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Original Research

Study on the Spatiotemporal Differentiation of Traditional Villages and the Factors Influencing Tourism Responsiveness: A Case of Three Provinces and One Municipality in the Yangtze River Delta Region of China

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Abstract

The development of traditional village tourism destinations is an effective way to ensure the inheritance and development of traditional villages. Scientific analysis of the spatial and temporal distribution patterns and influencing factors of traditional villages can provide a scientific basis and decision-making reference for the protection and development of traditional villages. This study focuses on the development of traditional village tourism in the Yangtze River Delta region, including the provinces of Anhui, Jiangsu, and Zhejiang, and the city of Shanghai, and evaluates the tourism responsiveness of village attributes, ecology, socio-economics, and tourism vitality using 14 indicators. This study investigated the spatial and temporal differentiation characteristics of traditional villages at different spatial scales in the Yangtze River Delta region using entropy, TOPSIS, spatial autocorrelation analysis, and a geographic detector. Key findings included (1) spatial differentiation of "high in the southeast and low in the northwest"; (2) Jiangsu leading in tourism responsiveness and Anhui lagging behind; (3) low tourism responsiveness despite the abundance of resources in traditional villages; and (4) the vitality of tourism and the socioeconomic environment are crucial to responsiveness. In summary, although traditional villages are distributed in clusters, their tourism economic potential is still not fully tapped.

Keywords: Yangtze river delta region, traditional villages, spatiotemporal differentiation, influencing factors, tourism responsiveness

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Introduction

Traditional villages (TVs) represent resilient cultural and material composite legacies of agrarian civilizations, encapsulating the traces of village history and civilizational advancement. They constitute vital spaces for rural life and production. Moreover, safeguarding these TVs holds significant value in advancing rural revitalization initiatives [1-2]. However, the degree of tourism in TVs varies across different regions, where their tourism development and utilization are influenced not only by their resource endowments but also profoundly impacted by the regional societal and economic milieu, as well as the level of tourism development [3-4]. Internationally, research on villages by foreign scholars begins at an earlier stage. Körl, in his work 'The Relationship between Human Settlements, Residence, and Topography' mentioned 'human settlements' while Schultze introduced the concept of 'settlement geography' for the first time. Since 2012, research on TVs in China has been continuously enriched, and the growing emphasis on the preservation and development of TVs in China has led to an increasing volume of research in this area [5-6]. Against the backdrop of rapid social changes, the current state of TV preservation in our country remains less optimistic. Issues such as material, demographic, and cultural hollowing out, ecological degradation, cultural discontinuity, and excessive commercialization have emerged, all of which impede the sustainable development of TVs [7]. Therefore, how to revitalize TVs and infuse them with vitality from the inside out has become a hot topic of academic interest [8-9]. Tourism development serves as a significant approach to the conservation and revitalization of the TV. The tourism responsiveness (TR) of TVs is a symptom of the tourism of heritage resources. The magnitude of this responsiveness serves to evaluate both the current status and potential of the tourism development of TVs. Moreover, it also reflects the degree of transformation of TVs into tourist destinations [10]. The study of TR in TVs holds significant practical implications for the heritage preservation of settlements within a watershed, the enhancement of human habitats, and the revitalization of the TV [11].

Currently, research on TVs has garnered widespread attention across various sectors of society and, therefore, more relevant analyses. The specific content of this research can be summarized as the construction of an evaluation of indicator systems for research subjects [12], clarification of research scales, and the innovative application of research methods [13]. Specifically, research on TVs primarily focuses on various aspects. These include the spatial distribution characteristics of a TV [14], influencing factors of spatial distribution [15], development and evolution [16], landscape morphology [17], the evolution of a TV, and the development of tourism in TVs [18]. TVs are scattered across various regions in China, and their spatial distribution exhibits variations due to regional disparities. Research scales encompass multiple levels of spatial differentiation patterns, including national, regional, watershed, cultural area, provincial scales, etc. [19]. In the realm of methodologies, numerous approaches are employed to uncover their distribution characteristics, such as GIS spatial analysis tools [20], kernel density analysis [21], nearest neighbor index [22], spatial autocorrelation [23], Gini coefficient [24], or standard deviation ellipse [25]. Furthermore, the analysis of influencing factors involves the use of methods such as buffer analysis [26], Geographically Weighted Regression (GWR) [27], Geographically and Temporally Weighted Regression (GTWR) [28], and geographic detectors [29]. Unfortunately, the research on TVs still encompasses several aspects that warrant further investigation. Firstly, many existing studies are conducted at the same scale, calling for the exploration of TV spatial characteristics from a multiscale perspective of the same study region. There is a need for supplementary research on the spatial distribution characteristics of densely populated TVTA (such as the Yangtze River Delta region (YRDR) and the effects of relevant factors [30-31]. Secondly, while considerable theoretical achievements have been made in studying the relationship between TVs and tourism [32], there is a requirement to strengthen quantitative analyses of their specific relationship. The distinct tourism value inherent to TVs continually attracts diverse protective practices from various sectors of society, which holds particular significance and offers valuable insights for the future development of other TVs. Thirdly, the existing research tends to concentrate on the overall spatial distribution and influencing factors of TVs within specific regions, with relatively less attention given to TVs in various areas that have already successfully undertaken tourism practices [33]. An imbalance in research areas exists where the study on the spatial distribution of TVs at the smaller provincial and municipal scales is inadequate. Fourthly, in terms of temporal analysis, the prevailing approaches often employ a single representative year or relatively short time span, often using multi-year averages. This approach tends to only analyze the temporal or spatial dimension, lacking a systematic description of the regional Traditional Village Tourism Responsiveness (TVTR) [34]. Presently, there is limited research in China specifically focused on TVTR. Constructing a suitable set of evaluation indicators conducive to the tourism transformation of TVs constitutes an essential methodological foundation for researching TVTR.

Previous research has proposed potential methods to achieve this goal. Multiple studies on the TR of TVs primarily focus on spatiotemporal differentiation [35], TR [36], and analysis of influencing factors [37]. This study is built upon the achievements of predecessors and addresses research gaps, centered on the YRDR and comprehensively considering the complexity across provincial boundaries. Data from the years 2012, 2013, 2014, 2016, 2019, and 2022 are selected. Nine evaluation indicators are chosen from four domains: village resource endowment, socio-economics, ecological environment, and tourism vitality. The EM is applied to determine indicator weights, TOPSIS is used to calculate TVTR, and ArcGIS 10.8 is employed for visualizing spatial differentiation of TVTR across various scales. Additionally, the geographic detector is employed to identify and analyze key driving factors in the spatiotemporal differentiation of TVTR in the YRDR. The objective of this research is to provide scientific reference points for the development, conservation, and holistic coordination of TVs in the YRDR.

Materials and Methods

Study Areas

This study encompasses the YRDR in China, as depicted in Fig. 1. The YRDR is situated between 32°34'—29°20'N and 115°46'—123°25'E, representing the largest deltaic plain and alluvial plain in China. With numerous coastal ports along the river, it serves as a pivotal economic growth center in the eastern region of the country. The study period spans from 2012, 2013, 2014, 2016, and 2019, to 2022. The three provinces and one municipality of the YRDR, covering a total area of approximately 358,000 square kilometers, include Shanghai, Jiangsu, Zhejiang, and Anhui. In accordance with the latest 'Development Plan of the YRDR Urban Agglomeration,' and considering the distribution of TVs within the three provinces and one municipality of the YRDR, the study narrows its focus to 41 cities in the region and explores the functional divisions within the YRDR urban agglomeration.

