Liu *et al. Heritage Science* (2023) 11:123
https://doi.org/10.1186/s40494-023-00967-8

Heritage Science

RESEARCH

Open Access

Uncovering the factors influencing the vitality of traditional villages using POI (point of interest) data: a study of 148 villages in Lishui, China

Sheng Liu[1,2*], Jian Ge[2], Ming Bai[3], Min Yao[3] and Zhenni Zhu[1]

Abstract

Improving vitality has been a major bottleneck in the revitalization of traditional village heritage worldwide. The vitality of traditional village (VTV) varies greatly depending on socioeconomic factors and natural conditions. Significant spatial variation exists in VTV, even within the same urban jurisdictions in China; however, the main determinants for this have not yet been quantified owing to the difficulty of obtaining data from large rural samples, making targeted invigoration difficult. Thus, we applied point of interest data, which are easily accessible big data, to bridge the data source gap. To assess the VTV's influencing factors and analyze the spatial variations among the factors' impacting intensity, we used the Ordinary Least Squares and Geographically Weighted Regression models and conducted empirical studies involving 148 traditional villages in Lishui, China. Seven factors influenced the vitality of traditional villages in the study area, with the most significant being topographic relief, elevation, scenic spots and commercial industry. Moreover, the factors' impacting intensity varied by region. Topographic relief and elevation had the greatest impact intensity in the north and south of Lishui, whereas primary education, transportation facility and agricultural bases had the greatest impact in the north, and scenic spots and commercial industry had the greatest impact in the middle of Lishui. Taken together, this method makes a large sample of VTV's impact factor analysis feasible, has global implications, and can provide a foundation for the scientific and precise regional promotion of VTV, which is beneficial for rural heritage revitalization.

Keywords Traditional village vitality, Rural heritage, Heritage revitalization, POI data

Introduction

Background

Vitality is defined as the ability to survive and to live or grow [1]. In 1979, the International Council on Monuments and Sites developed the concept of enhancing the vitality of heritage areas to support regional development [2]. Currently, rural heritage conservation is being globally emphasized; however, the vitality of rural heritage with similar historical protection values and production modes varies greatly over time under different heritage managements [3].

Typically, traditional villages are formed early in history and are a rural heritage of precious traditional resources with non-renewable historical, cultural, architectural, and research value [4, 5]. There are numerous, widely dispersed traditional villages in China. However, rapid urbanization has rendered their preservation

---

*Correspondence:
Sheng Liu
lius@hzcu.edu.cn
[1] Hangzhou City University, Hangzhou 310011, Zhejiang, China
[2] College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, Zhejiang, China
[3] Zhejiang University Urban-Rural Planning and Design Institute, Hangzhou 310030, Zhejiang, China

challenging. According to an early field survey, the total number of traditional villages in the Yangtze and Yellow River basins has decreased by 7.3% annually from 2004 to 2010 [6]. Thus, since 2012, China has placed a high value on the preservation of traditional villages, and the revitalization of these villages has been granted legal status [7]. As of 2019, approximately 6819 villages have been designated as Chinese national traditional villages [8].

However, the vitality of traditional village (VTV) within the same city can vary significantly. For example, 148 and 119 national traditional villages in Lishui City and Hunan Xiangxi Prefecture, respectively, had a significant normal distribution of vitality values or rural hollowing as well as large differences in polarization [9, 10]. Moreover, urbanization, rural tourism, cultural values, and community resilience influence heritage revitalization in different regions [11–14]. However, disparities in VTV within the same municipality cannot be explained merely through these compound macroscopic factors [15]. Thus, for the traditional villages in the prefecture-level city, there is a pressing need to investigate more specific key variables in the local situation to provide a more detailed scientific basis for the development of effective vitality enhancement strategies. Therefore, we propose the following research questions in the present study: What factors cause disparities in the VTV within a region? Is there spatial variation in the impact of these factors?

Related works

Recently, an increasing number of studies have focused on identifying the factors influencing heritage vitality. However, most of the studies are still focused on the vitality of historic urban districts. According to these studies, the overall vitality of a historical heritage area is significantly influenced by land use patterns [16]; it may also be influenced by 23 factors in four dimensions: physical, functional, visual, and traffic [17]. Meanwhile, one specific aspect of the factors driving vitality has been investigated: public space vitality. This aspect is influenced by 12 factors, including spatial accessibility, functional mix, historical value, and cultural experience [18]. By contrast, commercial vitality is influenced by tourist attractions, accommodations, and leisure service facilities [19].

Few studies have also focused on the vitality of suburban heritage sites. For instance, Accordino et al. examined the balance between preserving historic fabrics and enhancing economic vitality in historic downtowns surrounding metropolitan areas [20]. Dhingra et al. discovered that the vitality of India's suburban historical communities was threatened by vacant and dilapidated housing, traffic congestion, and gentrification [21]. Moreover, studies on rural vitality have primarily focused on the general villages, as previous research has examined the impacts of environmental factors, farm consolidation, and non-agricultural activities on the vitality of rural public spaces, rural communities, and rural vitality, respectively [22–24].

Methods for assessing the vitality of a large sample of traditional villages at the regional scale have been developed using only multi-data fusion [9]; moreover, research on the relative influencing factors is limited to individual village exploration. For example, previous surveys have revealed that the vitality of a religious tourism village in Indonesia was influenced by the government's support and housing facility conditions [25], and the sociocultural vitality of a traditional village in Guangzhou was significantly related to the integrity of landscape preservation [26]. Thus, the factors influencing VTV in large samples require further enhancement, and the spatial characteristics of their drivers and research on whether they differ from the vitality of suburban heritage and general villages warrant further investigation.

