

Article

Spatio-Temporal Differentiation and Influencing Factors of Rural Tourism Network Attention: A Chinese Case Study Based on Multi-Source Data

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Abstract

Identifying the spatio-temporal evolutionary patterns and driving mechanisms of rural tourism network attention is essential for predicting the development trends of the rural tourism industry and delivering refined industrial governance. Taking 356 prefecture-level cities in China from 2015 to 2024 as basic research units, this paper constructs a comprehensive evaluation system for rural tourism network attention based on multi-source data. Furthermore, its spatio-temporal evolution characteristics and internal influencing factors are systematically investigated by means of spatial autocorrelation analysis and geographically weighted regression. The results indicate that the overall level of rural tourism network attention in China shows an obvious fluctuating growth trend, which can be divided into three successive stages, namely steady growth (from 0.8530 in 2015 to 1.2028 in 2019), explosive growth (from 1.9563 in 2020 to 3.7471 in 2021) and high-level fluctuation (maintained in the high range of 2.4–3.4). In addition, with the continuous iteration of internet communication media, the guiding influence of traditional search platforms has gradually weakened, while emerging social media and short-video platforms have become the core carriers of online tourism traffic. Correspondingly, media innovation persistently reshapes the spatial distribution pattern of rural tourism network attention. In terms of spatial characteristics, rural tourism network attention has undergone a significant transformation from geographical gradient polarization to overall regional equilibrium. Specifically, from 2015 to 2024, the overall Moran's I index remained positive, with values ranging from 0.0116 to 0.1358, indicating an overall trend of gradual decline. High-attention areas are predominantly concentrated in economically developed urban agglomerations, whereas remote and economically underdeveloped regions exhibit contiguous low-value aggregation characteristics, which reveals a remarkable trend of balanced development nationwide. In view of driving mechanisms, highway network density, tourism income, rural tourism resource and enrollment of university students are identified as the core driving factors dominating the spatio-temporal evolution of rural tourism network attention. Moreover, the intensity of the influence of each factor presents distinct spatial heterogeneity. This study further reveals that the spatial heterogeneity of rural tourism network attention calculated using multi-source fused data shows a remarkable convergent characteristic, which can reflect the actual distribution of the rural tourism market more objectively and accurately. Meanwhile, rural tourism network attention is typically characterized by scale-dependent with the spatial distribution at the macro-scale being more balanced than that at the meso- and micro-scales.



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Keywords: rural tourism; network attention; spatio-temporal characteristics; influencing factors; multi-source data

1. Introduction

It has been widely recognized worldwide that rural tourism plays an important role in advancing poverty alleviation and local economic and social development [1,2], so tourists' travel patterns can serve as an important basis for formulating market policies and marketing strategies [3]. As a key analytical tool, tourism network attention can comprehensively characterize the aggregated intensity of netizens' online activities toward tourism targets, including information retrieval, page browsing, likes, comments and reposts. Consequently, this metric has become an important forward-looking indicator for gauging the appeal of potential tourism markets [4,5]. Nevertheless, affected by the changing external environment, as well as individual travel intentions of internet users, tourism network attention keeps changing and remarkable spatio-temporal disparities can emerge due to inherent regional heterogeneity. For instance, the rural tourism hotspot "lonely tree" incident on Xi'an Bailuyuan in 2026 triggered a nationwide online debate. The tree went viral on Douyin and Kuaishou, attracting massive tourists who trampled farmland and damaged crops. After repeated fruitless dissuasion, the farmer cut off most branches of the tree, pushing the village's rural tourism search and discussion volume to multiple times the normal level and generating sustained negative online public opinion. Local homestay and agritainment visitor numbers dropped sharply afterward, directly demonstrating the linkage between fluctuating network attention and offline rural tourism performance [6]. Since fluctuations in tourism can be quickly transmitted to economic, cultural and social development, governments worldwide have placed high emphasis on tourism network attention [7]. In particular, for large territorial countries featuring a large number of cities such as China, regional tourism development varies significantly across different cities. As a result, such spatial heterogeneity gives rise to geographical disparities in tourism network attention to different extents [8]. Compared to the provincial macro-scale, the municipal level effectively addresses the limitation of provincial units in masking heterogeneities among prefecture-level cities regarding economic performance, consumption capacity, tourist demographics, and resource endowments [9]; compared to the county micro-scale, municipal boundaries are closely aligned with both the actual travel radius of rural tourism activities and the range of tourist mobility. Conducting research on rural tourism network attention at the municipal level enables a more accurate representation of the spatial behavioral patterns underlying tourists' information searches and travel decisions [10]. Existing studies concerning rural tourism network attention are limited to provincial-scale samples or individual scenic sites and commonly adopt global-based OLS models, which neglect spatial non-stationarity and fail to identify heterogeneous effects of influencing factors across prefecture-level cities. It is significant to evaluate the spatio-temporal differentiation of tourism network attention and explore its driving factors objectively for effectively revealing the spatio-temporal behaviors of potential tourists and support local governments in developing proactive governance schemes. Accordingly, taking 356 prefecture-level cities across China as basic research units, this paper conducts an investigation into the spatio-temporal differentiation rules and influencing factors of rural tourism network attention on the basis of multi-source data, so as to construct a universal analytical framework for relevant academic studies and underpin the formulation of differentiated regional development policies. The rest of the paper is organized as follows: The Section 2 is literature review and points out research gaps. The Section 3 illustrates

the research design, covering indicator system, data sources and methods. The Section 4 explores the spatio-temporal features of rural tourism network attention and the spatial heterogeneity of its influencing factors. The Section 5 concludes the research and presents relevant discussions.

2. Literature Review

2.1. Digital Economy and Network Attention

As an emerging economic paradigm, the digital economy relies on networked intelligent technologies and takes information and data as core elements [11,12]. Since the 1990s, with the rapid development of computer science and internet technologies, big data, mobile internet and intelligent algorithms have been extensively adopted across communication equipment manufacturing, information technology services and digital content sectors, and internet platforms become an essential vehicle for digital economy activities [13,14]. As an economic form that takes data as a key production factor and online platforms as major carriers, the digital economy has transformed information dissemination from one-way passive output into two-way interaction and precise matching. On the one hand, it greatly cuts the costs of information searching, replication, transmission, tracking and verification. On the other hand, it reshapes the entire process whereby users acquire information, make decisions and engage in expression behaviors. Furthermore, it reconstructs the rules of information communication and the logic of social consumption, and has ultimately become the fundamental driving force behind the digital transformation of user behaviors [15,16]. Since the beginning of the 21st century, fueled by ongoing technological upgrades and worldwide digital transformation, the digital economy is no longer restricted to the internet sector. It has deeply integrated with the real economy and permeated agriculture, industry, services and other industries across the board. As a result, it stands as a key driver of global economic reform, industrial digitalization and market competition restructuring [17]. At present, the development connotation, industrial forms and enabling mechanisms of the digital economy are continuously being enriched and extended, which offers broad scope for scholars to carry out relevant empirical research and theoretical expansion.

Academic research on the digital economy mainly falls into three major categories such as digital infrastructure economy, digital products and services economy and digital empowerment economy. Among them, as a fundamental research field, the digital infrastructure economy primarily explores the construction rules, technological evolution paths and industrial spillover effects of digital support systems such as artificial intelligence, blockchain, cloud computing and big data. Therefore, it is regarded as an essential pillar of the modern economic system [18,19]. The digital empowerment economy focuses on the enabling effects generated by the integration of digital technologies and the traditional real economy. It mainly analyzes the transformation mechanisms through which digital tools renovate traditional industries, improve industrial efficiency and restructure consumption scenarios. As indicated by relevant studies, digital innovation acts as a key driver for industrial transformation and efficiency improvement [20]. Meanwhile, the digital products and services economy represents the most dynamic and diversified core research field within the digital economy, which covers internet platform operation, digital content production, user-generated content (UGC) co-creation, and social interaction, as well as digital marketing. Scholars have noted that digital innovative products and services are featured with rapid iterative updates. Users' active searching, instant engagement, content co-creation and re-dissemination all significantly influence public attention [21–23]. Specifically, derived from fragmented online interactions, network attention directly mirrors individual preferences and potential needs, and thus serves as a vital quantitative indicator for evaluating the development of digital products and services [24].

