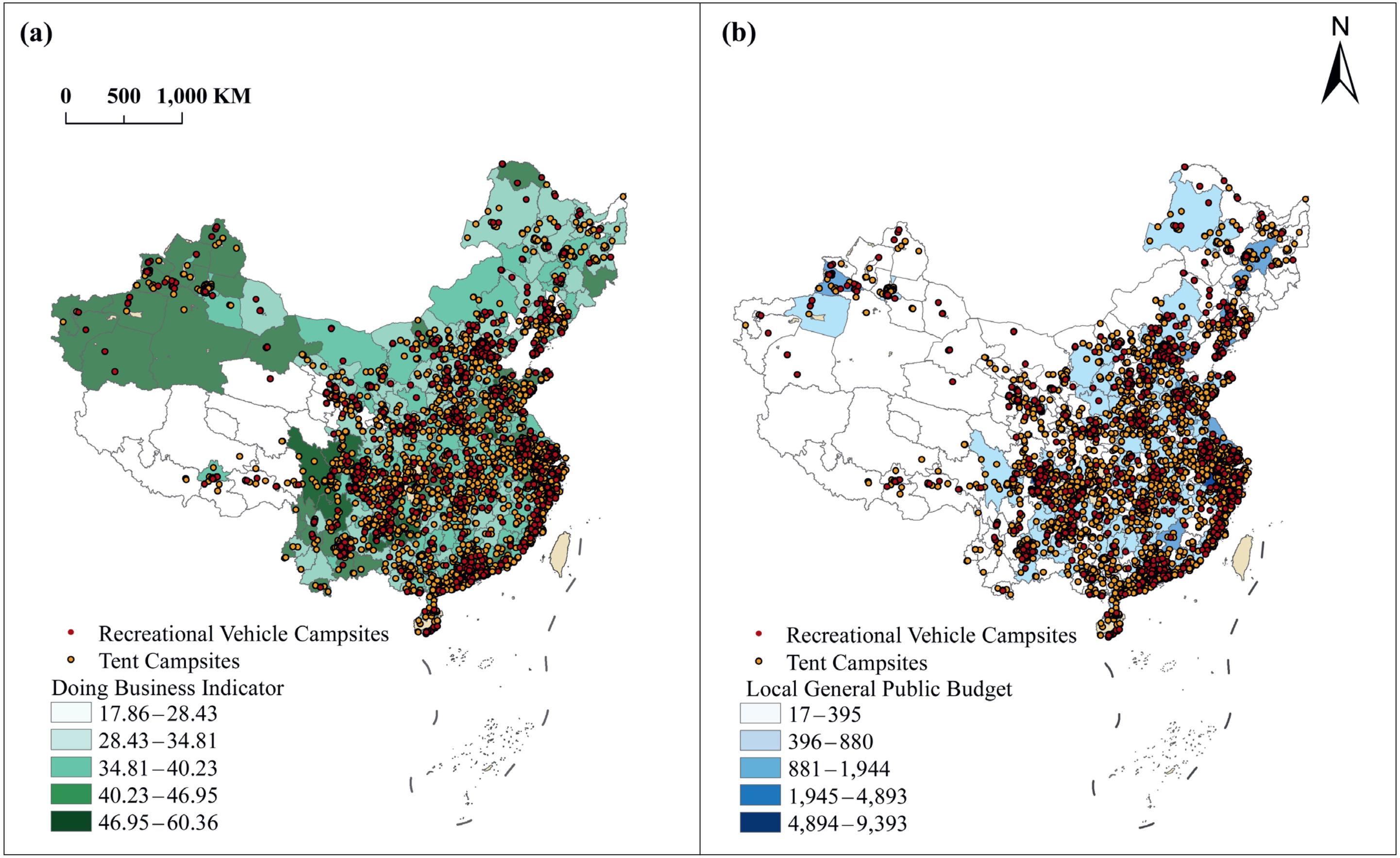


Fig. 9 – The overlay analysis of campsites, doing business index and Local General Public Budget in China. Note: Based on the standard map with the approval number of GS (2023) 2767 on the standard map service website, the base map was not modified.