The factors influencing heritage vitality are complex, and the quantitative analysis of large samples often requires rich data. The recent emergence of geographic big data technology has rapidly promoted refined heritage site vitality evaluation, particularly in urban areas, by making extensive use of new data, which has the benefits of large data volume, high accuracy, and easy access. For instance, one study examined the factors influencing the vitality of eight historical preservation zones using social media, location-based service, point of interest (POI), and street view data [17]. Another study used POI and land use data to investigate the factors influencing heritage vitality in 12 cities [16].

Traditional villages are sparsely populated and big data resources are limited; this is the primary reason why a large sample of the impact factors of vitality cannot be identified. In the past, relevant studies have mainly used questionnaire surveys and on-site monitoring to collect data. For example, one study used expert scores and questionnaires to conduct regression analysis on the traditional landscape vitality of 16 villages [26]; another study used the Fortis Emotional Questionnaire to investigate and analyze the factors affecting the vitality of 170 rural families [27]; some other studies had tourists and villagers wear GPS tracking devices to collect data [22]. Although these methods can provide detailed and comprehensive information about human activities or building environment characteristics, they have limitations, such as the high time–costs associated, low efficiency, and limited coverage [28, 29]. Thus, for rural heritage areas with relatively scarce geographical big data, the effective selection of variables, composition of the data source, and practical mathematical analysis methods to solve rural heritage vitality research in large samples at the prefecture-level remain to be empirically explored.

Research aims

In summary, because of the bottleneck in rural data acquisition, previous studies lacked applicable methods in the analysis of key factors assessing the disparities of VTV with large samples in the prefecture-level city, resulting in their influencing factors not being measured quantitatively and practical revitalization not being targeted. Therefore, in this study, we aimed to conduct an in-depth exploration of (1) an appropriate index system of influencing factors and (2) the composition of data sources comprising the spatial information of a large sample of traditional villages.

Our main aim was to develop a quantitative method to identify the variables influencing the vitality of a large sample of traditional villages at the prefectural level and the spatial variation of impact intensity. This study innovatively applied POI data, which are easily accessible big data, to fill the data source gaps and construct impact factors from three dimensions (terrain, facilities, and industry). We then used the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models to conduct empirical studies assessing 148 traditional villages in Lishui, China, to investigate the impact factors of VTV and the spatial variations in impact intensity. This method has global implications, and our study findings can serve as a foundation for the scientific and precise promotion of VTV at the regional scale.

Method

Study area

Chinese traditional villages are primarily found in mountainous regions, hills, river valleys, and foothills, where the terrain is undulating and generally fragmented [30, 31]. Approximately 53% of Chinese traditional villages have gradually developed rural tourism based on their physical and cultural heritage, while the majority them still rely on their traditional agricultural economy [32]. Lishui is located in Zhejiang Province, Yangtze River Delta region of China, about 2.5 h by train from Shanghai. About 90% of the traditional villages in this area are located in mountainous and hilly areas, relying primarily on agriculture for a living. Meanwhile, the tourism industry in Lishui's traditional villages is rapidly expanding, based on the Shanghai metropolitan area [33]. In the first four batches of the Chinese Traditional Village List, Lishui has 158 traditional villages, making it the third largest traditional village in China. We included 148 traditional villages with sufficient data in the present study. Our previous research revealed that the vitality of these 148 traditional villages has a significantly low average value, most of which are in urgent need of improvement [9]. Moreover, their VTV varied significantly, with an olive-shaped distribution of 18.2% for high vitality, 47.3% for middle-high and middle-low vitalities, and 20.9% for low vitality [9] (Fig. 1). However, the factors influencing VTV remain unclear, giving them high experimental value. Therefore, we selected Lishui as the study area based on Lishui's typicality of traditional villages in terms of number, topography, industry type, and vitality variability.

Variables

Dependent variables

For the VTV assessment Table 1, we used the method of weighted summation of evaluation indicators based on our recent research [9], which was published as an article in Land Use Policy. To avoid repetition, a brief introduction is provided here. First, the calculation of VTV is based on its interpretation. As both government reports and related studies have proposed that the sustainable revitalization of traditional villages needs to be harmonious and unified in terms of protection and development [34], we defined VTV as the comprehensive capacity for protection and development. Second, we referred to relevant papers, "Traditional Village Evaluation and Identification Index System (Trial)", and the opinions of experts, government officials, and rural sages; to develop six element and 13 vitality indexes under the protection and

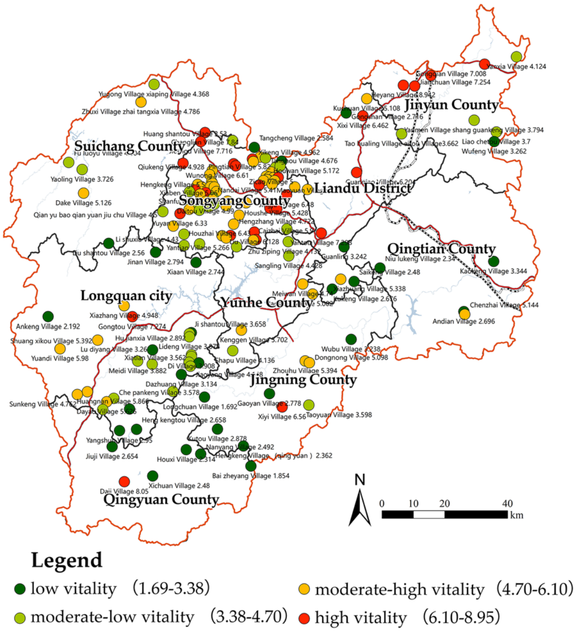

Fig. 1 Spatial distribution of the VTV grade in Lishui (published in Land Use Policy [9])