As a concept rooted in the economics of attention and digital communication theories, early research on network attention mainly focused on the scarcity-driven allocation mechanism of user attention under the circumstance of information overload. In their book, *The Attention Economy: Understanding the New Currency of Business*, taking internet media formats, corporate digital marketing strategies and users' online information screening behaviors as research subjects, Davenport and Beck systematically analyzed the inherent mechanisms of platforms in aggregating, redistributing and steering public attention by means of cross-industry field surveys and inductive case study approaches, which established the theoretical underpinning for academic explorations into network attention within the framework of attention economics [25]. Voorveld et al. further refined the research dimensions and constructed an analytical framework for users' online participation behaviors [26]. They categorized activities such as searching and browsing, interactive liking and original content creation into different manifestations of attention, and proposed adopting a hierarchical indicator system to quantify internet users' online engagement. Currently, with the continuous iteration of big data technologies and the growing prominence of online public opinion guidance, the research of network attention has gone beyond the single scope of communication studies. It has been widely applied in industrial and academic fields, including industrial economic measurement [27], consumer market forecasting [28], and regional cultural and tourism development [5]. Scholars generally agree that network attention serves not only as a core proxy variable linking the behavioral preferences of online users to the demands of offline real industries, but also as a primary quantitative tool for measuring niche market popularity, unpacking the mechanisms behind user decision-making behaviors and predicting the medium and long-term development trends of various industries. Accordingly, it constitutes an indispensable component in the quantitative research of the digital economy [8,29].

2.2. Tourism Network Attention

As a key derivative of network attention in cultural tourism research, tourism network attention derives from such tourists' whole-process online activities as pre-trip information searching and travel planning and post-trip content sharing. It captures the real-time dynamic changes in public preferences and interest levels regarding tourism destinations, depicts potential tourism consumption intentions and market demands, and forecasts the development and trends of regional tourism [29–31]. In addition, with the booming development of digital cultural tourism and smart tourism, research on tourism network attention has gradually integrated theories and methodologies from multiple disciplines including tourism geography, big data science and tourism management, evolving into a core research hotspot within the field of digital cultural tourism.

Spatio-temporal differentiation patterns represent the core research direction of studies on tourism network attention. Due to limitations in big data accessibility and data crawling techniques, early quantitative research primarily adopted search data from Baidu Index and Google Trends as the main measurement basis [32]. In recent years, as online travel platforms, social media and short-video platforms grow rapidly, channels for tourists to obtain information and share content have become increasingly diversified. Against such a backdrop, a number of scholars conduct relevant research based on new media datasets derived from short-video and social platforms for the reason that single search engine data fail to adapt to the complicated behavioral features of internet users [33–35]. On the basis of data collected from various platforms, researchers have integrated multiple analytical tools such as seasonal index, Moran's I , kernel density estimation and geographic concentration index to analyze the evolutionary characteristics of tourism network attention from temporal and spatial dimensions. For example, Luo et al. and Zhang and Gu utilized short-video

platforms represented by Douyin to respectively analyze the spatio-temporal characteristics of network attention to red tourist attractions and national forest parks [33,34]. Giglio et al., by contrast, adopted social media data to depict the spatio-temporal variations in tourism appeal of six Italian cities [35]. Existing studies have also revealed that tourism network attention presents obvious seasonal fluctuations from the perspective of temporal evolution [36]. Periodic peaks and troughs are shaped within a year by statutory holidays, climatic conditions and folk custom activities [37], whereas its inter-annual evolution is subject to disturbances from exogenous shocks including industrial policies and major public emergencies [38–40]. In terms of spatial distribution, tourism network attention follows a typical core–periphery differentiation pattern. Regions with high network attention are mostly concentrated in economically developed and densely populated urban agglomerations, whereas inland remote and less developed regions remain stuck in low-value ranges of network attention, showing prominent spatial agglomeration disparities [34]. In terms of research scale, existing studies are predominantly conducted at provincial and regional levels. Employing spatial analytical approaches including spatial autocorrelation, coefficient of variation, and geographic concentration index, scholars have uncovered the agglomeration patterns of national network attention to rural tourism with provinces as the basic research units. Their findings reveal a nationwide spatial pattern characterized by “high values in eastern China, steady levels in central China, and differentiated distribution across western China” [41,42]. A small body of literature further narrows its focus to specific regions such as the Yellow River Basin [43] or individual cities like Nanjing [44], mapping the internal spatial distribution characteristics of network attention to rural tourism within these territories.

On the basis of clarifying the spatio-temporal distribution patterns of tourism network attention, scholars have further probed into the mechanisms driving its spatio-temporal disparities. From the perspective of influencing factor screening, the current literature has established relatively sophisticated indicator frameworks, where key determinants cover natural geographical conditions [45], tourism resource endowment [46], transportation accessibility [47], socio-economic status [48], internet penetration [49] and educational level [50]. Furthermore, to fully reveal the inherent linkages between diverse elements and tourism network attention, some scholars have additionally adopted supplementary indicators including cultural tourism policies, festival activities, tourist market structure and public opinion context [40]. In addition, relevant studies have found that the action intensity and leading role of core influencing factors are not constant. Instead, they change with temporal evolution and the division of spatial units, presenting typical temporal effects and spatial scale effects. For instance, at the provincial level, road density and tourist reception capacity always play dominant roles, while per capita disposable income exerts a significant positive effect on the popularity growth of tourism projects in their early stage. By contrast, at the municipal level, resident population size and tourism resource endowment serve as the primary influencing factors, and the impacts of air quality and regional media attention are gradually strengthened [2,51]. From a methodological perspective, the current literature mostly employs tools including correlation analysis, conventional linear regression and the geographical detector model to quantify the global impacts of driving factors on tourism network attention, and determine the overall magnitude and statistical significance of such influences [2,50,52].

The theoretical research on driving mechanisms has further promoted the practical transformation of research achievements. Numerous scholars have conducted in-depth discussions on the coupling relationship and predictive efficiency between tourism network attention and actual tourist flows, thereby forming an applied research system centered on tourist flow prediction. Early applied research was dominated by conven-

tional time series and econometric models, which concentrated on linear associations between network attention and tourist volume to predict medium-to-long-term tourism market trends at a low frequency [53,54]. For example, Wang et al. adopted the Baidu Index and verified a significant positive correlation between scenic spot network attention and on-site tourist volume via the OLS regression model [55]. Sun et al. further differentiated mobile and PC search data and found that the Baidu Index from mobile terminals exhibited stronger explanatory power for fluctuations in actual tourist arrivals [56]. With the in-depth application of machine learning and intelligent algorithms in quantitative tourism research, high-precision intelligent prediction models have gradually replaced traditional econometric models and they have been widely adopted for tourist flow forecasting and tourism market trend deduction [57,58]. Li et al. constructed a Back Propagation (BP) neural network model optimized by the Fruit Fly Optimization Algorithm (FOA) based on web search data to forecast the daily tourism demand of Huangshan Scenic Area in China [59]. The results revealed that the FOA-BP method integrated with web search data achieved significantly higher prediction accuracy than alternative models during the tourist peak season. By contrast, Xie et al. developed a deep bidirectional DBi-GRU model based on Bidirectional Recurrent Neural Network and Gated Recurrent Unit (GRU) algorithms to realize high-frequency, high-precision dynamic forecasting of scenic tourist arrivals [60]. Existing studies have consistently verified that tourism network attention and on-site tourist flows are highly coupled in both temporal and spatial dimensions. Their dynamic changes can effectively predict core industrial indicators including regional tourist reception volume, cultural and tourism consumption scale and total tourism revenue, which provides vital data support and decision-making references for tourist flow early warning in tourism destinations, refined scenic area operation and cultural tourism market regulation [61].