Research Method and Process

Research Methodological Framework

In this study, we present a novel approach to establishing an indicator system for TV tourism from the perspective of new developmental concepts. Our empirical study employs the entropy-weighted TOPSIS method and nearest neighbor index analysis. We conduct research on the spatiotemporal distribution of TVTR in the YRDR, using relevant data from the National Bureau of Statistics of the People's Republic of China. Data preprocessing is conducted, incorporating various dimensions of TVTR evaluation into the indicator system. We establish a framework comprising four dimensions, which include village resource endowment, ecological environment, socio-economics, and tourism vitality. The EM is subsequently utilized to ascertain the individual importance of each indicator. Thereafter, the TOPSIS is employed to evaluate the alignment between the TVTR assessment and the most favorable resolution. Employing comprehensive evaluation scores and analyzing various dimensions of TVTA development, we conduct an assessment and analysis of TVTA development in the YRDR. Furthermore, we explore the spatiotemporal evolution trends of six batches of TVs. Finally, the Geographic Detector method is employed to discern the driving factors among TVs. The procedural diagram of the mapping approach is depicted in Fig. 2.

Evaluation Methodology

The entropy method (EM) is employed to ensure the weights of indicators, and TOPSIS is utilized to compute the TVTR in the YRDR. ArcGIS 10.8 is employed to visually express the spatiotemporal differentiation of TVTR across various scales. Additionally, the Geographic Detector approach is employed to probe the determinants affecting the spatial variances of TR among TVs within the drainage basin [38].

Indicator Standardization Processing

Various indicators possess distinct units and dimensions, rendering direct comparison and calculation unfeasible. Therefore, before calculating the weights of each indicator, we tend to standardize the indicators.

For positive-oriented indicators, the formula for standardization is:

$$\dot{x_{ij}} = \frac{x_{ij-i}min\{x_{ij}\}}{{}_{i}max\{x_{ij}\}-{}_{i}min\{x_{ij}\}} \quad (1)$$

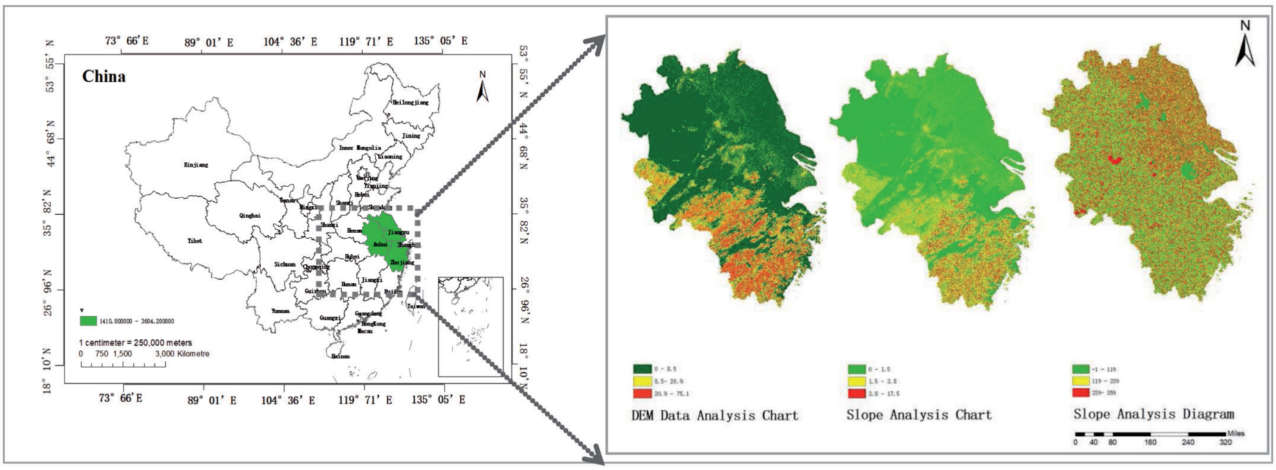

Fig. 1. Study area introduction.

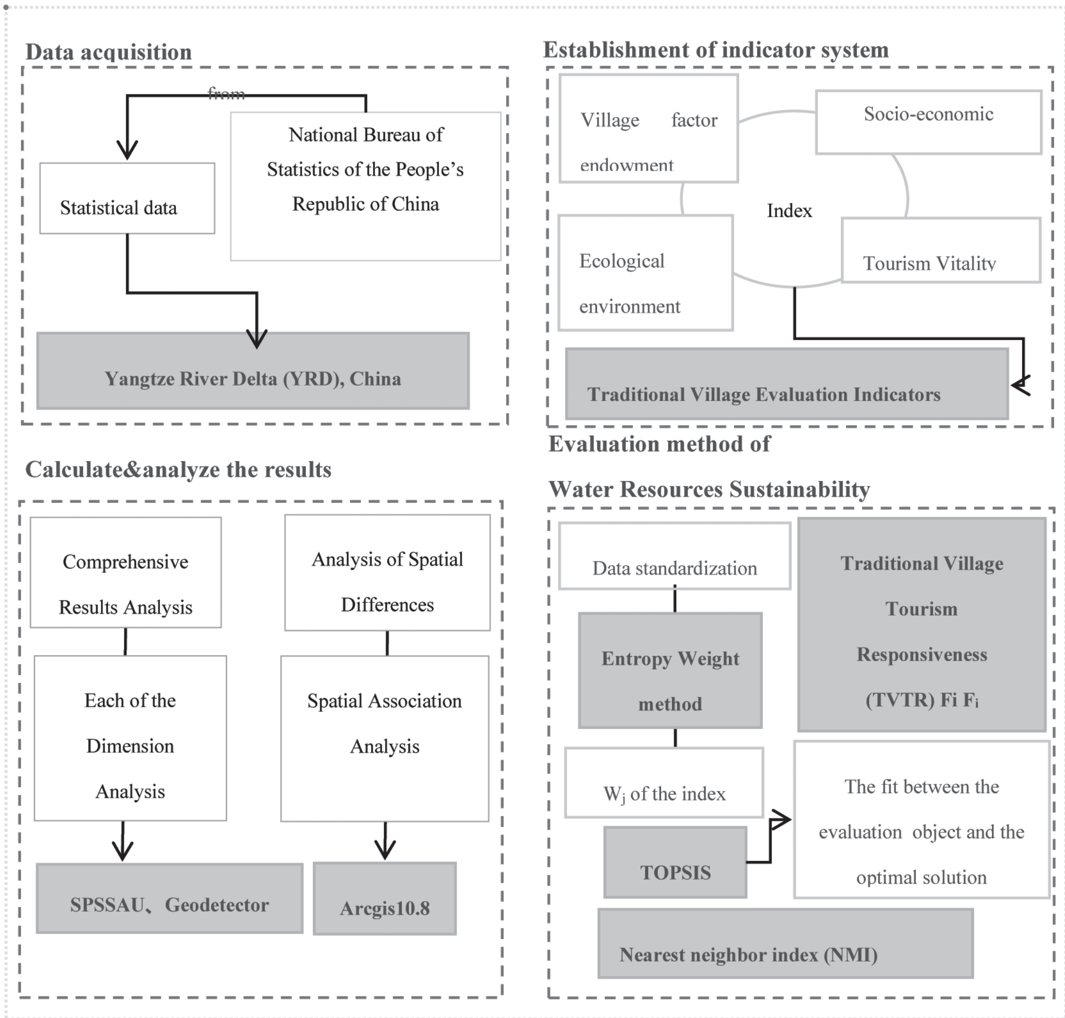

Fig. 2. Methodology flow chart.