Table 1 VTV assessment indexes, weight, and scoring standard

Element	Index	Unit	Scoring standard						Weight
			0	2	4	6	8	10	
B1 Population	C1 Resident population[1]	–	0–100	100–300	300–500	500–700	700–900	> 900	0.097
	C2 Visitor arrivals[2,3]	Weibo check in times/year	0	1–20	20–100	100–300	300–500	> 500	0.083
B2 Construction	C3 Area of construction land[1]	acre	< 50	50–100	100–150	150–200	200–250	> 250	0.053
	C4 Distance between highway entrance and exit[2,4]	km	> 20	15–20	10–15	5–10	2–5	0–2	0.059
B3 Economy	C5 Collective village income[1]	10,000 CNY	0–20	20–40	40–60	60–80	80–100	> 100	0.104
	C6 Per capita income of residents[1]	10,000 CNY	< 0.7	0.7–0.9	0.9–1.1	1.1–1.3	1.3–1.5	> 1.5	0.082
B4 Historic environment	C7 Proportion of traditional buildings[1]	%	< 50	50–60	60–70	70–80	80–90	> 90	0.095
	C8 Number of historic environment elements[1]	–	< 2	2–5	5–10	10–15	15–20	> 20	0.056
	C9 Grade of cultural relic protection units[1]	–	0–2	2–4	4–6	6–8	8–10	> 10	0.087
B5 Intangible Culture	C10 Types of intangible cultural heritage[1]	–	0	0–2	2–4	4–6	6–8	> 8	0.055
	C11 Grade of intangible cultural heritage[1]	–	0	1	2	3	4	> 5	0.099
B6 Resilience to disaster	C12 Grade of geological disaster risk susceptibility[5]	–	-	8	6	4	2	–	0.060
	C13 Occupancy rate of traditional buildings[1]	%	< 19	20–40	40–60	60–80	80–90	> 90	0.070

[1] Traditional village survey registration form; [2]Village point data, was acquired from the POI data of the Gaode map; [3]Weibo check-in number; [4]The highway toll station data separated from the POI data in the whole area of Lishui; [5]Zone map of geological disaster distribution and susceptibility in Lishui

development aspects. Third, since there are still large differences in the development stage of traditional villages across China, we conduct targeted indicator weighting studies for the study area. We used the AHP method to conduct a questionnaire survey of relevant experts who understand the case study object, traditional villages in China's Yangtze River Delta region, to determine the appropriate indicator weights for Lishui. Finally, we calculated the VTV for each village using the weighted sum of indicators (Formula 1) and classified them into four grades (Fig. 1), from lowest to highest, using the natural break point method [35]. The grade of the VTV is a reflection of the villages' integrated capacity to protect and develop. We enclosed the indicators, scoring methods, weights and data source in Table 1. A more thorough explanation can be refer to the original paper [9]. The specific formula used is as follows:

$$Z_{\mathrm{j}} = \sum_{i=1}^{13} W_{\mathrm{i}} C_{\mathrm{ji}}, \qquad (1)$$

where Z_j denotes the village's jth VTV value, C_{ji} denotes the village's jth score for each index, and W_i denotes the weight of each index. Higher Z_j values indicated higher vitality.

Independent variables

The factors that influence VTV are relatively complex. A couple of studies have shown that topographic relief and elevation affect the vitality of settlements at the terrain [36, 37], and the traditional villages in Lishui are located in the varied terrain of plains, hills and mountains. In terms of facilities, distance to primary education, medical services, and transportation services affect the vitality of rural communities or historical heritage [27, 38, 39]. In Lishui, due to a lack of these facilities, some villagers moved to the town, which led to the village's deactivation as a result of population loss. Meanwhile, industries in the study area, such as agricultural bases, industrial factories, scenic spots, commercial streets has brought economy and jobs to the villages, and these factors have also been shown in the literature to have a significant impact on village vitality [24, 40, 41]. Therefore, based on the literature and field visit, we established an index of nine influencing factors from the aspects of terrain, facilities, and industry (Table 2).

Data source

First, among the independent variables, the DEM data required for topographic relief and elevation were obtained from the Geographic Information

Table 2 Influencing factors for VTV and their measurement

Dimension	Code	Indicator	Unit	Measurement method	
Terrain	X1	Topographic relief	°	The number of altitude changes between the highest and lowest points within a unit (Bayesian change-point analysis showed that the best statistical unit for Lishui region is 0.176 km^2)	(1)
	X2	Elevation	m	The altitude of the village	(1)
Facility	X3	Distance to primary education	km	Distance from the village to the nearest kindergarten or primary school	(2)
	X4	Distance to medical facility	km	Distance from the village to the nearest clinic, health station, and hospital	(2)
	X5	Distance to transportation facility	km	Distance from the village to the nearest gas station and parking lot	(2)
Industry	X6	Distance to agricultural bases	km	Distance from the village to the nearest agricultural bases (bases of farm, forestry, animal husbandry, and fishery)	(2)
	X7	Distance to industry	km	Distance from the village to the nearest industrial factory	(2)
	X8	Distance to scenic spots	km	Distance from the village to the nearest to the scenic spots above AAA level	(2)
	X9	Distance to commercial industry	km	Distance from the village to the nearest commercial facility	

(1) Digital elevation model (DEM) data; (2) Sorting data from POI and calculating spatial distance using ArcGIS 10.6

Monitoring Cloud Platform (www.dsac.cn), with a precision of 30 m. Second, data related to primary education, medical facilities, transportation facilities, agriculture bases, industry, scenic spots and commercial facilities were derived from the POI data. The POI data are high-accuracy recordings of the function point locations and can be obtained from many map platforms; these data are used in a variety of urban heritage vitality studies [16, 17, 28]. Lishui's 2018 POI data were obtained through the application programming interface (API) from the Gaide Open Map Platform (http://lbs.amap.com/). The POI data obtained included the name, type, and coordinates of the function points required for the study, such as scenic spot, industrial factory, primary education, agricultural base, medical service, and transportation service POI.