In general, with the rapid development of the digital economy, tourism network attention has become a research hotspot in cultural tourism academia. Current studies have developed a hierarchical research framework covering spatio-temporal features, driving determinants and tourist flow coupling forecasting. Nevertheless, the existing literature still has the following limitations. In terms of data sources, most studies conduct quantitative estimations relying on data from a single platform, while comprehensive estimation systems based on the fusion of multi-source big data remain scarce. A small number of studies adopting multi-source data mainly focus on popular tourist cities or well-known scenic spots, and few have constructed differentiated comprehensive measurement systems for network attention targeting rural tourism from a nationwide macro perspective. For research scale, most existing studies take small- and medium-scale samples such as a single province or typical scenic spots as research objects, lacking systematic analyses at the municipal nationwide macro-scale. In particular, few investigations have explored the spatial evolution patterns of rural tourism network attention and the spatial heterogeneity of its driving factors from a large-scale perspective. Accordingly, this study integrates multi-source heterogeneous network big data to examine the spatio-temporal differentiation and driving mechanisms of rural tourism network attention at the municipal scale across China. It can not only effectively address the limitations of single data sources and small-scale research, but also further refine and improve the research framework within the field of rural digital tourism, thereby offering theoretical support and practical references for the high-quality development of rural cultural tourism.

3. Materials and Methods

3.1. Determination of Indicator System and Weights

Data from a single source can hardly fully characterize the actual level of network attention. Most existing studies related to rural tourism network attention adopt only search engine data for measurement, resulting in the problem of insufficient data comprehensiveness [2,62]. Against the backdrop of the rapid development of digital cultural tourism, search engines, social media, tourism websites and short-video platforms have evolved into four mainstream media channels for tourists to retrieve travel information, share travel experiences and engage in online word-of-mouth interactions [29,35,63]. In this study, seven leading mainstream platforms from the four types of media in China are selected to obtain network attention data, namely Baidu, WeChat, Weibo, Ctrip, Mafengwo, Douyin and Kuaishou. These leading platforms cover more than 90% of the online information generation and dissemination chain related to rural tourism in China, and the acquired data can completely restore tourists' whole-chain online behavioral characteristics ranging from information searching and content browsing to interactive communication [4,64]. After determining the data collection platforms, this study further constructs a comprehensive evaluation system for rural tourism network attention according to the data attributes of each platform. The system takes four dimensions as first-level indicators, namely search engine index, social media index, tourism website index and short-video index, and contains seven second-level indicators: Baidu search index, reading volume of WeChat articles, likes of Weibo images and texts, reading volume of Ctrip travel notes, reading volume of Mafengwo travel notes, likes of Douyin videos and likes of Kuaishou videos. On this basis, the entropy weight method is adopted to calculate the weight of each indicator. Firstly, the original data of all indicators are subjected to positive normalization to eliminate the dimensional effect. The sample proportion, information entropy and utility coefficient of each indicator are calculated sequentially. Afterwards, the objective weight of each indicator is determined according to the proportion of utility coefficients. Finally, the comprehensive score of rural tourism network attention in each city is obtained by weighted summation of the standardized data and corresponding weights of all indicators (Table 1).

Table 1. Comprehensive evaluation indicator system of rural tourism network attention.

First-Level Indicator	Weight (%)	Second-Level Indicator	Weight (%)
Search engine index	3.1513	Baidu search index	3.1513
Social media index	31.7338	Reading volume of WeChat articles	21.5264
		Likes of Weibo images and texts	10.2074
Tourism website index	22.0158	Reading volume of Ctrip travel notes	12.0387
		Reading volume of Mafengwo travel notes	9.9771
Short-video index	43.0991	Likes of Douyin videos	23.5426
		Likes of Kuaishou videos	19.5565

3.2. Research Method

(1) Spatial Autocorrelation Analysis

Global spatial autocorrelation is a common method for describing the spatial agglomeration characteristics of research objects, and the Moran's I index is usually adopted to reflect the degree of spatial agglomeration and correlation of variables [2]. This method reveals the spatial disparities of rural tourism network attention from a global perspective but fails to reflect the spatial heterogeneity of different cities in local spatial distribution. Therefore, this study further employs Local Indicators of Spatial Association (LISA) to identify four spatial clustering types, namely high-high, high-low, low-high and low-low

clusters, so as to analyze the local spatial correlation among cities [65]. The calculation formula is expressed as follows:

$$I = \frac{n \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_i \sum_j w_{ij}) \sum_i (x_i - \bar{x})^2} \quad (1)$$

$$I_i = \frac{n^2}{\sum_i \sum_j w_{ij}} \times \frac{(x_i - \bar{x}) \sum_j w_{ij} (x_j - \bar{x})}{\sum_j (x_j - \bar{x})^2} \quad (2)$$

In Equations (1) and (2), I denotes the global Moran's I index and I_i is the local Moran's I index. n refers to the number of cities. x_i and x_j are the rural tourism network attention values of city i and city j respectively. $\bar{x}$ stands for the average rural tourism network attention across all cities in a specific year, and W_{ij} is the spatial weight matrix. The value of I ranges from -1 and 1 . If $I < 0$, and the rural tourism network attention across cities presents negative spatial autocorrelation. If $I > 0$, it exhibits positive spatial autocorrelation. When $I = 0$, the spatial distribution is random.

(2) Geographically Weighted Regression Analysis (GWR)

GWR serves as an effective approach to test spatial non-stationarity, which can depict the varying relationships between the dependent variable Y and as set of explanatory variables X_j at the regional scale. This study adopts the GWR model, with the corrected Akaike information criterion (AICc) applied to select its optimal bandwidth, to investigate the spatial non-stationarity of factors driving rural tourism network attention. As an extension of the traditional linear regression model, GWR incorporates geographic location information and specifies parameters as functions of spatial position i . It supports local rather than global parameter estimation with each spatial sample unit corresponding to an independent coefficient value. Therefore, the model results can better reflect local characteristics [66]. The calculation formula is presented as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i \quad (3)$$

In Equation (3), (μ_i, v_i) refers to the central geographic coordinates of the i spatial unit. $\beta_k(\mu_i, v_i)$ stands for the estimated value of the continuous function at the location of unit i , and $\beta_0(\mu_i, v_i)$ is the regression intercept and ε_i is the error term.

3.3. Source of Data

Taking "rural tourism" as the keyword, this study collects network attention data from four categories of internet platforms: search engines, tourism websites, social media, and short-video platforms. For search engines, data were obtained from the Baidu Index, the most dominant search engine in China, covering the period from 1 January 2015 to 31 December 2024. We gathered annual city-level rural tourism search indices for both PC and mobile terminals. In total, 3560 valid records were obtained, with a cumulative search index of 11,471,489. For social media, WeChat and Weibo were adopted. WeChat official account articles were collected, with reading volume used to measure public attention. Weibo graphic text posts were retrieved via web advanced search, with likes adopted as the attention indicator, and posts with fewer than five likes were excluded. A total of 53 valid WeChat articles (2020–2024) were obtained, with a total reading volume of 544,749, alongside 5804 valid Weibo posts (2015–2024) with 1,007,778 total likes. For tourism websites, Ctrip and Mafengwo were selected, and the reading volume of rural tourism travel notes was taken as the statistical index. Qualified travel notes were screened by title and content and summarized by year. Limited by platform retrieval rules, we obtained 2668 valid Ctrip travel notes (2020–2024) with a total reading volume of 6,725,623 and 1106 valid Mafengwo travel

notes (2015–2024) with a total reading volume of 5,425,371. For short-video platforms, Douyin and Kuaishou were used, with video likes as the attention metric. All videos were categorized by city according to their titles and content. Due to platform retrieval constraints, 73 valid Douyin videos (2020–2024) were collected with 2,004,508 total likes and 75 valid Kuaishou videos (2021–2024) with 380,276 total likes.

For the 15 explanatory indicators covering six dimensions, all statistical data covering were collected from standardized official publications. Specifically, the primary data sources include the China Urban Statistical Yearbook (2024), municipal and provincial statistical yearbooks of corresponding years, annual national economic and social development communiqués released by all prefectural and provincial governments in 2023, provincial and municipal meteorological climate bulletins of 2023, as well as the annual Statistical Report on Internet Development in China. To handle scattered missing statistical records of individual cities in partial years, two complementary filling strategies were adopted. We first filled gaps using authentic statistical data from adjacent complete years; for long-term continuous missing indicators, linear temporal interpolation was implemented to generate continuous balanced panel data. This dual supplementation strategy effectively eliminates data discontinuity and guarantees the time series integrity and cross-city comparability of all driving factor datasets used in subsequent correlation, OLS and GWRs.