(q-value = 0.5347***). A similar pattern emerges for tent campsites, with q-values of 0.3053*** for DBI and 0.6643*** for LGPB, indicating a stronger influence of financial conditions on campsite distribution.

Subsequent analysis involving an overlay of the DBI and LGPB index across 337 cities (including municipalities) with campsite development (see Figure 9) reveals that cities boasting higher scores in these indices generally exhibit more advanced development of this emerging tourism model. This correlation underscores the importance of incorporating insights from enterprise managers, who highlight that these factors are critical for research and should not be overlooked by the academic community.

4.2. Analysis of detection factor interaction results

4.2.1 The interactions among primary indicators

Upon analyzing the interactions between the six primary indicators after conducting single-factor detection, it was found that the impacts of these indicators on the spatial distribution of campsites are not independent. Some interactions exhibit nonlinear enhancement and dual-factor enhancement effects, indicating that multi-factor interactions can better explain the regional differences in the spatial distribution patterns of campsites(see Figure 10).

For recreational vehicle campsites, the most significant interaction effects were observed between Transportation Infrastructure and Location (TIF) and Social and Demographic Environment (SDE), Tourism and Cultural Resources (TCR) and SDE, and TCR and TIF, with q-values of 0.6159, 0.5893, and 0.5677, respectively, all reaching a 1% significance level. This suggests that the interaction effects between transportation infrastructure and location, social and demographic environments, and tourism and cultural resource endowments are particularly prominent in influencing the spatial differentiation patterns of recreational vehicle campsites. Enhancing accessibility to tourist areas, placing campsites in regions with higher population density and human capital levels, and leveraging the layout of tourist attractions can accelerate the development of the recreational vehicle camping tourism.

The study reveals that although the direct impact of Natural Ecology and Environmental Resources (NER) on the spatial distribution of tent campsites is limited, there are significant synergistic effects when this factor interacts with Economic Development Level (EDL), Social Development Environment (SDE), and Transportation Infrastructure (TIF). The presence of rich natural and ecological resources, when coupled with favorable economic conditions and efficient transportation networks, substantially enhances the viability and attractiveness of