For negative-oriented indicators, the formula for standardization is:

$$x_{ij}^{`} = \frac{{}_i^{min}\{x_{ij}\}-x_{ij}}{{}_i^{max}\{x_{ij}\}-{}_i^{min}\{x_{ij}\}} \quad (2)$$

The first step involves standardization, and the formula for standardization is:

$$Y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

yij represents the standardized indicator value after nondimensionalization for the jth indicator of the ith unit; xij stands for the original value of a specific sub-evaluation indicator; i denotes the ith (i=1,2,⋯,n) assessment region; j signifies the jth (j=1,2,⋯ ⋯,m) sub-evaluation indicator. Among the 14 indicators, all except the third indicator are positive-oriented.

Entropy Method for Weight Determination

The entropy weight method (EWM) is an objective assignment technique relying on the inherent discreteness of the data. The weight assigned to each evaluation indicator increases as the degree of discreteness of the indicator itself increases [39]. The core concept of this method is to standardize all indicators and sort them in order of their superiority or inferiority using the TOPSIS method. In this study, data processing is conducted using SPSSAU software, employing the EWM to determine the weights of sustainability evaluation indicators for water resources in China's western region.

The first step involves calculating the information entropy value for the jth indicator using the following formula:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} Y_{ij} \ln Y_{ij} \quad (4)$$

The second step entails calculating the information utility value using the following formula:

$$d_j = 1 - e_j \quad (5)$$

The third step entails deriving the weight of the jth indicator using the formula:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (6)$$

After computing the entropy values, the weights for the ith evaluation indicator are then determined according to the formula (Table 1).

$$W_j = \frac{1-H_j}{m-\sum_{i=1}^{m} H_i}, \text{ where } \quad W_i \leq 1, \qquad W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (7)$$

In this context: ej denotes the entropy value for the jth metric; dj symbolizes the superfluity of the entropy information for the same metric, commonly known as the coefficient of variation, where a larger figure suggests heightened significance; Wj signifies the weighting assigned to the jth metric, and wj represents the assigned weight to the ith metric.

Calculating Responsiveness Using the TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method that ranks alternatives based on their closeness to an ideal solution. It is widely applied in systems engineering to evaluate and prioritize options in the presence of multiple, often conflicting, objectives [40]. It is an approximate ideal value ranking method suitable for assessing superiority and inferiority based on multiple indicators and various alternatives. The method utilizes the Euclidean distance between the alternatives and the positive and negative ideal resolutions to quantify the advantages and disadvantages of each alternative.

The TOPSIS method is applied to comprehensively evaluate the overall situation of the 41 cities (prefectures) within the YRDR urban agglomeration. Firstly, the positive and negative ideal solutions are computed [41]. Secondly, the distances between the indicator data for each city and the optimal and worst scenarios are calculated. Lastly, the proximity degree 'fi' is determined based on the computed ideal optimal and worst-case solutions. The 'fi' ranges between 0 and 1, with larger values indicating higher levels of TVTR in the respective region.

Firstly, the original matrix is constructed and normalized to obtain the canonical decision matrix:

$$B = \left(b_{ij}\right)_{mn} \quad (8)$$

Secondly, forming the weighted normalized matrix, where the weight vector is denoted as W=[W_1,W_2,⋯,W_n]^T, as computed using the EWM:

$$C_{ij} = W_j \cdot b_{ij}, i = 1,2, \cdots, m; j = 1,2, \cdots, n \quad (9)$$

Where cij represents the weighted normalized matrix, wj signifies the weight, with i representing the sample value and j representing the indicator value.

Third, the process involves identifying the positive ideal outcome C* and the negative ideal outcome C0. Presuming the jth attribute value for the positive ideal outcome C* is Cij, and for the negative ideal outcome C0 it is c0j, the equation used to calculate the positive ideal outcome is:

$$Y^+ = \left(maxY_{i1} maxY_{i2} \cdots maxY_{ij}\right) \quad (10)$$

The formula for computing the negative ideal solution is:

$$Y^- = \left(minY_{i1} minY_{i2} \cdots minY_{ij}\right) \quad (11)$$

Here, Y+ signifies the positive ideal outcome and Y- denotes the negative ideal outcome; i and j correspond to the sample and indicator values, respectively.

Fourth, the step entails computing the distances that separate each alternative from both the positive and negative ideal outcomes.

$$s_i^+ = \sqrt{\sum_{j=1}^{n} \left(c_{ij} - Y^+\right)^2} \quad i = 1,2, \cdots, m \quad (12)$$

$$s_i^- = \sqrt{\sum_{j=1}^{n} \left(c_{ij} - Y^-\right)^2} \quad i = 1,2, \cdots, m \quad (13)$$

In this context, Cij signifies the weighted and normalized figure for the jth metric concerning the ith option; s+i and s-i stand for the positive and negative ideal values, respectively, for the jth metric across all available alternatives.

Fifthly, calculate the proximity degree for each alternative, i.e., the TR score for each city within the YRDR. The formula is:

$$f_i^* = \frac{s_i^0}{s_i^0 + s_i^*} \quad i = 1,2, \cdots, m \quad (14)$$

Where a larger fi indicates that the level of the ith evaluation alternative is closer to the optimal level.

Nearest Neighbor Index

The Nearest Neighbor Index method, also known as Nearest Neighbor Distance Analysis, is a method used to assess the distribution pattern of point geographical features by comparing the value of the average nearest neighbor distance with the theoretical nearest neighbor distance [42-43]. It employs the Completely Spatially Random Pattern (CSR) as a reference for comparison. When the observed pattern's nearest neighbor distance is greater than that of a random distribution, the pattern is dispersed; when it is less, the pattern is clustered [36]. The formula to calculate this is as follows:

$$R = \frac{r_{obs}}{r_{exp}} = \frac{\frac{\sum_{i=1}^{n} d_{min}(s_i)}{n}}{\frac{1}{2\sqrt{n/A}}} = \frac{2\sqrt{p}}{n} \sum_{i=1}^{n} d_{min}(s_i) \quad (15)$$

Here, R designates the Nearest Neighbor Index value, rF symbolizes the empirically observed nearest neighbor distance, and rE represents the theoretical nearest neighbor distance. The variable n counts the number of villages, dmin indicates the minimum observed distance between two TVs, and A refers to the area of the region in question. An R value greater than 1 signals a random dispersion; less than 1 implies clustering and an R value of 1 indicates uniform distribution.

Table 1. Indicators of TV Tourism Development in the YRDR.

Criterion Layer	Indicator Layer	Unit	Attributes	Weight	Code	Level
Physical Geography	Average Temperature	℃	+	0.038	X1	5
	Average Precipitation	mm	+	0.091	X2	5
Socioeconomic	Per capita GDP	yuan per person	+	0.076	X3	5
	Per capita disposable income in rural areas	CNY	+	0.082	X4	5
Ecological Environment	Forest Coverage	%	+	0.091	X5	5
	Total Water Resource	billion cubic meters	+	0.156	X6	5
Tourism Virality	National AAAAA Class Scenic Spot		+	0.126	X7	5
	Cultural and Tourism Expenditure	10K CNY	+	0.248	X8	5
	Public Service Expenditure	10K CNY	+	0.092	X9	5

Kernel Density Analysis

Kernel Density Analysis computes the point feature density across each resulting raster, offering a visual depiction of TV's clustering and dispersal [44]. The corresponding equation is:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x-x_i}{h}\right) \quad (16)$$

In this equation, k $\left(\frac{x-x_i}{h}\right)$ serves as the kernel density function, h signifies the bandwidth, n counts the points within the threshold radius, and (x-xi) indicates the distance separating the estimation point x from the occurrence xi.