4. Results

4.1. Spatio-Temporal Characteristics of Rural Tourism Network Attention

4.1.1. Temporal Characteristics

The comprehensive network attention shows an overall fluctuating upward trend, which can be divided into three stages: the steady growth stage, the explosive growth stage and the high-level fluctuation stage (Figure 1). The period from 2015 to 2019 belongs to the steady growth stage. The comprehensive network attention rose slowly from 0.8530 in 2015 to 1.2028 in 2019 with the average annual growth rate of 10.25%. During this period, rural tourism had not yet become a core hotspot of mass tourism, and the overall activity of users in active information retrieval and content sharing remained relatively low. The period from 2020 to 2021 witnessed explosive growth. Affected by the COVID-19 pandemic, suburban and short-distance trips became the dominant travel options, driving a sharp surge in public attention toward rural tourism. The comprehensive network attention reached 1.9563 in 2020, representing a 62.64% increase compared with 2019, and climbed to a periodic peak of 3.7471 in 2021 with a year-on-year growth rate of 91.53%. This indicated a structural shift from steady growth to explosive expansion, which was directly attributable to restrictions on offline tourism scenarios and the soaring demand of tourists for natural, ecological and low-density travel experiences. The period of 2022 to 2024 was characterized by high-level fluctuations. Since the tourism market enjoyed full recovery in this period, the comprehensive network attention declined moderately yet remained within a high range of 2.4 to 3.4. In 2023, the attention rebounded to 3.3276, second only to the peak recorded in 2021. This shift signified that rural tourism had evolved from an emergency travel alternative during the pandemic into a regular tourism product, accompanied by gradually stabilized market demand.

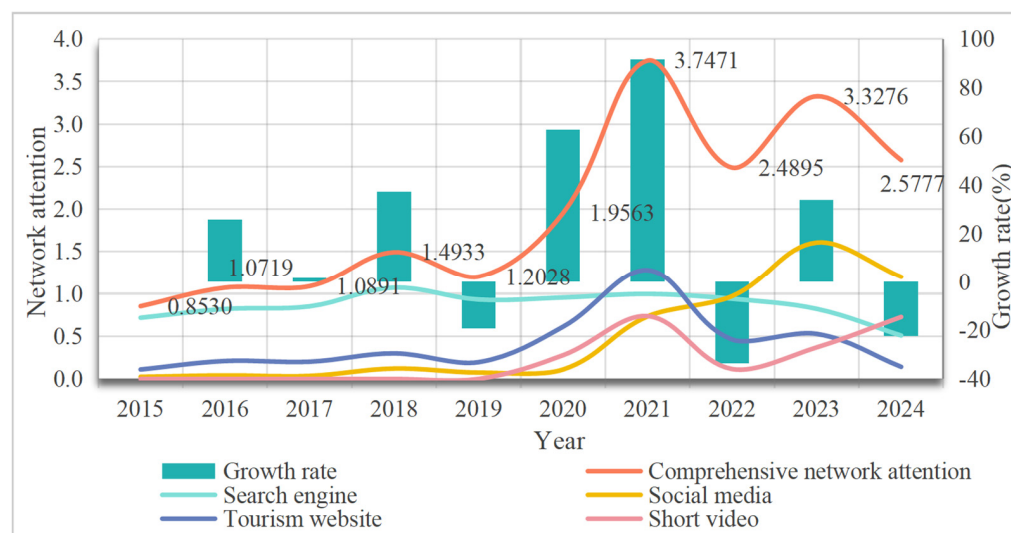


Figure 1. Inter-annual variation in rural tourism network attention in China from 2015 to 2024.

The evolutionary differentiation characteristics of network attention across the four types of platforms are prominent, showing a structural iterative trend of “decline of traditional platforms and rise in emerging platforms”. Among them, the temporal trend of search engine platform attention is basically consistent with the early trajectory of comprehensive network attention. It maintained steady development from 2015 to 2019 and achieved slow growth driven by tourists’ demand for information retrieval before travel, serving as the primary channel for people to obtain online rural tourism information at that time. Nevertheless, its proportion gradually declined in the later stage along with the rise in diversified platforms. Social media platforms started relatively late in terms of network attention, staying at a low overall heat level from 2015 to 2019. The public rarely followed or shared rural tourism content via social platforms, and a mature industrial communication ecosystem had not yet taken shape. These platforms entered a period of rapid development between 2020 and 2024. Fueled by the wide spread of cultural and tourism articles on WeChat and tourism-related topics on Weibo, network attention on these platforms rose sharply, establishing them as a vital channel for the online dissemination of rural tourism information. Short-video platforms had the latest launch but recorded the fastest growth, with their network attention surging from 0.2781 in 2020 to 0.7263 in 2024. Together with social media platforms, they formed a two-wheel driving pattern and evolved into the core carrier for online traffic attraction and brand communication in the rural tourism sector.

4.1.2. Spatial Characteristics

With the support of ArcGIS 10.2 software, this study adopts the Jenks Natural Breaks Classification method to divide the rural tourism network attention of 356 municipal units in China into five levels: low-attention, relatively-low-attention, medium-attention, relatively-high-attention and high-attention. To clearly depict its spatial evolutionary trajectory, spatial visualization analysis is carried out at four key time nodes: 2015, 2018, 2021 and 2024 (Figure 2). Overall, the municipal-level rural tourism network attention in China from 2015 to 2024 shows a spatial gradient with high values in the east and south and low values in the west and north with an overall stable spatio-temporal evolution trend. High municipalities with high and relatively high attention have long been agglomerated in urban agglomerations along the eastern coastal areas, centering on the Yangtze River Delta, Pearl River Delta and the Beijing–Tianjin–Hebei (Bohai Rim) metropolitan area. In the meantime, central and western provincial capitals including Chengdu, Chongqing, Wuhan and Xi’an have developed into high-value cores within their respective regions by virtue of

locational advantages, solid economic foundations and abundant resource endowments, thereby forming a core–periphery radiation pattern. In contrast, municipalities with low and relatively low attention are contiguously distributed across the Qinghai–Tibet Plateau, inland northwest China, Hainan and most parts of Northeast China, constituting stable low-value agglomeration zones. The spatial differentiation of rural tourism network attention among regions is remarkably prominent.