Methodology

The main steps of this study are shown in Fig. 2. First, based on the literature review, the potential drivers were selected from three aspects (terrain, facilities, and industry); then, the POI data required for the calculation of facilities and industry-related variables were preprocessed and all variables were calculated. Second, effective variables were screened for using Spearman's correlation analysis [42]. Third, based on the effective variables, OLS regression was used to analyze the impact factors globally, and the variables that passed the significance test were then selected. Finally, if the VTV had significant spatial autocorrelation, the GWR model was used for local variable analysis to investigate the spatial variation of the factors' impacting intensity.

Spatial autocorrelation

Global Moran's I was used to determine whether the disparities in VTV were spatially related. This index evaluates the similarity of the attribute values of the unit adjacent to or near a space and then judges the spatial distribution pattern of the entire area. The formula is as follows:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2}, \tag{2}$$

where I is the Global Moran's I index; n is the number of village units; xi and xj are the PRP values of the ith and jth administrative units, respectively; $\bar{x}$ is the average VTV value of all administrative units; and w is the binary weight determined using the Queen-based adjacency method. The Global Moran's I index ranges from −1 to 1. Values > 0 indicate a positive spatial correlation, whereas those < 0 indicate a negative spatial correlation. The higher the absolute value, the greater the degree of spatial correlation.

This study examined the local spatial correlations of VTV values using the Local Indicators of Spatial Association (LISA) [43]. Local spatial correlations were described using Moran's I scatter plot generated using ArcGIS 10.6. Four cluster types were identified based on the LISA results: a cluster of high values surrounded by high values (H–H), a cluster of low values surrounded by low values (L-L), a cluster of high values

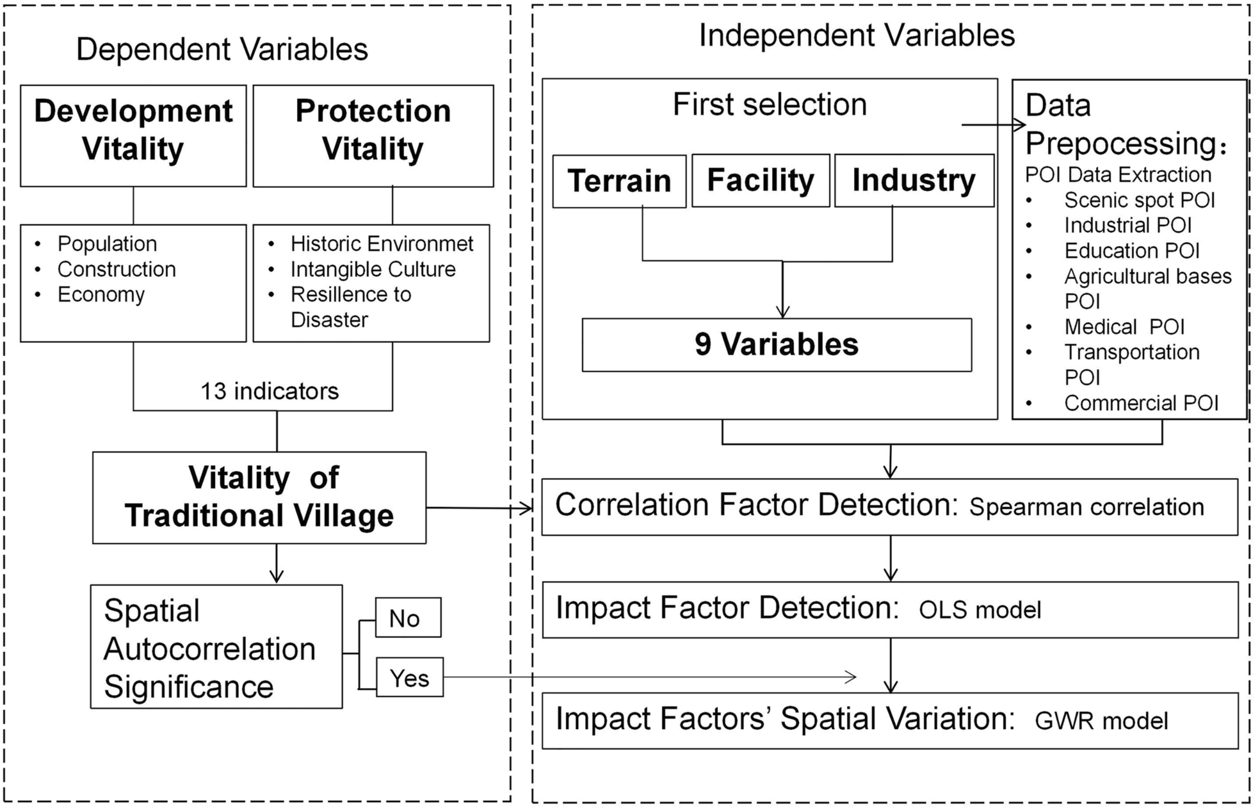

Fig. 2 Technical route

surrounded by low values (H–L), and a cluster of low values surrounded by high values (L–H).

OLS model

Linear regression is a global regression model used to explore the causal relationships between dependent and independent variables. The OLS method is the most commonly used linear regression method [44]. Here, we used spss21.0 to carry out Multivariate Regression Analysis to analyze all potential variables globally and then selected the variables that passed the significance test. The classic OLS model is formulated using the following formula:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots\ldots \beta_p x_p + \varepsilon, \quad (3)$$

where y is the response variable, x is the matrix of the predictor variables, β is the spatial regression coefficient of the predictor variable that represents the effect of the predictor variable on the response variable, and ε ε is a random disturbance or error (residual).

GWR model

GWR is an extension of the OLS regression method that models relationships as they vary across space by evaluating where locally weighted regression coefficients deviate from global coefficients; thus, GWR helps explore the characteristics of the spatial variation of variables [45]. We conducted the GWR analysis in ArcGIS 10.6 using the spatial analyst extension [46].

Results

Analysis of correlation factors

This study analyzed the correlations between the vitality values of 148 villages in Lishui and nine potential factors. Spearman's correlation analysis (Table 3) revealed that VTV was significantly negatively correlated with all factors, all of which were effective for further impact factor detection.