Geographical Detector

The Geographical Detector, a statistical approach, is employed to investigate spatial discrepancies and the underlying causes [45-46]. Currently, it is mainly applied in research fields such as land use, public health, regional economics, regional planning, tourism, archaeology, etc. The central premise determines that if an explanatory variable substantially affects the spatial fluctuation of a dependent variable, then a notable resemblance should exist between the spatial distributions of both variables. In this study, this model is employed to detect the influencing factors of spatial variation in TVTR across 35 cities in the YRDR. By discerning the varying influences of these elements, the goal is to offer constructive guidelines for the judicious exploitation and preservation of TV heritage assets, as well as for the growth of tourism in TV regions across the YRDR.

Utilizing the Factor Detector, the 14 influencing factors from the indicator system are introduced into the geographical detector model [47]. This yields the influence value (q) and explanatory power value (p) of each influencing factor on TVTR. The q value ranges from 0 to 1. And if the value is closer to 1, it indicates greater influence [24]. A value closer to 0 implies a lesser influence of the factor on TVTR. The numerical expression formula is as follows:

$$q = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{k} n_i\sigma_i^2 \quad (17)$$

Where q represents the magnitude of the detecting factor's influence, with q ranging from 0 to 1. A larger q value indicates a higher degree of impact of the driving factor on TV tourism. K denotes the number of secondary samples. Ni and n stand for the number of regions in each sub-region and the research area, respectively. σ21 and σ2 refer to the variance of indicators for region i and the research area.

Evaluation System Construction – Selection of Influencing Factors

The factors of village endowment, socio-economic conditions, ecological environment, and tourism vitality are important influencing factors for regional differentiation in tourism development [48-49]. The YRDR spans across the Northwest, North China, Central China, and East China regions, possessing diverse geographical elements. The levels of tourism development vary among provinces and cities, and the conditions for TV tourism development and utilization differ. Drawing on an exhaustive survey of existing literature and following tenets of methodological rigor, a systematic framework, and measurability, the identification of tourism responsiveness metrics is bifurcated into two dimensions: the sensitivity of tourism in village heritage entities and the support from the regional socio-economic context. Specifically, factors such as average temperature, average precipitation, per capita GDP, per capita disposable income in rural areas, forest cover, total water resources, number of 5A-grade scenic areas, cultural and tourism expenditures, and public service expenditures are selected for investigation. This selection establishes a comprehensive evaluation index system for TVTR in the YRDR (refer to Table 1). The purpose of this framework is to investigate the tourism responsiveness and spatiotemporal differentiation characteristics of TVs in the YRDR.

Data Sources and Processing

The roster of TVs and historical cultural towns originates from the “List of Chinese TVs,” publicly disclosed on the official portal of China’s Ministry of Housing and Urban-Rural Development. The geographic information of the 1,712 TVs located in Anhui, Jiangsu, Zhejiang, and Shanghai is obtained using the Map Location tool. The compilation of TVs and historical cultural towns stems from the “List of Chinese Traditional Villages (TV),” as declared on the authorized online platform of China’s Ministry of Housing and Urban-Rural Development. Economic, transportation, and tourism data at the provincial, prefectural, and county levels are obtained from the respective statistical annual report and statistical communiqué. The map boundaries and provincial administrative boundaries are based on the national standard map. Geographical coordinates for TVs in the YRDR are acquired using Google Earth. Administrative boundary maps of Anhui, Jiangsu, Zhejiang, and Shanghai are sourced from their respective provincial geographic information bureaus and registered by ArcGIS software. Digital elevation data are obtained from the SRTMDEM UTM 90m resolution DME dataset of the China Geographic Spatial Data Cloud. The collected information is imported into ArcGIS to construct the TV database in the YRDR.

Results

Spatiotemporal Differentiation of Traditional Village Tourism Responsiveness

Overall Scores Differences on Traditional Village Tourism Responsiveness

In this study, the TOPSIS method is employed to quantitatively assess the tourism responsiveness of 41 cities in the YRDR. The specific overall scores (fi) can be obtained in Table 2. From the perspective of provinces, Jiangsu Province ranks first in terms of

Table 2. Tourism Responsiveness of TV in Various Cities of the YRDR.

Sequence	City Name	S_I^O	S_i^*	fi	Sequence	City Name	S_I^O	S_i^*	fi
1	Hangzhou	1.12	2.152	0.658	22	Tongling	2.396	0.954	0.285
2	Shanghai	1.361	2.154	0.613	23	Anqing	2.353	0.918	0.281
3	Ningbo	1.415	2.091	0.597	24	Zhenjiang	2.312	0.896	0.279
4	Wenzhou	1.513	1.933	0.561	25	Wuhu	2.366	0.891	0.274
5	Shaoxing	1.565	1.957	0.556	26	Yangzhou	2.354	0.87	0.27
6	Quzhou	1.65	1.953	0.542	27	Taizhou	2.454	0.756	0.236
7	Jiaxing	1.615	1.91	0.542	28	Liu’an	2.468	0.738	0.23
8	Zhoushan	1.714	1.951	0.532	29	Ma’anshan	2.511	0.719	0.223
9	Jinhua	1.612	1.822	0.53	30	Xuzhou	2.488	0.659	0.209
10	Taizhou	1.617	1.812	0.529	31	Yancheng	2.455	0.638	0.206
11	Huzhou	1.754	1.764	0.501	32	Huai’an	2.559	0.569	0.182
12	lishui	1.775	1.784	0.501	33	Suqian	2.584	0.54	0.173
13	Suzhou	1.817	1.734	0.488	34	Lianyungang	2.603	0.543	0.173
14	Huangshan	2.06	1.634	0.442	35	Huai’nan	2.795	0.436	0.135
15	Wuxi	2	1.443	0.419	36	Fuyang	2.739	0.38	0.122
16	Nanjing	2.067	1.2	0.367	37	Chuzhou	2.754	0.33	0.107
17	Changzhou	2.123	1.205	0.362	38	Bengbu	2.819	0.305	0.098
18	Xuancheng	2.208	1.142	0.341	39	Suzhou	2.819	0.305	0.098
19	Hefei	2.317	1.191	0.34	40	Bozhou	2.823	0.303	0.097
20	Chizhou	2.284	1.157	0.336	41	Huaibei	2.836	0.283	0.091
21	Nantong	2.24	0.933	0.294					

tourism responsiveness among all surveyed regions, while Anhui Province lags behind, occupying the last position. Delving into the city level, we observe that 15 cities have scores exceeding 0.4, including but not limited to Hangzhou, Shanghai, and Ningbo. These cities collectively account for 37% of the total of 41 cities in the YRDR. They demonstrate outstanding performance in various domains such as village endowment, socio-economic factors, ecological environment, and tourism activity. In contrast, 10 cities have scores below 0.2, such as Huai'an, Suqian, and Lianyungang, accounting for 24% of the total. This suggests that these cities need to enhance their performance in the selected evaluation indicators, and the future development and planning of their tourism industry may require corresponding optimization and adjustments.

Spatial Distribution of TV Tourism Responsiveness in Different Cities Within the YRDR Metropolitan Region

In this study, the natural breakpoint method is employed to categorize the tourism responsiveness of each city (prefecture) into five levels, ensuring maximum similarity within each group and maximum differences between groups. The specific classification is as follows: high responsiveness area, moderately high responsiveness area, moderate responsiveness area, moderately low responsiveness area, and low responsiveness area. The visualization of the results is presented in Fig. 3. In the YRDR, there are 15 cities (prefectures) at Level 2 or above, accounting for 37% of the total, primarily distributed in Zhejiang Province and Shanghai. Moreover, the tourism responsiveness of two-thirds of the provinces and cities in the YRDR falls below Level 3, mainly concentrated in Jiangsu Province and Anhui Province. Considering the difference in the number of cities within each province, we calculated the average score to determine the TVTR of each province (region). The results demonstrate that Shanghai ranks first with a score of 0.613, followed by Zhejiang with a score of 0.5499. Jiangsu scores 0.2814, while Anhui has the lowest score of 0.2188. This is positively correlated with the number of TVs in the provinces (regions), where Shanghai has the highest number of villages while Anhui has the least.