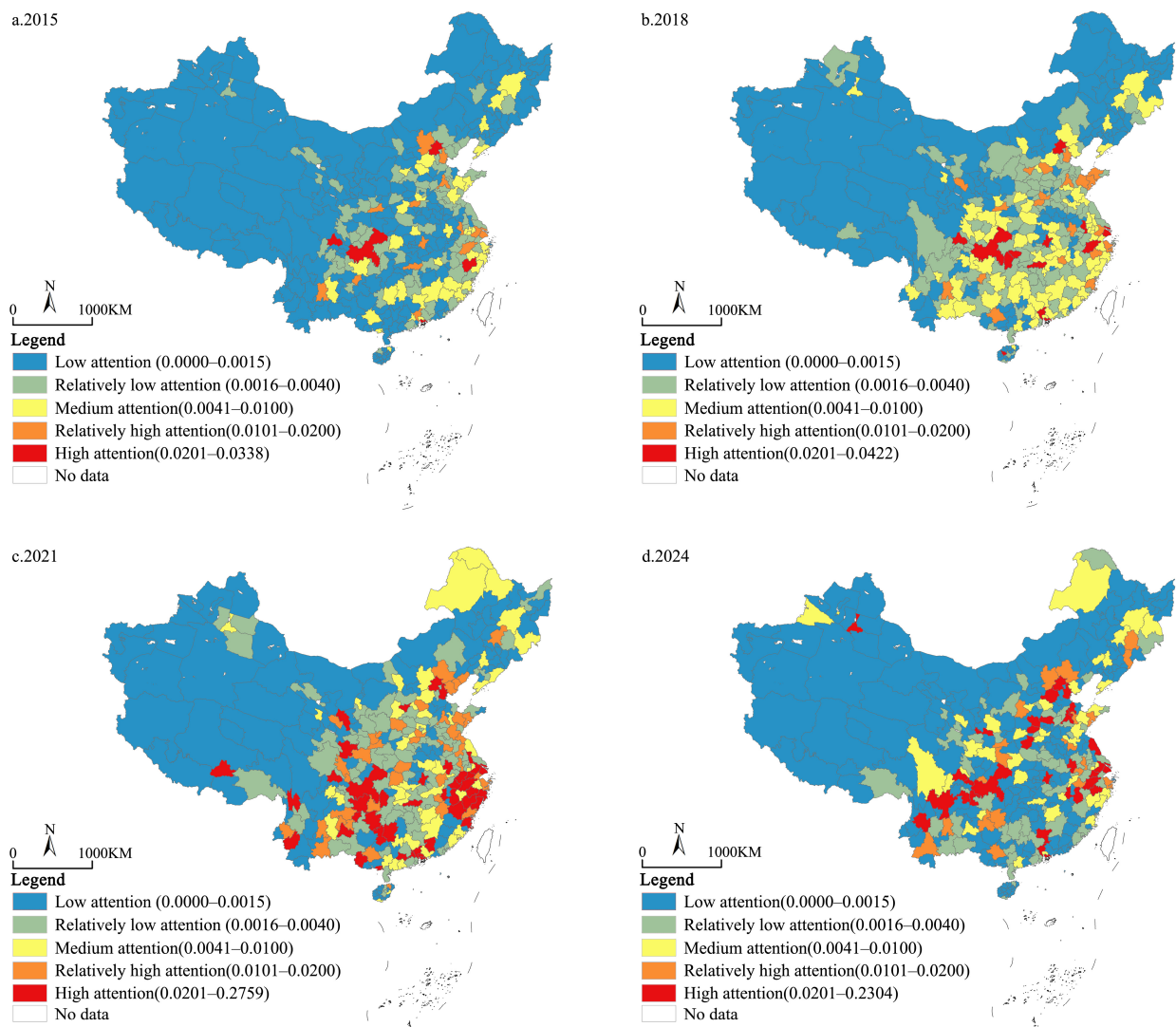


Figure 2. Spatial distribution pattern of rural tourism network attention in China from 2015 to 2024.

4.1.3. Spatial Autocorrelation

This study adopts the global Moran's I index to test the spatial autocorrelation of rural tourism network attention in China from 2015 to 2024. As shown in Table 2, the global Moran's I indices of rural tourism network attention are all positive during the study period, ranging from 0.0116 to 0.1358 and presenting an overall fluctuating downward trend. Specifically, the Z-scores were greater than 1.96 and the p-values were less than 0.05 from 2015 to 2019 and from 2021 to 2022, passing the significance test at the 5% level. In contrast, the p-values in 2020, 2023 and 2024 were 0.3327, 0.2772 and 0.5477 respectively, which failed to pass the significance test. This phenomenon can be explained from two perspectives. First, affected by external shocks, the COVID-19 pandemic severely disrupted the domestic tourism market in 2020. Total domestic tourists plummeted to 28.79 billion person-times, a year-on-year decrease of 31.27 billion person-times, with a sharp drop of 52.1% year-on-year,

domestic tourism revenue fell by 61.1% to 2.23 trillion yuan [67]. And the restructuring of tourism consumption patterns in the post-pandemic era from 2023 to 2024 significantly increased the randomness in the spatial distribution of rural tourism network attention [40]. Second, with the advancement of balanced development of rural tourism across regions, some regions with originally low attention have gained growing online popularity relying on distinctive resources, breaking the original contiguous low-value pattern and thus reducing the statistical significance of spatial agglomeration [2]. Overall, rural tourism network attention in China at the municipal scale is still mainly characterized by positive spatial agglomeration during the study period, which means that cities with high attention tend to be adjacent to each other while cities with low attention form contiguous clusters, yet the significance of such agglomeration effects is gradually weakening.

To address the limitation of the global Moran's I index, which only reflects the overall spatial agglomeration level rather than local spatial heterogeneity, this study calculated the local Moran's I indices in 2015, 2018, 2021 and 2024 using ArcGIS 10.2 and produced LISA cluster maps (Figure 3). The results indicate that high–high agglomeration areas exhibit obvious core polarization characteristics. They were predominantly distributed around the Yangtze River Delta, Pearl River Delta, and Beijing–Tianjin–Hebei metropolitan circle, forming three stable high-attention clusters from 2015 to 2021, while the agglomeration center shifted toward the Chengdu–Chongqing region in central and western China in 2024, which broke the long-term pattern of eastern China's absolute dominance. High–low agglomeration areas follow a single-core distribution pattern dominated by provincial capitals in central and western China. Provincial capitals such as Wuhan and Chengdu have evolved into regional growth poles by virtue of superior resources and communication advantages, yet their surrounding cities fail to achieve coordinated growth in network attention, leading to a polarized spatial pattern with high values in the central area and low values in peripheral regions. The number of low–low and low–high agglomeration areas remains quite small throughout the study period and the stable contiguous clusters were not formed. From the perspective of temporal evolution, the quantity of high–high agglomeration areas fluctuates over time, standing at 20 in 2015, dropping to 19 in 2018, rebounding to 20 in 2021, and declining sharply to only six in 2024. This finding verifies the balanced development trend that the network attention advantage of early-developed eastern regions is gradually weakening while the popularity of central and western regions is rising rapidly. The number of high–low agglomeration areas keeps decreasing from eight in 2015 to merely one in 2024, which implies that the isolated growth pole status of provincial capitals in central and western China has been weakened, and the trend of regional coordinated development has gradually emerged.

Table 2. Global Moran's I of rural tourism network attention in China from 2015 to 2024.

Year	Moran's I	Z-Score	p -Value
2015	0.1358	3.9980	0.0000
2016	0.1268	3.7084	0.0002
2017	0.1293	3.7769	0.0001
2018	0.0908	2.6829	0.0072
2019	0.0876	2.5942	0.0094
2020	0.0231	0.9686	0.3327
2021	0.0817	2.5469	0.0108
2022	0.0837	2.5064	0.0121
2023	0.0116	1.0865	0.2772
2024	0.0170	0.6011	0.5477

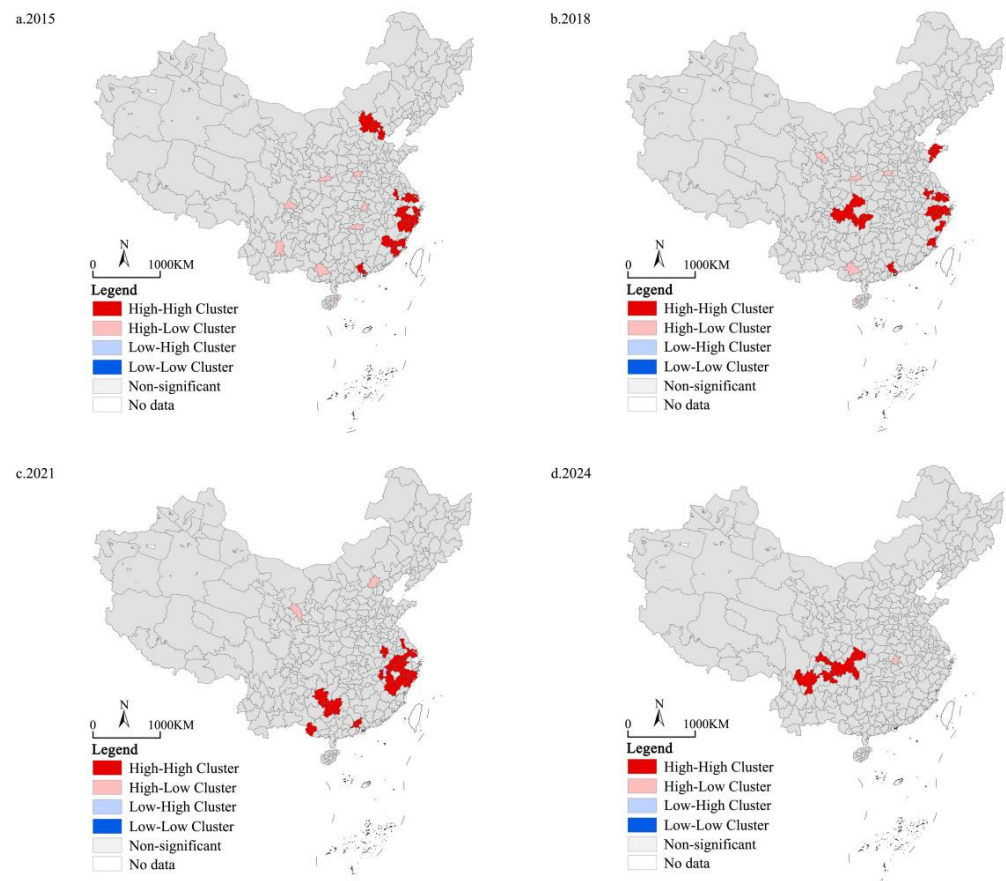


Figure 3. LISA cluster map of rural tourism network attention in China from 2015 to 2024.