Analysis of impact factors

First, we used VTV as a dependent variable and the nine correlated factors as independent variables to build an OLS analysis model. The regression results (Table 4) showed that the tolerance of each parameter

Table 3 Correlation analysis between VTV and each potential factor

Code	X1	X2	X3	X4	X5	X6	X7	X8	X9
Correlation Coefficient	− 0.422**	− 0.474**	− 0.492**	− 0.285**	− 0.513**	−0.425**	− 0.514**	− 0.511**	− 0.605**
Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000

*Significant at the 5% level (two-tailed)

**Significant at the 1% level (two-tailed)

Table 4 Summary of the OLS results: model parameters and diagnostics

	Variable	Standardized coefficients	t_	Sig.	Collinearity statistics		Model summary	
		Beta			Tolerance	VIF		
	Intercept		28.196	0.000***		–	Number of observations	148
X1	Topographic relief	− 0.214	− 3.769	0.000***	0.866	1.155	R	0.785
X2	Elevation	− 0.193	− 2.736	0.007***	0.561	1.783	R^2	0.616
X3	Distance to primary education	− 0.145	− 1.483	0.048**	0.292	3.430	Adj. R^2	0.601
X4	Distance to medical facility	0.068	0.870	0.386	0.452	2.213	Std. error	0.940
X5	Distance to transportation facility	− 0.119	− 1.712	0.089*	0.578	1.730	Durbin-Watson	2.021
X6	Distance to agricultural bases	− 0.107	− 1.771	0.079*	0.755	1.324		
X7	Distance to industry	− 0.086	− 0.849	0.397	0.271	3.687		
X8	Distance to scenic spots	− 0.160	− 2.010	0.008***	0.439	2.280		
X9	Distance to commercial industry	− 0.243	− 3.409	0.001***	0.549	1.822		

*The correlation is significant at the 0.1 level; **the correlation is significant at the 0.05 level;*** the correlation is significant at the 0.01 level

was greater than 0.1, and the variance inflation factor (VIF) was much less than 4.0. Therefore, it concludes that there is no multicollinearity exists among the independent variables in the observed data set. Second, the adjusted R^2 value was 0.601, which was greater than the benchmark of 0.5 and was sufficiently explicable for the regression model, according to Hair Jr's theory [47]. Moreover, the model's residuals were independent, as the Durbin Watson value is close to 2. They were also normally distributed (Appendix Fig. 6), and there was no heteroscedasticity as shown by the standardized residual scatter plot (Appendix Fig. 7). Finally, we tried recalculating after randomly removing 20% of the sample size, and found that the variation in Adj R^2 was less than 5%, showing that the model was robust and well-fitted. According to Table 4, seven influencing factors were significant, with topographic relief, elevation, and distance to scenic spots having very significant negative effects on VTV.

Spatial variations of the impact factor

VTV's spatial autocorrelation significance

We calculated the global spatial autocorrelation of the VTV in Lishui, which was statistically significant at the 0.01 level; the Global Moran's I index was 0.318, the P value was 0.001, and the Z value was 6.66 (Fig. 3). This showed that Lishui's VTV had a significantly positive spatial correlation, clearly displaying a cluster structure. We conducted a local spatial autocorrelation

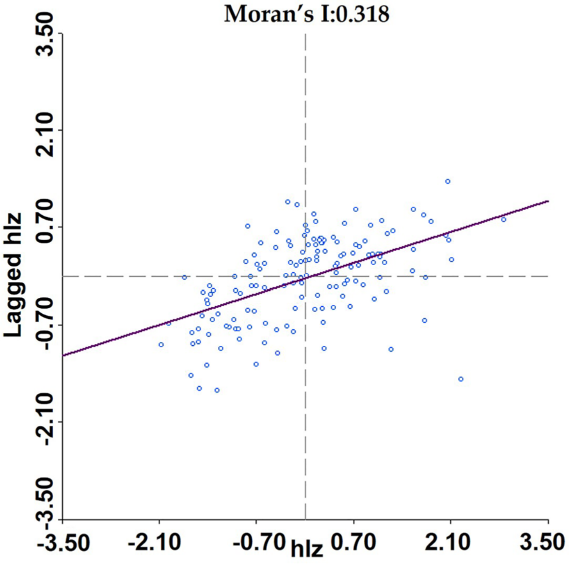

Fig. 3 Global Moran's I scatter plot of VTV values

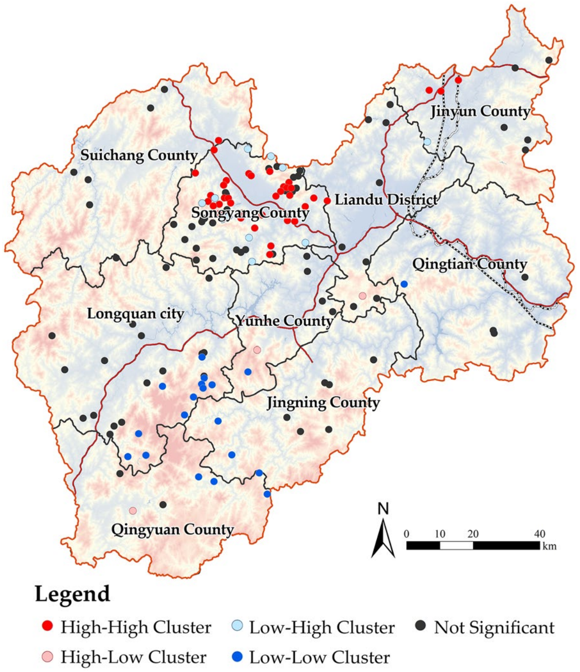

Fig. 4 Spatial map of VTV local spatial correlation

Table 5 Comparison of the GWR and OLS models

Model parameters	AICC	R^2	Adjusted R^2	Moran's I of the Residuals	
				Moran's I	P-value
OLS model	415.409	0.626	0.601	0.085	0.022
GWR model	393.331	0.789	0.716	– 0.010	0.922

analysis, which showed significant spatial heterogeneity (Fig. 4). High-vitality villages (H–H cluster) were mainly concentrated in the Songgu Basin of Songyang, whereas low-vitality villages (L–L cluster) were mainly concentrated at the administrative junction of counties and cities, with the most obvious concentration noted at the junctions of Qingyuan, Jingning, and Longquan in the south.