In general, TVTR in Shanghai and Zhejiang ranks at the forefront, followed by Jiangsu. The responsiveness of Anhui, which is located inland, is generally lower, highlighting the spatial imbalance across different areas in the Yangtze River Delta. The TVTR in the YRDR exhibits a notable spatial imbalance, with coastal areas significantly outperforming inland regions. This disparity may be attributed to geographical location, transportation convenience, and other regional factors.

Spatiotemporal Evolution of Traditional Village Tourism Responsiveness in the YRD Urban Agglomeration

In this study, the TOPSIS method is employed to quantitatively assess the tourism responsiveness of 41 cities in the YRDR. The specific overall scores (fi) can be obtained in Table 2. From the perspective of provinces, Jiangsu Province ranks first in terms of tourism responsiveness among all surveyed regions, while Anhui Province lags behind, occupying the last

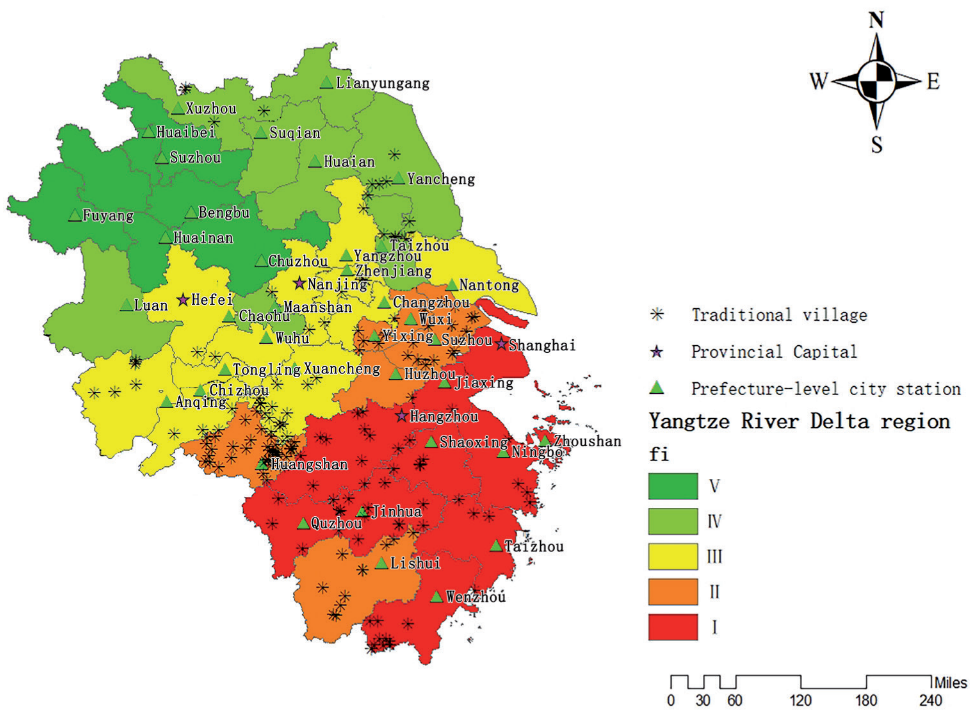

Fig. 3. Methodology flow chart

Table 3. Nearest Neighbor Indices of TVTR in Different Phases of the YRD Urban Agglomeration.

Year	2012	2013	2014	2016	2019	2022
Yangtze River Delta	0.7244	0.6765	0.7543	0.7118	0.7235	0.8967

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Spatial Distribution of TV Tourism Responsiveness in Different Cities Within the YRDR Metropolitan Region

In this study, the natural breakpoint method is employed to categorize the tourism responsiveness of each city (prefecture) into five levels, ensuring maximum similarity within each group and maximum differences between groups. The specific classification is as follows: high responsiveness area, moderately high responsiveness area, moderate responsiveness area, moderately low responsiveness area, and low responsiveness area. The visualization of the results is presented in Fig. 3. In the YRDR, there are 15 cities (prefectures) at Level 2 or above, accounting for 37% of the total, primarily distributed in Zhejiang Province and Shanghai. Moreover, the tourism responsiveness of two-thirds of the provinces and cities in the YRDR falls below Level 3, mainly concentrated in Jiangsu Province and Anhui Province. Considering the difference in the number of cities within each province, we calculated the average score to determine the TVTR of each province (region). The results demonstrate that Shanghai ranks first with a score of 0.613, followed by Zhejiang with a score of 0.5499. Jiangsu scores 0.2814, while Anhui has the lowest score of 0.2188. This is positively correlated with the number of TVs in the provinces (regions), where Shanghai has the highest number of villages while Anhui has the least.

In general, TVTR in Shanghai and Zhejiang ranks at the forefront, followed by Jiangsu. The responsiveness of Anhui, which is located inland, is generally lower, highlighting the spatial imbalance across different areas in the Yangtze River Delta. The TVTR in the YRDR exhibits a notable spatial imbalance, with coastal areas significantly outperforming inland regions. This disparity may be attributed to geographical location, transportation convenience, and other regional factors.

Spatiotemporal Evolution of Traditional Village Tourism Responsiveness in the YRD Urban Agglomeration

Based on the spatial positioning of TVTA in the YRDR, the geographical coordinate distribution areas of TVs in the region for the years 2012, 2013, 2014, 2016, 2019, and 2022 are selected, as shown in Fig. 4. At the provincial level, TVs can be considered a point feature, with their geographic locations represented by coordinate points. Geographical coordinates for Traditional Villages (TVs) within the YRDR are incorporated into the ArcGIS 10.8 platform. Utilizing the Average Nearest Neighbor instrument from the Spatial Statistics suite, the nearest neighbor indices across six distinct time frames in the YRDR are computed. The findings are presented in Table 3. The Nearest Neighbor Index (R) for the TVTA in the YRDR for the six time periods is all less than 1, indicating that the TVTA is in an aggregated state during these periods. From the temporal changes in R, the value of R for 2022 is relatively high at 0.8967, approaching 1, with a confidence level (P) of 0.0079. The value of R for 2013 and 2016 decreases, and both of these periods have a P-value close to zero, indicating a confidence level of over 99%. This suggests that the spatial clustering trend of TVTA in the YRDR has been gradually strengthening during these periods. Furthermore, the values of R are between 0.6 and 0.9, all greater than 0.5, indicating that there is still some room for development in the maturity of TVTA in the YRDR.