4.2. Influencing Factors of Rural Tourism Network Attention

4.2.1. Variable Selection and Identification of Significant Impact Factors

Rural tourism is an emerging form of tourism carried out in rural areas. It shares common characteristics with traditional tourism projects, and its spatial pattern evolution is affected by the distribution of traditional tourist attractions. Meanwhile, it also possesses distinctive features, such as tourists mainly originating from urban areas and self-driving being the dominant travel mode [51]. On this basis, referring to existing relevant research and following the principles of scientificity and data availability for indicator selection, this study selects 16 indicators across six dimensions for analysis, namely natural climatic conditions, transportation development level, socio-economic development level, tourism development level, internet development level, and educational development level [5,36]. Among these dimensions, natural climatic conditions lay the foundation for the development of rural tourism, and a sound ecological environment serves as a crucial attraction for rural tourism [45]. The level of transportation development determines the spatial accessibility of rural tourism. Since rural tourism mainly relies on self-driving trips, highway transportation as the primary travel mode directly affects the accessibility of rural tourist attractions [2]. Socio-economic development level restricts residents' consumption capacity and travel intention. The growth of per capita disposable income drives rising market demand for tourism, and residents in economically developed regions tend to engage more actively in information retrieval and public attention toward rural tourism [50]. Tourism development level determines tourism supply capacity and market competitiveness. Tourism revenue provides capital for the sustainable development of the tourism industry, while tourism resources act as the core carrier of rural tourism development. Regions rich in high-quality tangible and intangible rural tourism resources generally exhibit stronger

rural tourism appeal [51]. The level of internet development affects the volume and enthusiasm with which tourists share their rural tourism experiences online. Regions with more developed internet infrastructure offer tourists diversified channels for information acquisition [62]. Individuals with higher educational attainment tend to have stronger travel intentions and information-seeking capabilities, which exert a more prominent driving effect on the growth of network attention toward rural tourism [52]. After variable selection, this study standardized the independent variables using the Z-score method via SPSS 27.0 software and conducted correlation analyses between the comprehensive network attention of rural tourism and each indicator respectively. The results reveal that all 15 factors are significantly correlated with rural tourism network attention except railway network density (Table 3).

Table 3. Descriptive statistics and correlation analysis of variables.

Dimension	Indicator Factor	Indicator Description	Mean	Std. Dev.	Pearson
Natural climatic conditions	Annual average temperature	Annual average temperature (°C)	15.268	5.882	0.091 *
	Annual precipitation	Total annual precipitation (mm)	992.733	556.637	0.103 *
	Air quality	Proportion of days with good and excellent air quality (%)	87.095	11.812	−0.101 *
Transportation development level	Highway network density	Highway mileage per hundred square kilometers of administrative area (km/100 km ²)	117.696	62.817	0.203 **
	Railway network density	Railway operating mileage per 100 square kilometers of administrative area (km/100 km ²)	3.621	7.142	0.033
Socioeconomic development level	Resident population	Year-end resident population (10,000 persons)	394.822	379.369	0.388 **
	Urbanization level	Urbanization rate (%)	61.373	14.056	0.183 **
	Regional economic level	Per capita GDP (yuan)	77,009.356	39,850.904	0.178 **
	Resident living standard	Per capita disposable income of urban residents (yuan)	44,803.660	10,803.237	0.280 **
Tourism development level	Tourist arrivals	Number of domestic tourist receptions (10,000 person-times)	5115.776	5966.228	0.395 **
	Tourism income	Total domestic tourism revenue (100 million yuan)	523.898	707.453	0.454 **
	Rural tourism resources	Number of national key rural tourism villages (quantity)	3.837	4.116	0.323 **
Internet development level	Fixed internet users	Number of fixed broadband internet access users (10,000 households)	183.090	193.205	0.380 **
	Mobile internet users	Number of mobile phone users (10,000 households)	487.741	563.760	0.390 **
Educational development level	Primary and secondary school students	Total enrollment of primary, junior high and senior high school students (person)	535,527	486,067	0.314 **
	Enrollment of university students	Total enrollment in higher education (person)	111,352	210,854	0.403 **

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$.

On the basis of correlation analysis, this study further constructs an ordinary least squares (OLS) model with the 15 influencing factors as independent variables and rural tourism network attention as the dependent variable to identify significant influencing factors. Specifically, we perform backward elimination OLS regression with a $p = 0.10$ threshold, conducting 11 rounds of iterative elimination to finally screen out four significant influencing factors. The model results show that the goodness of fit is 0.215 and the variance inflation factor (VIF) of each parameter is less than 5, indicating no multi-collinearity and reasonable model setting. Finally, four factors are identified to exert significant effects on rural tourism network attention, namely highway network density, tourism income, rural tourism resources and enrollment of university students (Table 4).

Table 4. Parameter estimation and test results of the OLS model.

Variable	B	t	VIF
Highway network density	0.094 *	1.851	1.167
Tourism income	0.223 **	2.185	4.693
Rural tourism resources	0.118 *	1.760	2.037
Enrollment of university students	0.160 **	1.983	2.953
Adjusted R ²		0.215	
Durbin–Watson		2.108	
Sample size		356	

Note: B refers to the standardized coefficient; t refers to the result of t-test; * indicates $p < 0.10$, ** indicates $p < 0.05$; VIF refers to the result of multi-collinearity test; blank means no corresponding item.

4.2.2. Analysis of GWR Results

For the reason that the OLS model can only reveal the global average influence degree of each influencing factor while ignoring the spatial heterogeneity of regression coefficients, this study further employs the GWR tool embedded in ArcGIS 10.2 software to conduct geographically weighted regression analysis on the four significant factors affecting rural tourism network attention on the basis of identifying significant influencing factors via the OLS model (Table 5). This paper explores the influence magnitude and spatial heterogeneity of each factor on rural tourism network attention, and visualizes the parameter estimates spatially by adopting the Jenks Natural Breaks Classification method.

Table 5. The parameter estimation and test results of GWR model.

Model Parameter	Value
Bandwidth	2040115.871
ResidualSquares	0.109
Sigma	0.017
AICc	−1851.508
R ²	0.236
Adjusted R ²	0.217

The impact of highway network density on rural tourism network attention presents a differentiated pattern featuring high coefficients in southern and northeastern border regions, as well as low values in the inland northwest and eastern plains (Figure 4a). The influence coefficients ranged from 0.001625 to 0.002137, with a mean value of 0.001774. Specifically, high-impact zones are concentrated in southern border areas and northern Northeast China, which feature rugged terrain and dispersed rural tourism resources. Accordingly, marginal upgrades to highway infrastructure deliver far greater gains in spatial accessibility within these regions. For instance, rural tourist destinations in Yunnan, Hainan, Heilongjiang and other regions are mostly located in remote ethnic villages or forested

areas. Restricted by poor transportation in the past, these places were difficult for potential tourists to reach. A moderate increase in highway network density can directly alleviate travel accessibility constraints, substantially reduce travel costs, and accordingly drive a rapid rise in network attention toward local rural tourism. In contrast, highway network construction in the North China Plain started early with a high baseline density, so the marginal effect of further infrastructure improvement diminishes markedly. Rural tourism in the middle and lower reaches of the Yangtze River has entered a mature development stage, where network attention is mainly driven by content marketing, product innovation and other factors, thus diluting the fundamental impact of highway networks. Although the highway network density in inland northwest China remains relatively low, constraints such as small population size, insufficient tourist source markets and low resource exploitation make it difficult for transportation improvements to be translated into actual tourist trips and online popularity.