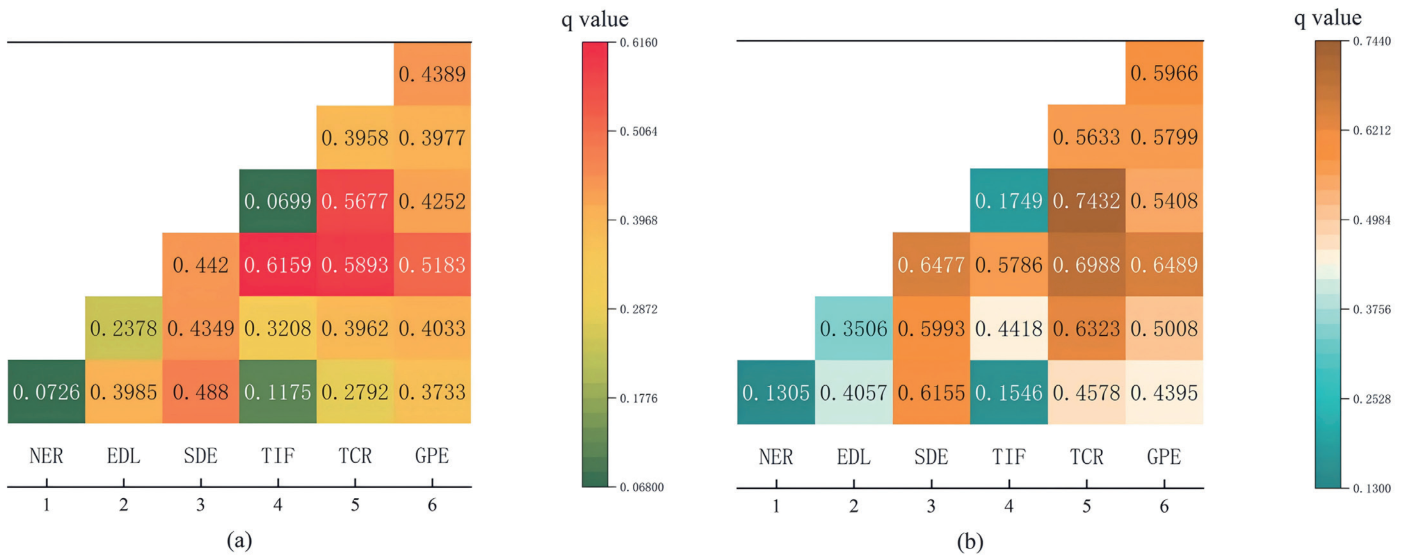


Fig. 10 – Interaction effect analysis of Primary indicators (a – recreational vehicle campsites, b – tent campsites). When factors x1 and x2 interact, the influence is quantified as $q(x1 \cap x2)$; If $q(x1 \cap x2) > q(x1) + q(x2)$, the interaction is characterized as nonlinear enhancement; If $q(x1 \cap x2) = q(x1) + q(x2)$, the factors are considered independent; If $q(x1 \cap x2) > \max[q(x1), q(x2)]$, the interaction between the factors is a dual-factor enhancement; If $\min[q(x1), q(x2)] < q(x1 \cap x2) < \max[q(x1), q(x2)]$, the interaction is a single-factor nonlinear weakening; If $q(x1 \cap x2) < \min[q(x1), q(x2)]$, the interaction is classified as nonlinear weakening.

locations for tent camping tourism. Additionally, the availability of high-quality tourist attractions and a supportive social environment for recruitment further catalyzes the establishment and growth of tent campsites. The interactions between economic development and transportation infrastructure, as well as their conjunction with tourism and cultural resources, also demonstrate notable enhancement effects. Strategic site selection for tent campsites, therefore, should prioritize accessibility and proximity to tourist attractions to leverage these interactions fully.

Furthermore, the Government and Policy Environment (GPE), identified in the single-factor analysis as a secondary but significant influence, shows a pronounced interactive enhancement with the Social and Demographic Environment (SDE). This interplay becomes a critical determinant in the success of both recreational vehicle and tent campsites. Regions with robust government support, favorable business environments, and policies that promote camping tourism – combined with high levels of human capital, dense population, and substantial motor vehicles – are identified as optimal locations for campsite enterprises. These areas offer enhanced prospects for the development and long-term success of camping tourism.

4.2.2. Analysis of interaction effects among secondary indicators

The application of the OPGD model has elucidated significant interactive effects among twenty-five secondary indicators. Table 5 displays the optimal secondary indicators detected within each primary category, along with their corresponding optimal interactive secondary indicators and their interactive explanatory power.

For recreational vehicle campsites, among the secondary indicators influencing the spatial heterogeneity of recreational vehicle campsites, factors with dual-factor enhancement interaction include: RDR ∩ SH, VIIRS-NLI ∩ RDR, MVS ∩ DGAQ, EXD ∩ MVS, NHAM ∩ RN, LGPB ∩ PCDI, RDR ∩ RD. The reasons are clear: (1) The existence of natural features like river density represents a potential resource for camping tourism. However, their effectiveness depends on aligning with specific motivations for camping, such as enjoying riverside sunlight, fishing, or stargazing; (2) The development of recreational vehicle campsites necessitates accompanying road or highway facilities. The interaction between road and highway network density and the quantity of recreational vehicles (part of the broader vehicle ownership) naturally provides essential preconditions for enhancing recreational vehicle camping tourism; (3) A high local fiscal level means local governments can support the development of camping tourism, including but not limited to investment and public infrastructure construction. However, the tourism activity itself must be backed by a high disposable income to afford such leisure activities.