To further analyze the changing characteristics of spatial clustering of TVTA in the YRDR, the Density Analysis tool in ArcGIS 10.8 is employed to analyze the spatial distribution density of TVTA in the six time periods. The findings are depicted in Fig. 5. The overall evolution trend of the kernel density of TVTA in the YRDR over the six time periods shifts from a dispersed structure to a 'clustered structure and then to a combination of clustered and ribbon-like structures', generally forming a C-shaped high-density distribution area. In 2012, a C-shaped kernel density structure emerged with the Huangshan-Anqing high-density belt as the vertex, the Jinhua-Lishui-Quzhou high-density belt, and the Huzhou-Shanghai high-density belt as the wings. In 2013, the C-shaped kernel density structure became clearer with the addition of Zhenjiang and Taizhou to the existing high-density belt. In 2014, the high-density areas decreased significantly, leaving only the Huangshan-Lishui high-density belt. By 2016, the high-density distribution areas of TVTA in the YRDR experienced rapid growth, with the Lishui-Taizhou high-density belt as the vertex and areas including Huangshan, Xuancheng, Anqing, Lishui-Jinhua, Hangzhou, and Wenzhou as the

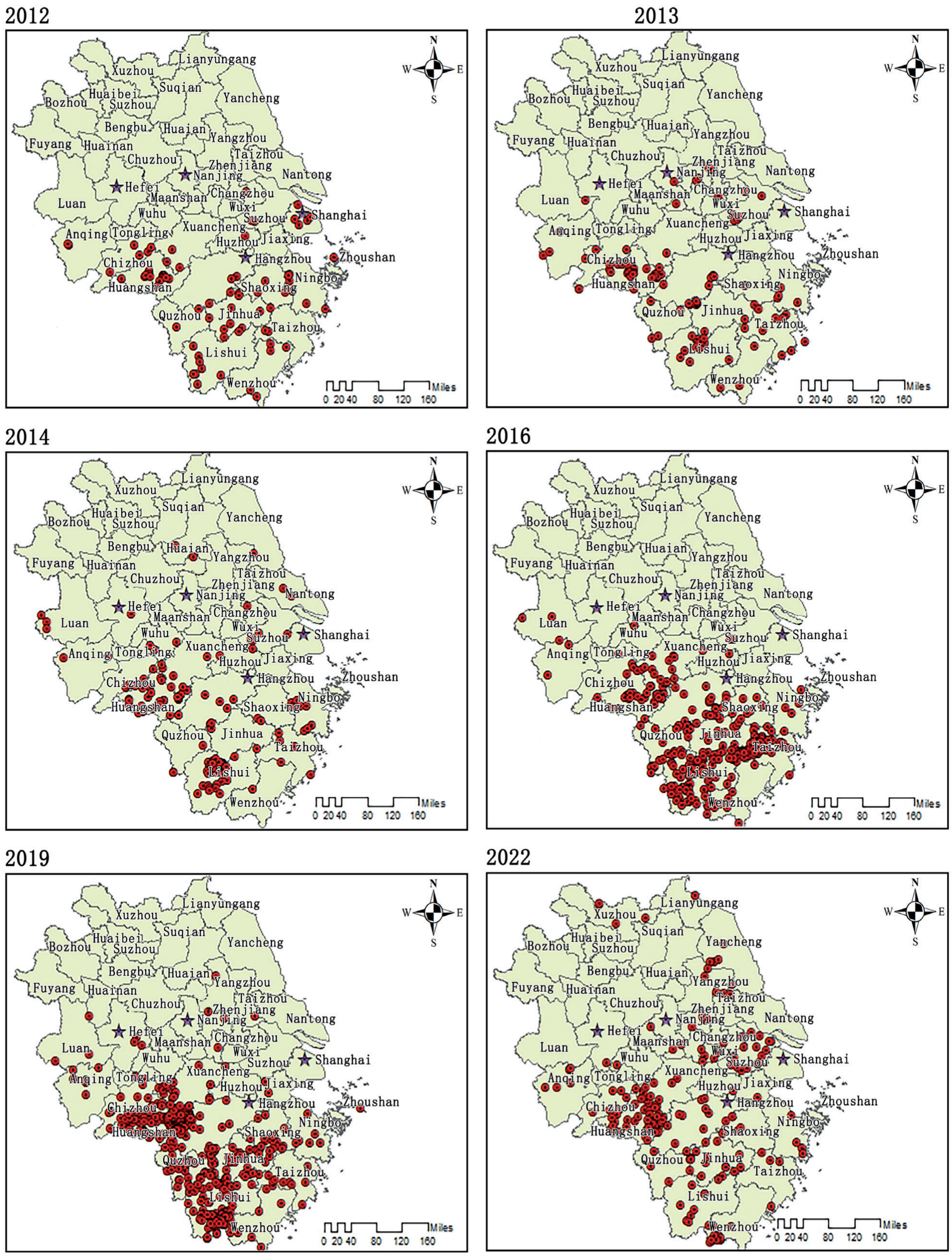

Fig 4. Schematic Diagram of Spatial Distribution of TV in Different Time Periods in the YRDR

high-density belts. In 2019, the high-density distribution areas of TVTA in the YRDR were relatively sparse. Only sporadic high-density distribution points were observed, mainly in Huangshan, Quzhou, Jinhua, and Lishui, primarily within Anhui Province. By the year 2022, with the number of TVTAs increasing in the YRDR, the overall kernel density intensified. In addition to the stable growth of kernel density in Huangshan, Quzhou,

Table 4. Detection Results of Influencing Factors for TVTR in the YRD Urban Agglomeration.

Detection Factors	Natural Factors		Socio-economic		Ecological Environment		Tourism Vrality		
	X1	X2	X3	X4	X5	X6	X7	X8	X9
q statistic	0.252	0.376	0.157	0.117	0.308	0.394	0.074	0.106	0.021
P value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