GWR model analysis

The OLS model only considers the regression coefficient globally; thus, we further used the GWR model to analyze the local spatial variations in the factors affecting VTV. We conducted a GWR analysis based on the seven explanatory variables that passed the 10% significance test in the OLS analysis. Compared with the OLS results (Table 5), the GWR model's R^2 was 0.789, which was 26.04% higher than that for the OLS model, whereas the AICC of GWR decreased from 415.409 to 393.331. According to Fotheringham's evaluation criteria [48], if the AICC value obtained from the GWR model decreases by > 3 from that of the OLS model, the GWR model would be considered superior. In addition, the Moran's I of the OLS model's residual was 0.085, with $P < 0.05$, while the Moran's I of the GWR model's residual was – 0.010, with $P > 0.05$. This indicated that GWR model improved the reliability of the relationships by reducing the spatial autocorrelations in residuals. Therefore, the GWR model was more accurate.

Based on the GWR model calculations (Table 6), the difference between the maximum and minimum values of the coefficients of each variable coefficient is large, and the coefficient median lies in the same direction and close to the mean value. Thus, the impact intensity of VTV's

Table 6 Regression coefficient statistics of the GWR model

Variable	Minimum	Upper quartile	Median	Lower quartile	Maximum	Mean
X1 Topographic relief	– 0.009563536	– 0.000901511	– 0.002579364	– 0.004257216	– 0.001631335	– 0.00597517
X2 Elevation	– 0.004581425	0.004301775	0.002623922	0.00094607	0.000410502	– 0.000736727
X3 Distance to primary education	– 0.000170971	0.004992256	0.003314404	0.001636552	1.19284E–05	– 4.15796E–05
X5 Distance to transportation facility	– 9.43586E–05	0.004996726	0.003318874	0.001641021	2.39194E–05	– 3.70797E–05
X6 Distance to agricultural bases	– 0.00011619	0.004975821	0.003297969	0.001620116	2.34144E–05	– 5.8126E–05
X8 Distance to scenic spots	– 0.000127768	0.004982395	0.003304543	0.001626691	3.26883E–05	– 5.15074E–05
X9 Distance to commercial industry	– 0.000250309	0.004855446	0.003177594	0.001499742	2.86285E–05	– 0.000179314

(See figure on next page.)

Fig. 5 Spatial distribution of the standardized residuals and regression coefficients of the GWR Model. **a** Standardized residuals; **b** topographic relief; **c** elevation; **d** distance to primary education; **e** distance to transportation facility; **f** distance to agricultural bases; **g** distance to scenic spots; **h** distance to commercial industry