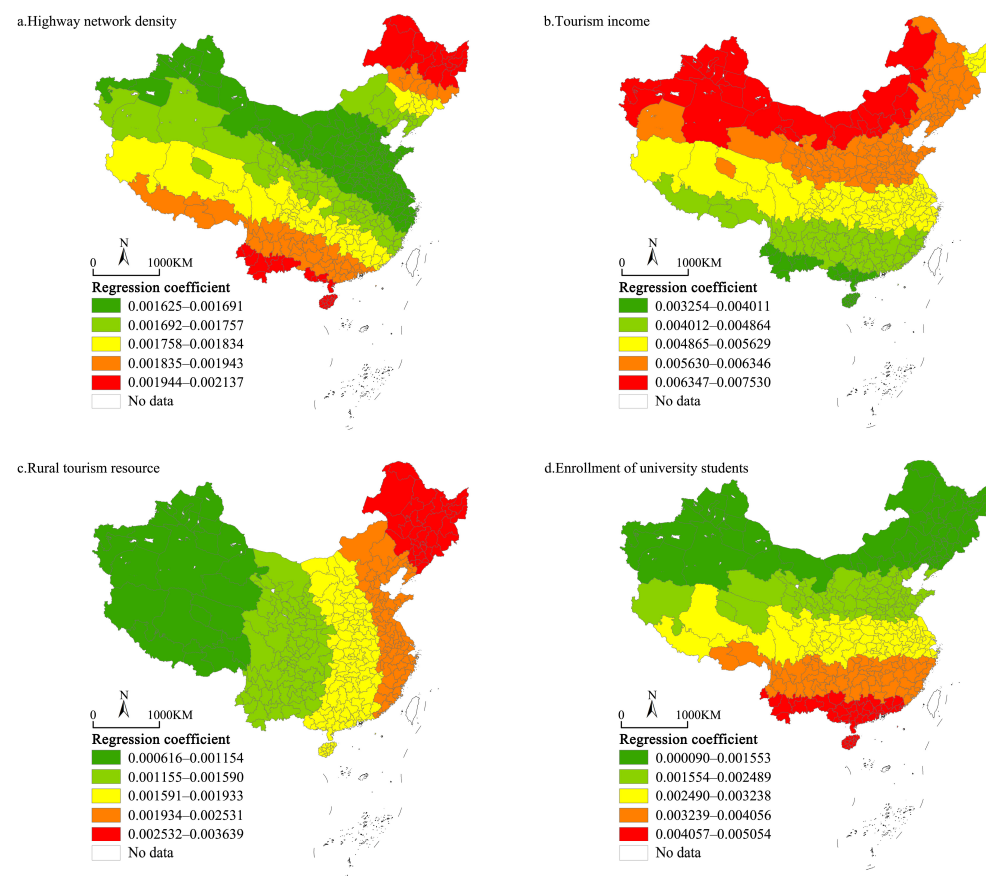


Figure 4. Spatial pattern of GWR coefficients.

The impact of tourism income on rural tourism network attention shows a remarkable spatial differentiation pattern of strong effects in northern China and weak effects in southern China (Figure 4b). The influence coefficients range from 0.003254 to 0.007530, with a mean of 0.005324. All regression coefficients across the study area are positive, which indicates that the growth of tourism income generally exerts a positive driving effect on rural tourism network attention, while the intensity of such influence varies distinctly across different regions. Since the tourism industry in northern China is still in a stage of rapid overall expansion and the growth of tourism income can be directly converted into investment in destination marketing, infrastructure upgrading and brand promotion, network attention can be significantly boosted by expanding market exposure and optimizing tourist experience. In contrast, the tourism economy in southern China is

more mature, and rural tourism has established a stable tourist base and brand reputation. Its online popularity is driven by multiple factors such as content marketing, product innovation and social media communication. Therefore, the marginal pulling effect of tourism income growth on network attention is relatively weakened, demonstrating that the higher the industrial maturity, the more diluted the fundamental impact of tourism income.

The impact of rural tourism resources on rural tourism network attention presents a typical spatial differentiation pattern with strong effects in eastern China and weak effects in western China (Figure 4c). The influence coefficients ranged from 0.000616 to 0.003639, with a mean of 0.001815. All regression coefficients across the whole study area are positive, which means that the abundance of rural tourism resources exerts a sustained and stable positive influence on network attention. Boasting highly concentrated and diversified rural tourism resources and early-developed branding and standardization systems, the eastern region hosts abundant high-quality tourism resources, including national key rural tourism villages and leisure agriculture demonstration counties. These superior resources effectively form industrial cluster effects and generate online communication hotspots, thereby greatly stimulating tourists' information retrieval and attention demands. Furthermore, supported by mature digital platforms and a comprehensive publicity system, the eastern region has established an efficient transformation mechanism that converts inherent resource endowments into online popularity, ultimately producing a significantly stronger driving effect of tourism resources on rural tourism network attention. In contrast, despite possessing distinctive rural tourism resources, western China is constrained by scattered resource distribution, shallow development, low brand recognition and insufficient publicity promotion. These deficiencies hinder the transformation of inherent resource advantages into stable and sustained network attention. Moreover, restricted by a limited source market and low tourist activity in online retrieval and communication, the positive driving effect of resource endowments on rural tourism network attention is further weakened, resulting in an overall low influence intensity in western regions.

The influence of enrollment of university students on rural tourism network attention presents a spatial differentiation pattern of strong effects in southern China and weak effects in northern China (Figure 4d). The influence coefficients range from 0.000090 to 0.005054, with a mean of 0.002789. All regression coefficients across the study area are positive, indicating that the expansion of university student scale universally exerts a positive driving effect on rural tourism network attention. Universities are densely distributed in southern China, where the large group of college students maintains high activity in online social interactions. As the core source market for short-distance rural tourism, college students also serve as the main creators and disseminators of travel content on new media platforms including Douyin, Xiaohongshu and Weibo. They are inclined to share travel experiences and practical guides on social networks, generating prominent online drainage effects through secondary communication and directly boosting the search volume and public attention of rural tourist destinations. In contrast, northern college students show relatively low enthusiasm for online information retrieval, content sharing and communication related to rural tourism. On the one hand, constrained by regional climatic conditions and consumption habits, northern students participate in short-distance rural trips less frequently than their southern counterparts. On the other hand, the online operation system and content communication ecosystem of rural tourism in northern regions are relatively underdeveloped, which fails to fully stimulate college students' willingness to create and share relevant content. Consequently, the driving effect of enrollment of university students on rural tourism network attention is far weaker in northern China than in the south.

5. Conclusions and Discussions

5.1. Conclusions

In this study, multi-source data from search engines, social media, tourism websites and short-video platforms are integrated to construct a comprehensive indicator system for rural tourism network attention. This study systematically reveals the spatio-temporal evolution patterns and driving mechanisms of rural tourism network attention by adopting spatial autocorrelation and geographically weighted regression (GWR) methods. The main conclusions are as follows:

From the temporal perspective, rural tourism network attention is featured by phased evolution coupled with the continuous iteration of media patterns, and its temporal changing trend is jointly dominated by market demand, external environment and media technology. More specifically, its evolutionary trajectory complies with general market development rules and can be divided into three distinct stages. To start with, public participation was relatively limited and network attention rose steadily at a low rate during the incubation period. Subsequently, the concentrated release of short-distance tourism demand brought network attention to a stage of explosive growth driven by consumption transformation and external events. Eventually, as the market entered a mature stable state, the overall popularity declined slightly and fluctuated persistently at a high level. From the perspective of communication structure, media iteration has continuously reshaped the pattern of traffic distribution. The influence of traditional search platforms has gradually diminished, while emerging media including social media and short-video platforms that integrate content creation, real-time interaction and social communication have become the core traffic channels. This rule verifies that the innovation of media forms has restructured the cultural tourism information communication system, and tourists' diversified online behaviors have in turn promoted the continuous upgrading of communication carriers for cultural tourism.