Table 5 – The dominant secondary indicators and the maximum q value of interaction

	The Primary indicators	The dominant secondary indicators	q value	The dominant interactive secondary indicators	q value	Interaction Type*
Recreational vehicle Campsites	TER	RDR (X6)	0.1528	∩ SH (X3)	0.1931	bi-E
	EDL	VIIRS-NLI (X11)	0.3275	∩ RDR (X6)	0.445	bi-E
	SDE	MVS (X16)	0.5528	∩ DGAQ (X2)	0.6127	non-E
	TIF	EXD (X18)	0.1578	∩ MVS (X16)	0.6038	bi-E
	TCR	NHAM (X23)	0.5308	∩ RND (X17)	0.5685	bi-E
	GPE	LGPB (X25)	0.5347	∩ PCDI (X8)	0.5846	bi-E
Tent Campsites	TER	RDR (X6)	0.2337	∩ RD (X4)	0.2643	bi-E
	EDL	VIIRS-NLI (X11)	0.4649	∩ ENGEL (X10)	0.529	bi-E
	SDE	MVS (X16)	0.7211	∩ DGAQ (X2)	0.7518	bi-E
	TIF	EXD (X18)	0.2662	∩ MVS (X16)	0.7221	bi-E
	TCR	NHAM (X23)	0.7785	∩ RND (X17)	0.8289	bi-E
	GPE	LGPB (X25)	0.6643	∩ NHAM (X23)	0.8151	bi-E

Note: * non-E denotes nonlinear enhanced while bi-E denotes bivariate enhanced

Further, among the secondary indicators impacting the spatial heterogeneity of tent campsites, some exhibit interaction-enhancing effects within their primary categories, such as the night light index and Engel's coefficient, river density and rainfall days. Moreover, cross-primary category dual-factor enhancement interactions are evident between MVS and DGAQ, EXD and MVS, NHAM and RND, NHAM and LGPB. The interaction effects among the secondary indicators influencing tent campsites show high convergence with those affecting recreational vehicle campsites but also display certain differences. For example, the dual-factor enhancement interaction between NHAM and LGPB, it suggests that regions with robust fiscal health and extensive accommodation facilities can better support the growth of tent camping, providing diverse lodging options that can accommodate varying tourist preferences. This dynamic is particularly pronounced in cities like Chongqing and Beijing, which lead in the number of tent campsites and also boast substantial numbers of accommodation businesses – Beijing with 24,048 and Chongqing with 17,628. This alignment might explain the positive impact on tent campsites, contrasting with a potential negative influence on recreational vehicle campsites, where tourists typically seek more self-contained environments.

5. Discussion

Despite the explosive growth(2020–2023), the camping industry has faced challenges, such as disorderly practices and ongoing adjustments in business models by enterprises like the well-known tent campsite company – *Hiking camp*. The lack of theoretical exploration in camping tourism is a significant concern, as academic studies, including those conducted by Chinese scholars such as Li et al. (2017) and Li et al. (2023), remain in their infancy. These studies, though pioneering, did not fully capture the rapidly evolving phase between 2020–2023 and were limited in their analysis of spatial attributes, sample sizes, and the comprehensiveness of impact factors.

This study builds upon the work of previous scholars (such as Zhang et al. 2023) while also engaging deeply with enterprise managers, responding to calls from researchers (Li et al. 2023) for more comprehensive studies on campsite distribution. Employing an expanded dataset that encompasses prefectural-level city data, the research adopts a broader perspective to evaluate the factors influencing the spatial heterogeneity of campsites in China. Notably, the study integrates essential factors such as the government policy environment and introduces secondary indicators like the nighttime light index and the number of hotel accommodations within the region to its analytical framework. The findings reveal several intriguing characteristics of campsite locations, for example, "near-city" characteristic. The research indicates that the primary markets for many campsites are not confined to the administrative cities they are associated with; instead, these markets are significantly influenced by geographic proximity, specifically the distance to the nearest city center.