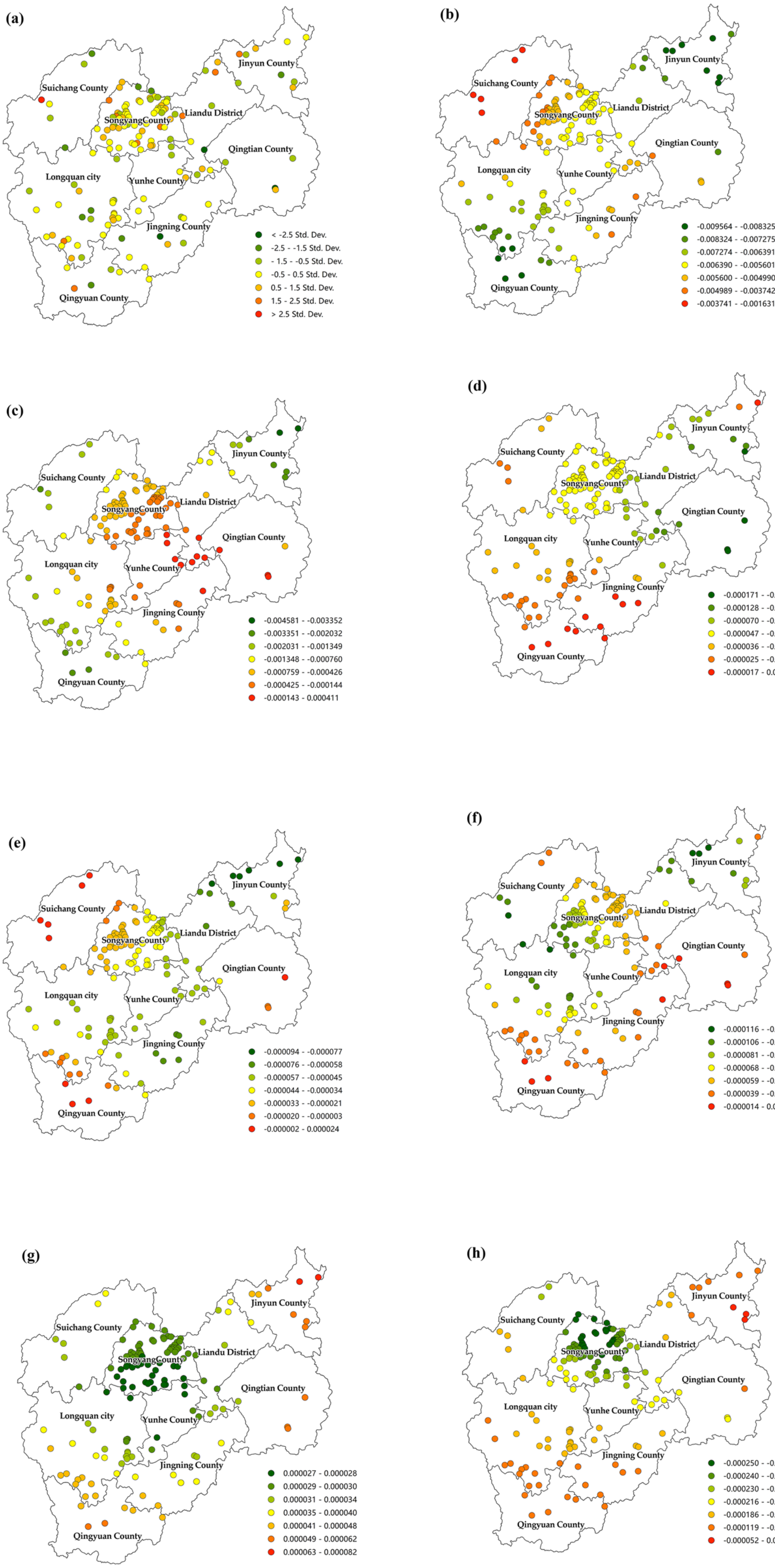

Fig. 5 (See legend on previous page.)

influence factors varies greatly in space among the 148 traditional villages in Lishui; however, the impact directions are convergent. We used ArcGIS10.6 software and the Jenks natural breakpoint method [35] to spatially display the regression coefficients of the GWR model (Fig. 5). Figure 5a shows that the standardized residual values of the local regression in traditional villages are in the range of [− 2.78, 2.50], of which 97.30% are in the range of [− 2.5, 2.5], indicating that the model has a very good overall effect.

Figure 5 shows obvious intensity differences in the influence of each explanatory variable on the local geographical space. Elevation and topographic relief have the greatest impact in Lishui's north (Jinyun County) and south (Qingyuan and Longquan County); primary education, transportation facility and agricultural base have the greatest impact in the north of Lishui (Jinyun County); and scenic spots and commercial industry are most influential in the middle region (Songyang County).

Discussion

The selection of the independent variables

Chinese traditional villages are a distinct type. Most are located far from cities, in mountainous areas, with inconvenient transportation, allowing them to remain unaffected by urbanization and industrialization while naturally preserving some rural historical relics and traditional customs [30, 31]. Thus, Chinese traditional villages lack the same amenities as ordinary villages. Many traditional villages retain only residential functions, with a severe lack of public service facilities and secondary and tertiary industries. Villagers usually depend on many external industries for their livelihood, and their basic needs often require the shared facilities among several villages or the far-off urban facilities. Considering these factors, we defined the majority of relevant influencing factors not by the number or type of facilities, but by the distance from the nearest facility or industry.

Influencing factors and their implications

In this study, we discovered that terrain, facilities, and industry are the driving factors of VTVs in the case area. In terms of terrain factors, topographic relief and elevation were the most significant because these usually affect the crop yields, and production and the farmers' living conditions [49, 50]. In Lishui's traditional villages, rice and tea are the main type agriculture. As the high altitude and undulating terrain may lower their product yield, these two factors are critical for the vitality of the traditional villages there.

In terms of facility factors, distance to primary education was the most important, perhaps because limited school access and demand for high-quality education are the immediate motivators for rural-town migration and resettlement [40], which directly lead to the significant abandonment of mountainous settlements such as traditional villages. Through interviews with local villagers, we discovered that some of the villagers moved to cities for good educational resources, leaving a large number of vacant houses in the village. This influence mechanism is consistent with that of education-driven rural immigrants in Japan [51]. Second, compared with the significant impact of medical services on general village vitality [27], its impact on traditional village vitality is not significant. This may be due to the fact that traditional villages in Lishui are generally remote and located far away from medical facilities, making the impact of medical facilities on their vitality insignificant. Third, the impact of transportation facilities on the vitality of traditional villages is general but significant in urban historical blocks [18]. This could be because residents and tourists in Lishui's traditional villages currently solve the parking problem primarily through lots of idle lands, thus the lack of parking facilities has just had a general impact on the vitality of the village. However, due to the tight land use around urban heritage sites, parking is of significant importance for the transportation convenience required by urban heritage tourism [52].

In terms of the industrial level, while the significance of agricultural bases is average, the commercial or scenic areas have a significant impact on the VTV, and the industry has had not obvious impact. First, Lishui's traditional villages, like most traditional villages, are geographically remote and located in mountainous areas. Like other research findings [53], they are less reliant on the industrial economy than ordinary plain villages, and many villagers' livelihood rely on the agriculture. Therefore, distance to farms has a significant impact. By contrast, urban heritage does not rely on agriculture, thus would not be affected by it. Second, commercial industry and scenic spots have a significant impact on the vitality of Lishui's traditional villages. Following our investigation, we discovered that the villages with the highest vitality in Lishui are located closer to natural scenic areas. The villagers have used the radiation from the scenic spots to set up commercial facilities in the village, such as homestays, restaurants, and shops, which has promoted the villagers' economy. Moreover, commercial industry and scenic spots also have a significant impact on the vitality of urban heritage, which perhaps because tourist attractions can bring commercial economies to heritage, whether in villages or cities, thereby enriching the attractiveness and economic vitality of heritage [19].

Meanwhile, the exploration of the influencing factors of VTV can serve as a strategic reference for the entire region to revitalize traditional villages. Based on the results, we propose that the factors having a significant impact on vitality should be prioritized in the implementation. Terrain factors like topographic relief and elevation are difficult to change. Thus, we suggest developing three anthropogenic factors with significant influence near traditional villages: commercial facilities, scenic spots and primary education, which can serve as the universal preferred factor for enhancing the VTV in Lishui.

The factors' spatial variations and their implications

Our results showed obvious intensity differences in the influence of each explanatory variable on the local geographical space (Fig. 5). This feature can be superimposed on traditional village revitalization strategies for scientific and targeted vitality enhancements.