From the spatial dimension, rural tourism network attention has evolved from geographically polarized gradient distribution to overall spatial equilibrium. The dynamic game between geographical and economic constraints as well as the empowerment of digital communication has reshaped its overall spatial pattern. In the early stage of development, the spatial distribution of rural tourism network attention conformed to the law of economic gradient differentiation with highly developed urban agglomerations forming high-attention core areas, while remote and underdeveloped regions presented contiguous low-value zones. Relying on the agglomeration advantages of resources and information, regional central cities evolved into local hotspots, forming a typical core-periphery spatial structure. In the middle and later stages of development, the decentralized communication mode of digital media broke the communication barriers restricted by geographical location and economic conditions. Many rural peripheral regions with distinctive cultural and tourism resources gained online exposure through short videos, live streaming and social content sharing. This change directly promoted the outward expansion of early high-attention areas to peripheral regions and areas with characteristic resources. Meanwhile, the degree of spatial agglomeration gradually decreased and local polarization was continuously weakened, indicating that rural tourism network attention is moving toward spatially balanced development across the whole study area.

The spatio-temporal evolution of rural tourism network attention is jointly driven by multiple factors, whose influencing intensities exhibit significant spatial heterogeneity. The efficiency derived from the optimization of transportation infrastructure complies with the law of diminishing marginal utility. That is to say, transportation upgrading yields more prominent benefits in regions featuring underdeveloped road networks and scattered resource distribution, whereas such marginal gains gradually diminish in areas

equipped with sophisticated transportation systems. The scale-driven enabling effect of the tourism industry is closely tied to the industrial life cycle. In regions in the stage of industrial expansion, rising tourism income can be rapidly transformed into brand marketing advantages and online traffic, while regions with mature tourism industries predominantly rely on content innovation to sustain online popularity. The conversion efficiency of tourism resource endowments into network attention hinges on regional market operation capacity and all-media communication capability. Areas with well-established brand development and comprehensive publicity frameworks are capable of translating inherent resource advantages into online popularity with higher efficiency. Furthermore, the driving role played by young demographic groups depends on the local new media ecosystem and social communication context, and regions with vibrant online communication demonstrate a more salient promotional effect of young populations on rural tourism network attention.

5.2. Discussions

Does multi-source fused data facilitate a more accurate depiction of the spatio-temporal pattern of rural tourism network attention? Compared with traditional single-platform data sources such as Baidu Index and independent short-video datasets widely adopted in prior literature, the regional heterogeneity of rural tourism network attention derived from multi-source fused data is remarkably reduced, and the spatial gradient of online popularity is more consistent with the actual development landscape of the rural tourism industry. Existing studies relying solely on single platforms have generally verified that rural tourism network attention fluctuates upward alongside industrial development [32,36,68], yet such mono-source data overstate inter-regional gaps and overestimate the degree of spatial polarization, which partially explains why the Moran's I values calculated from single-platform data in existing literature remain persistently high and rarely exhibit a sustained declining trend. In contrast, this study's multi-source integrated dataset captures cross-platform user behaviors covering search, reading, posting and interaction, which can reasonably interpret the gradual weakening of spatial agglomeration reflected by the continuously falling Global Moran's I from 2015 to 2024. On the one hand, the rise in short-video and social media breaks the information monopoly of economically developed urban agglomerations; remote peripheral regions with distinctive rural cultural resources can gain nationwide online exposure through decentralized content dissemination, disrupting the long-term contiguous low-value clustering pattern in inland underdeveloped zones. On the other hand, nationwide coordinated rural tourism development has fostered emerging high-attention growth poles centered on central and western provincial capitals, narrowing the spatial divide between high-value and low-value areas year by year. The dual effects of digital media decentralization and balanced industrial development jointly drive the fluctuating downward trajectory of Moran's I . Fundamentally, single data sources are confined to narrow user groups and fixed behavioral scenarios, producing homogeneous audience samples that exaggerate regional divergence and induce biased judgments of spatial patterns [33,35]. By integrating search engines, social media, travel OTA websites and short-video platforms, the composite index in this paper offsets the inherent defects of single platforms, including limited user coverage and biased audience composition, neutralizes extreme deviations from individual channels, and reproduces the authentic spatial distribution of rural tourism online attention [15,26,29].

Does scale difference affect the spatial distribution of rural tourism network attention? Scale dependence is a fundamental property of tourism geographic spatial patterns and a core research agenda in regional tourism studies [2]. Most previous empirical works adopt small- and medium-scale spatial units such as individual provinces, urban agglomerations

or scenic clusters, which amplify local differentiating factors, including resource endowments, geographic location and regional marketing capacity, and thus derive an obvious core–periphery polarized pattern of network attention [5,24,25,46]. Such scale-limited observations have long dominated mainstream academic cognition of rural tourism spatial characteristics, yet they cannot be generalized to national macro contexts due to strong local interference effects. Distinct from small-/medium-scale case studies, this paper takes all 356 prefecture-level cities nationwide as macro research units and systematically compares its spatial differentiation findings with conclusions from regional micro and meso research. At the national macro-scale, heterogeneous local advantageous and restrictive factors across different regions mutually counteract one another [8]. Coupled with the decentralized communication advantages of short-video and social media platforms [26,30,69], the highly agglomerated and polarized spatial structure observed at small and medium scales gradually fades, and a nationwide balanced development trend emerges prominently. This scale discrepancy directly accounts for the inconsistent spatial evolution conclusions between existing localized research and this national macro research. The comparative analysis across spatial scales clarifies the scale-dependent nature of rural tourism network attention's spatial differentiation, provides explicit references for follow-up research to select appropriate research scales and define the boundary of result applicability, and promotes the shift in relevant spatial differentiation research from isolated single-scale analysis to a unified multi-scale comparative analytical framework.

Combined with the spatial heterogeneity of the four core influencing factors reflected by GWR coefficients, and differentiated targeted strategies to elevate rural tourism network attention are proposed for four regional zones. For southern and northeastern border regions where highway network density exerts the strongest driving effect, local governments should take transportation optimization as the core breakthrough. By constructing interconnected rural tourist highways, marking remote characteristic villages on navigation platforms and launching self-driving travel routes via short-video channels, regions can convert improved traffic accessibility into sustained online search heat and moderately increase tourism marketing budgets to support online publicity for scattered rural tourism resources. For northern regions with tourism income as the leading influencing factor, local authorities ought to allocate a fixed share of tourism revenue to digital marketing investment. Special funds can be used for unified regional rural tourism live streaming and themed short-video production, amplifying online exposure relying on industrial scale advantages; meanwhile, tapping ice–snow and pastoral rural resources and launching student preferential travel activities can compensate for insufficient youth online communication power. For eastern coastal urban agglomerations dominated by rural tourism resource endowment, the core task lies in accelerating the transformation of resource advantages into online popularity. Local operators can integrate clustered leisure agriculture and boutique homestay resources into serialized tourism products and build cross-platform content matrices on travel websites and short-video platforms to trigger spontaneous user sharing, while only carrying out minor upgrades of rural road supporting facilities given the diminishing marginal return of transportation construction. For southern regions with dense university groups where student enrollment has the most prominent promotion effect on network attention, local governments should establish stable school–locality collaborative mechanisms. By launching student-exclusive rural tourism routes and setting UGC creation incentives, college students can be mobilized as the main force of online content dissemination, and matched improvements in rural branch roads and characteristic rural resource development can provide richer shooting and travel materials for youth creators.

This study acknowledges three key limitations. First, it is limited by platform data access permissions and web-scraping technologies, the time coverage of each dataset

varies, which undermines the integrity of long-term evolutionary analysis and reduces the depth of longitudinal comparative research. Meanwhile, different online platforms have distinct user demographic structures, which may bring sampling bias to the composite rural tourism network attention index constructed by multi-source fusion data. Second, the study only incorporates socio-economic indicators to quantify driving forces, while omitting episodic, context-dependent unstructured variables including cultural tourism festivals, industrial policies, viral social media events and public health emergencies. This omission restricts the model's capacity to interpret short-term volatility in rural tourism network attention. Meanwhile, potential endogeneity stemming from bidirectional causality may exist among several explanatory variables. Appropriate instrumental variables will be adopted in follow-up studies to reduce endogeneity bias and yield more robust causal inference conclusions. Thirdly, the current GWR framework is purely cross-sectional and static, without constructing a geographically and temporally weighted regression (GTWR) model, making it difficult to capture the spatio-temporal heterogeneity of driving factors simultaneously across both time and space [70]. In future research, the time series of multi-platform data can be further extended. By integrating machine learning, natural language processing, sentiment analysis and other methodologies, unstructured big data can be combined with socio-economic statistical data to deepen research on the formation mechanism, dynamic simulation and prediction of network attention toward rural tourism.

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