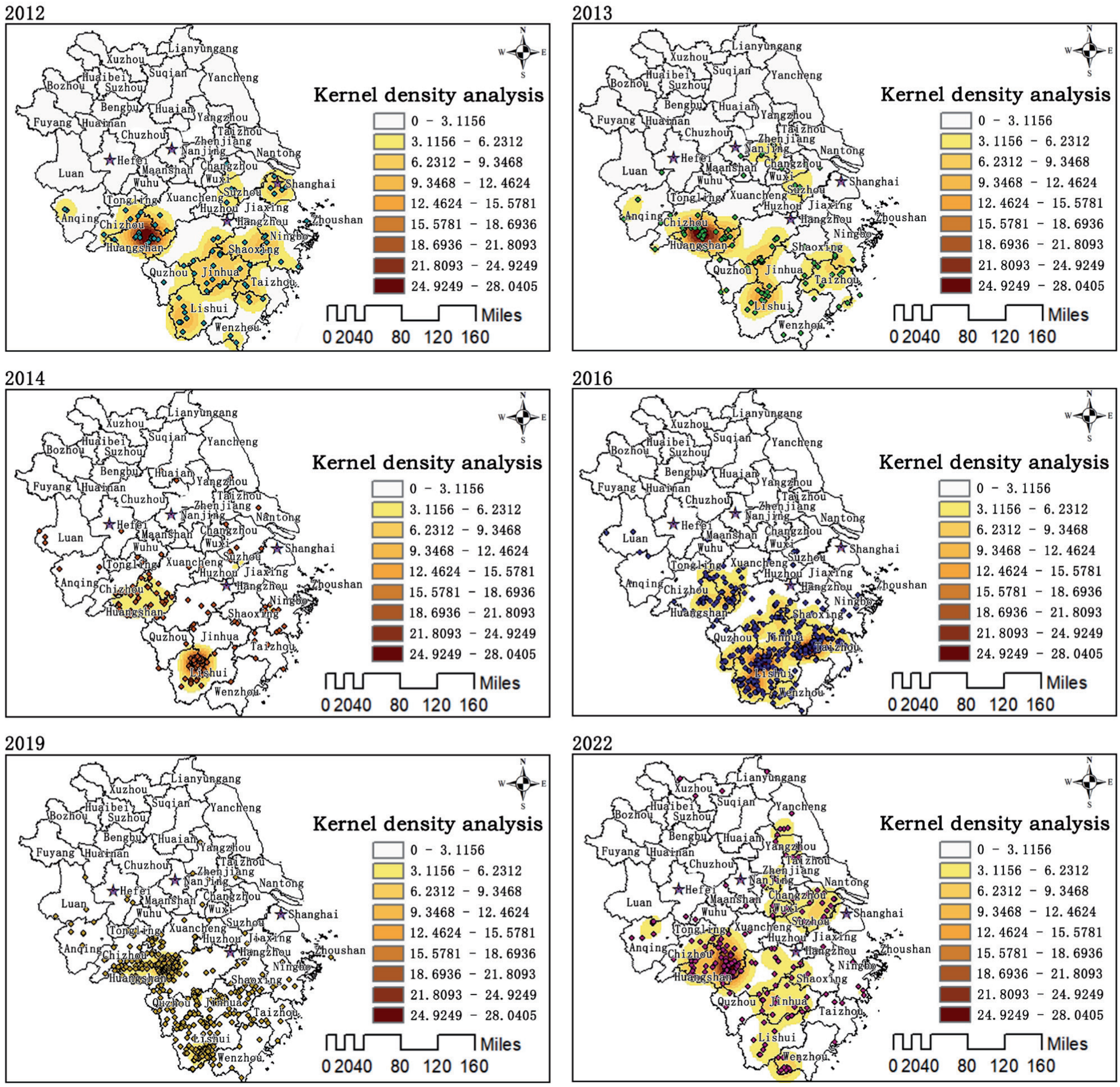

Fig 5. Analysis Diagram of TV Kernel Density in different period of the YRDR.

Jinhua, and Lishui, new high-density distribution points emerged, primarily within Jiangsu, including Suzhou, Huzhou, Yixing, Changzhou, Zhenjiang, and Yangzhou. This gradual emergence contributed to the formation of a high-density distribution belt, indicating a strengthening of kernel density due to the increased number of TVTAs in the region.

Analysis of Drivers for Traditional Village Tourism Responsiveness

Detection Result of Drivers

Within the 41 cities in the YRDR, we conducted a deep investigation of the influential factors on TVTR through geographical detector analysis. The results indicate that the P-values of 9 factors are less than 0.1, as depicted in Table 4. This confirms the diversified nature of factors affecting TVTR in the YRDR area. From the classification of each influential factor, their impacts on the spatial distribution of TV tourism vary, with the specific ranking as follows: X6 > X2 > X5 > X1 > X3 > X4 > X8 > X7 > X9. Notably, factors with q-values exceeding 0.3 are primarily associated with ecological and village endowment, involving X6, X2, and X5. These three factors exhibit significant explanatory power and influence over the spatial distribution of TV tourism. Conversely, the explanatory power and influence of X9 are comparatively limited, revealing a lower sensitivity of TV tourism responses in the YRDR and a stronger dependence on regional tourism development and the economic environment.

Initially, ecological elements had the most substantial impact on the spatial dispersion of TVTA. X5 and X6 emerge as key determinants in the layout of TVTR. This could be attributed to the fact that a healthy and vibrant ecological environment can provide a more appealing atmosphere, attracting tourists to experience a harmonious rural life coexisting with nature. In particular, forest coverage can impact climate regulation, biodiversity, and landscape aesthetics, while total water resources are directly linked to regional ecological health and sustainability. These ecological factors also align with the principles of sustainable development and ecotourism for TVs. From the data of the YRDR, these ecological indicators exhibit q-values greater than 0.3, indicating a strong correlation with TVTR. For decision-makers and planners, placing emphasis on the preservation of these critical ecological resources can not only enhance the region's tourism appeal but also play a vital role in ensuring long-term ecological health and the sustainable development of the tourism industry in the area.

Second, natural variables occupy the secondary rank concerning their sway on the spatial allocation of TVTA. Elements X1 and X2, primarily natural in essence, play a supportive but crucial role in the geographical patterning of TV tourism. They form the foundation of attraction for tourism destinations, influencing the seasonality of tourism, feasibility, and special activities of the areas. In the YRDR, these natural factors, along with ecological indicators X5 and X6, collectively contribute to providing TVs with a unique tourism backdrop and allure. While ecological factors play a significant role in tourism responsiveness, the contributions of the natural factors represented by X1 and X2 are not to be underestimated. Therefore, decision-makers must pay full attention to them when formulating tourism strategies.

Thirdly, socio-economic factors exhibit an influence on the spatial distribution of TV tourism destinations. Variables X3 and X4 serve as indicators of an area's economic health and residents' consumption capacity. The economic prosperity of a region is closely linked to the maturity of its tourism industry, the level of tourism facilities, and the effectiveness of external publicity. Particularly within the context of rural tourism, variable X4 might be associated with the willingness and capacity of local residents to engage in tourism-related activities such as providing accommodations, agritainment, and other services. From the data in the YRDR, although the influence of socio-economic factors in determining the responsiveness of TV tourism is not as prominent as ecological and natural factors, they still hold significant importance in comprehending the economic disparities and strengths within the region. Therefore, further analysis and research on these indicators will contribute to providing policymakers with a more comprehensive basis for decision-making.

Fourth, the factor of tourism vitality exhibits a relatively minor impact on the spatial distribution of TVTA. Both

Table 5. Exploratory Results of the Influencing Factors for the Spatiotemporal Evolution of TVTR in the YRD urban Agglomeration.

2012			2013			2014			2016			2019			2022		
Exploratory Factor	q statistic	P value	Exploratory Factor	q statistic	P value	Exploratory Factor	q statistic	P value	Exploratory Factor	q statistic	P value	Exploratory Factor	q statistic	P value	Exploratory Factor	q statistic	P value
X1	0.340	0.000	X1	0.232	0.000	X1	0.166	0.000	X1	0.533	0.000	X1	0.134	0.000	X1	0.126	0.000
X2	0.484	0.000	X2	0.339	0.000	X2	0.202	0.000	X2	0.403	0.000	X2	0.277	0.000	X2	0.269	0.000
X3	0.123	0.000	X3	0.130	0.000	X3	0.141	0.000	X3	0.125	0.000	X3	0.153	0.000	X3	0.130	0.000
X4	0.189	0.000	X4	0.146	0.000	X4	0.026	0.000	X4	0.161	0.000	X4	0.133	0.000	X4	0.154	0.000
X5	0.382	0.000	X5	0.270	0.000	X5	0.167	0.000	X5	0.350	0.000	X5	0.218	0.000	X5	0.229	0.000
X6	0.477	0.000	X6	0.360	0.000	X6	0.356	0.000	X6	0.499	0.000	X6	0.253	0.000	X6	0.312	0.000
X7	0.121	0.000	X7	0.117	0.000	X7	0.041	0.000	X7	0.010	0.000	X7	0.115	0.000	X7	0.206	0.000
X8	0.199	0.000	X8	0.066	0.000	X8	0.077	0.000	X8	0.268	0.000	X8	0.064	0.000	X8	0.058	0.000
X9	0.051	0.000	X9	0.058	0.000	X9	0.024	0.000	X9	0.017	0.000	X9	0.055	0.000	X9	0.053	0.000

X8 and X9 demonstrate limited influence on spatial distribution, particularly X9, which shows a relatively modest explanatory power. Possible explanations for this observation include regional characteristics specific to the YRDR, which might possess distinct geographical and socio-economic attributes that result in ecological and natural factors as primary driving forces. In addition, the type of tourism prevalent in this area, primarily centered around ecological and natural attractions, may render factors related to tourism vitality less pivotal in consideration.