Enterprise managers and government regulators should recognize that the spatial patterns and influencing factors of recreational vehicle campsites differ from those of tent campsites, and this understanding should guide campsite development and management. Optimal site selection for both types of campsites requires careful consideration of the local social and demographic environment. In this first-level indicator, motor vehicle stocks (MVS) play a pivotal role by linking personal vehicle ownership to the potential for campsite development. Enhanced vehicle accessibility promotes camping activity, and a higher motor vehicle ownership rate in a region reflects a broader customer base for tent campsites. Meanwhile, the success of campsite enterprises depends on high-quality human capital to improve decision-making, foster innovation, and enhance adaptability. However, the remote locations of most campsites make attracting skilled talent challenging. Regions with higher levels of human capital offer advantages in ensuring long-term sustainability, while higher population densities provide a larger customer base, increasing opportunities to attract visitors and generate revenue. This demand often drives investment in infrastructure and services, which supports campsite development and aligns with sustainable tourism principles. The aging ratio serves as a negative indicator for campsite demand, though its impact varies between tent and recreational vehicle campsites. Older populations generally participate less in outdoor camping, shrinking the tent campsite market. However, recreational vehicle campsites see positive trends in regions with higher aging rates, as retirees often use recreational vehicles to explore distant locations. For example, in China, retirees form a niche market for recreational vehicle camping, contributing to its sustainable development.

Furthermore, local fiscal environments and tourism resources are crucial for campsite sustainability. Government incentives, tax benefits, and investments in tourism infrastructure can boost feasibility and profitability. Access to diverse tourism and cultural resources, such as heritage sites and natural attractions, enriches the camping experience and enhances campsite appeal. Proximity to high-level scenic areas like national parks or lakes further increases attractiveness, catering to eco-tourists and outdoor enthusiasts. Complementary infrastructure, such as nearby hotels, creates a comprehensive tourism ecosystem, encouraging extended stays and promoting local economic growth.

Campsite planning should prioritize eco-friendly practices to support sustainability and integrate with natural landscapes. Renewable energy, water conservation, and waste management systems reduce environmental impact, while minimizing light pollution preserves the natural ambiance, enhancing outdoor nighttime activities like stargazing.

6. Conclusions

This study undertakes a detailed quantitative analysis of the spatial distribution, equilibrium states, and densities of recreational vehicle and tent campsites, utilizing ArcGIS software to generate precise mapping and spatial insights. The main conclusions are as follows:

(1) Campsites are predominantly located east of the Heihe-Tengchong Line, tent campsites show more pronounced clustering than recreational vehicle campsites. recreational vehicle campsites generally display a "multi-center clustered" distribution pattern, forming radial clusters around four primary cores and one smaller typical density centers, while the distribution of tent campsites also has four primary density cores and tends to converge with recreational vehicle campsites in overall trends, but their specific distributions more often appear in a "belted contiguous areas" pattern.

(2) The explanatory power of the factors influencing the spatial heterogeneity of tent campsites significantly differs from that of recreational vehicle campsites. Furthermore, the study used a geographical detector to identify common secondary leading factors for both recreational vehicle and tent campsites under the influence of their primary factors. Meanwhile, the analysis underscores that the influences shaping the spatial distribution of campsites are complex and interdependent, often exhibiting non-linear and dual-factor enhancement effects. This study reveals how these interactions can more effectively elucidate regional

variations in campsite distribution, particularly through the lens of primary and secondary indicators. These findings provide solid evidence for revealing the roots of spatial heterogeneity between recreational vehicle and tent campsites.

By tailoring campsite development strategies to the unique challenges and opportunities in densely populated and socio-economically complex regions, policymakers and developers can enhance the resilience, accessibility, and sustainability of camping tourism. These strategies not only address local needs but also serve as a blueprint for regions and countries aspiring to develop their camping tourism economies.

While this research advances our understanding of campsites distribution in China, it identifies certain limitations that future studies could address to enhance the depth and applicability of findings: (1) Exploring micro-level influencing factors; (2) Temporal and Spatial Data Analysis; (3) Utilizing Advanced Analytical and forecasting Techniques. This would not only enrich academic discourse but also significantly contribute to the high-quality tourism development and the broader tourism economy.

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