Detection Results of Temporal-Spatial Evolution Driving Factors

Table 5 comprehensively demonstrates the changing influence of core factors on TVTR in the YRD during six different time periods: 2012, 2013, 2014, 2016, 2019, and 2022. Among the nine factors, the explanatory power of X3 and X7 has gradually increased since 2012, while the impact of other factors has diminished year by year. Notably, the influence of X2 has decreased from 0.484 in 2012 to 0.269 in 2022, which might reflect the gradual expansion of development from core cities to all cities in the YRDR. Coinciding with this trend, the influence of X1 has noticeably decreased since 2016, validating the spatial-temporal evolution from the core cities toward all cities within the region, as highlighted in this study. Furthermore, the influence of X4, X5, X6, X8, and X9 has slightly decreased since 2012, though the overall changes are relatively modest. This may suggest that these factors have exhibited a relatively stable role in the spatial-temporal evolution of TVs in the YRDR. By analyzing the changes in the above factors across six different time points in the region, this study has unveiled the primary driving factors behind the spatial-temporal evolution of TVs. The variation of these factors reflects the interplay among cities in the region and the overall development trends. Future research could delve into the specific mechanisms underlying these factors and provide more targeted recommendations for regional tourism development policies.

Results of Interaction Exploration

Interaction Exploration is an analytical approach used to uncover the combined impact of two or more influencing factors on changes in a target variable. This section focuses on analyzing whether these interactions enhance or diminish the explanatory power of TVTA spatial distribution in the YRDR. As presented in Table 6, all pairwise combinations of influencing factors exhibit nonlinearity and augmentation effects. This suggests that the spatial distribution of TVTA is not solely governed by a single factor but by multiple factors. This finding is consistent with the previous analysis and emphasizes the importance of understanding the interactive mechanisms behind the complex geographic and spatial distribution. The strongest interaction combinations are X2 and X7, X6 and X7, and X7 and X9, all of which exhibit explanatory power exceeding 0.9. These strong interaction effects further validate the necessity of considering the interactions among multiple influencing factors when evaluating the spatial distribution of TVTA in the YRDR. The results of interaction detection underscore the complexity of spatial distribution in TVTA, and the analysis of multifactor interactions provides profound insights into understanding the spatiotemporal variations in tourism responsiveness in the region. By identifying and analyzing critical interacting factors, targeted guidance can be provided for the formulation of tourism development strategies in the YRDR. This analytical approach may also offer valuable references for studies in other regions or fields.

Discussion

This study has explored the spatial distribution, influence degree, and intrinsic connections among various factors related to TVTR in the YRDR from the perspectives of village endowment attributes, socio-economic conditions, ecological environment, and tourism vitality. The aim is to provide insightful recommendations for enhancing TVTR. The analysis results will be discussed in the following sections.

Table 6. Results of Interaction Exploration for Influencing Factors of TVTA in the YRD Urban Agglomeration.

Exploratory Factor	X1	X2	X3	X4	X5	X6	X7	X8	X9
X1	0.252								
X2	0.393	0.376							
X3	0.656	0.651	0.157						
X4	0.711	0.705	0.347	0.117					
X5	0.349	0.393	0.642	0.704	0.308				
X6	0.462	0.495	0.672	0.730	0.464	0.394			
X7	0.579	0.929	0.555	0.630	0.630	0.944	0.074		
X8	0.342	0.445	0.536	0.536	0.410	0.455	0.903	0.106	
X9	0.481	0.513	0.201	0.269	0.438	0.728	0.526	0.192	0.021

(1) This study has investigated the dynamics of the spatiotemporal distribution of TVTA in the YRDR and their influencing factors. However, there is still room for further improvement in the selection process for evaluation factors. Regarding village endowment variables, we have focused on average precipitation and temperature, which have been identified as having a considerable influence on the spatial arrangement of tourism villages. Other natural elements, while potentially relevant, were omitted due to data availability constraints or to maintain the clarity and focus of the analysis. In terms of socio-economic dimensions, the YRD's TV quantification relies on metrics like per capita GDP, rural per capita disposable income, and TV count, yet the precision of these indicators calls for additional refinement. In addition, this study doesn't differentiate between environmental and ecological factors and tourism vitality factors in detail. Therefore, selecting a more comprehensive set of influencing indicators and scientifically quantifying these indicators will be a direction for further research.

(2) By employing the EM and the TOPSIS, artificial influences on indicator weights are minimized, and panel data are utilized to objectively reflect the tourism responsiveness characteristics of different provinces in the YRDR. TVTR levels are high in Shanghai and Zhejiang, followed by Jiangsu. Conversely, the response level in the inland province of Anhui is generally lower, highlighting the spatial distribution imbalance within the YRD. Moreover, the distribution of TVs across the YRDR is extensive and dispersed. Due to limitations in data availability, certain influential factors, such as the declaration of TV listings and governmental policies, as well as the intentions of local communities (including village collectives) [25], are not incorporated into the indicator system. In future research, obtaining regional data through on-site investigations and incorporating external indicators related to policies, management, markets, and funding can enhance the accuracy of evaluations and better reflect the “living” attributes of heritage in traditional settlements and their dynamic tourism processes. Exploring the impact of spatial variations in TVTR at different scales will also enhance the credibility of the research.

(3) TVTR is closely related to factors such as village endowment and ecological environment and has a significant effect on the spatial distribution of this village. Existing research has often focused on the inherent natural resources of TVs within the entire region, primarily considering the tourism adaptability of these resources. Unlike the approach of singular evaluation on the TVs themselves, this study incorporates indicators related to the region’s economy, tourism environment, and other aspects, revealing regional disparities in TV tourism development. As a result, different regions should prompt TV tourism development based on local conditions and time.

Conclusions

Based on the traditional village tourism response evaluation index system in the Yangtze River Delta region, the article comprehensively uses Arc GIS10.8 and SPSSAU software, combines the TOPSIS method and geodetector, and analyzes the impacts of the factor endowment of traditional villages, socio-economy, ecological environment, and tourism vitality on the tourism response of the Yangtze River Delta region in the years of 2012, 2013, 2014, 2016, 2019, and 2022, respectively, from different regional scales. spatial distribution, influence degree, and difference of traditional village tourism response in the Yangtze River Delta region, on the basis of which the optimized layout countermeasures of traditional village tourist sites in the Yangtze River Delta region are proposed, and the main conclusions are as follows:

(1) From the overall perspective of the Yangtze River Delta region, the study found that the research showed that Shanghai and Zhejiang performed the best in terms of traditional village tourism response, followed closely by Jiangsu. This trend is mainly related to advanced transportation and rich cultural resources, while Anhui Province is relatively backward due to geographic factors, highlighting that the traditional village tourism responsiveness in the YRD region shows an obviously uneven spatial distribution.

(2) In terms of regional differentiation, the spatial differentiation of traditional village tourism responses in the YRD region is obvious. 15 cities, such as Hangzhou and Shanghai, performed well, accounting for nearly 37% of the 41 cities in the YRD. Relatively speaking, cities with scores below 0.2, such as Huai'an and Suqian, account for about 24% of the total. These cities need to be strengthened in the selected evaluation indicators, and the future development and planning of the tourism industry may need to be optimized and adjusted accordingly.

(3) From the viewpoint of spatial and temporal evolution, the growth rate of nuclear density in the six study periods has been increasing, and the high-density distribution area has been gradually increasing and showing a trend of evolution from "few and scattered to group structure and belt structure", forming an obvious "C" shape in Zhejiang, Anhui, and other regions. This phenomenon has been verified by statistical data and GIS.

(4) From the viewpoint of driving factors, the influence on the spatial distribution of traditional village tourism varies, and the specific order is as follows: X6>X2>X5>X1>X3>X4>X8>X7>X9. Especially, the influence of X6, X2, and X5 is significant, and from the viewpoint of spatial-temporal evolution, the explanatory power of only X3 and X7 is increasing. The strongest combinations of interacting factors are X2 and X7, X6 and X7, and X7 and X9, whose explanatory power reaches more than 0.9, which provides an important reference for optimizing the spatial layout of traditional village tourist sites in the future.

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Conflict of Interest

The authors declare no conflict of interest.

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