In terms of the traditional villages located in the northeast of Lishui (Jinyun County), the terrain there is flat, transportation is convenient, the agricultural economy is relatively developed. Our field investigations have found that, firstly, the villagers in traditional villages in this region rely heavily on agriculture, resulting in a stronger impact of agricultural bases on villages' vitality (Fig. 5f). Secondly, the plain terrain makes the land use of many villages here more compact and has fewer idle spaces. Therefore, transportation facilities such as parking lot can provide tourist access convenience and have a strong impact on the vitality of the villages (Fig. 5e). Finally, due to the relatively developed economy compared to other counties, the residents of this region place a higher emphasis on education, so the impact of primary educational facilities on villages' vitality is the strongest in this region (Fig. 5d). Thus, we proposed that the development of agricultural bases, transportation facilities and primary educational facilities near villages should be prioritized during the revitalization of traditional villages in this area.

Traditional villages in the central and western regions, particularly the Suichang and West Songyang counties, have many scenic areas near the villages. Some traditional villages have benefit from the scenic service work or commercial activities such as homestays and restaurants around the villages. Meanwhile, the traditional villages here are highly dependent on agriculture such as tea and mushroom. Therefore, village vitality is highly sensitive to the scenic spots, commercial facilities and agricultural base, and these indicators have the greatest influence on VTV in this region (Fig. 5e–g). Accordingly, we propose that the development of agricultural bases, scenic spots, and commercial facilities near the villages be prioritized during the revitalization of traditional villages in this area.

Limitations and future research

Herein, we focused on developing a quantitative method to identify the variables influencing the vitality of a large sample of traditional villages at the prefecture-level and the spatial variation in their impact intensity. First, the influencing factors currently chosen cannot fully explain the differences in the VTV. Further research on variable selection is required in the future to investigate in depth the complex relationship between village social organization, policy characteristics and vitality. Although it is difficult to measure factors such as village organizational form, social security, and policy differences in a large sample of universal traditional villages at the prefecture-level, in order to pursue the model's better interpretability, this requires further exploration in the future. In addition, there are also regional limitations to the applicability of this method. The independent variables for this method were chosen based on relevant literature and the conditions of the study areas. Although the study area is typical of Chinese traditional village clusters in terms of terrain and industry types, it is insufficient to represent all types of traditional village clusters at the prefecture-level around the world. Thus, the method we developed is suitable for most of Chinese traditional villages, which are located in mountainous area and rely on agriculture and tourism. Moreover, when applying this method to other regions or countries with significantly different geographical environments and levels of industrial development than this practical case, it is necessary to adjust independent variables based on the local situation, and the results of influencing factors may vary from region to region.

Conclusion

Herein, we developed a practical quantitative method to identify the variables influencing VTV for the precise implementation of traditional village revitalization. The main finding of this study is that we built an appropriate influencing factor system and introduced POI data, making it easier and more effective to evaluate the influencing factors of VTV in a large sample at the prefecture-level, thereby overcoming the limitation that only one or a small number of traditional village vitality influencing factors can be evaluated through questionnaire surveys or on-site monitoring. To the best of our knowledge, this is one of the first empirical studies on the factors influencing the vitality of a large sample of traditional villages. According to our empirical research, this method can screen for significant influencing factors and analyze the spatial variations among the factors' impacting intensity, thereby laying the groundwork for formulating universal and differential vitality promotion strategy priorities for the entire region and subcounties, respectively. This method could be applied to demand regions worldwide, containing many traditional villages with varying levels of vitality and requiring specific revitalization guidance, further expanding the revitalization strategic planning of global rural heritage.

Appendix A

See Figs. 6 and 7.

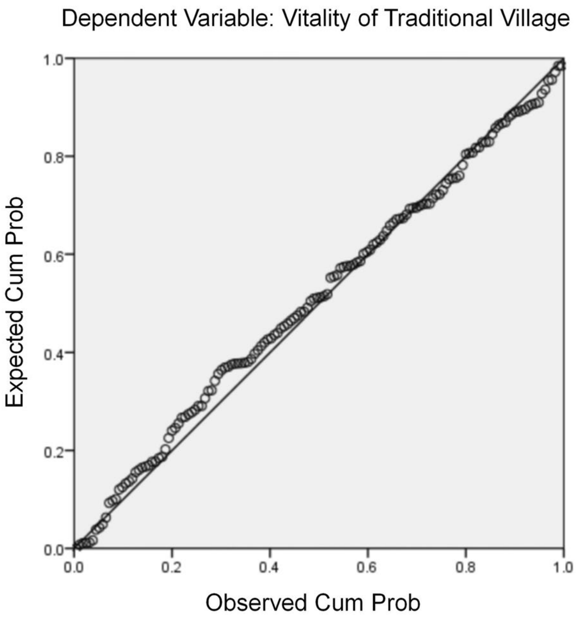

Fig. 6 Normal P–P plot of regression standardized residual

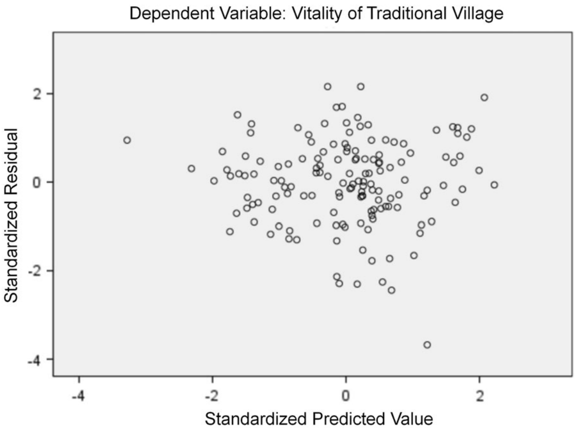

Fig. 7 Test of homoscedasticity of residuals (scatter plot for homoscedasticity)

Abbreviations

VTV	Vitality of traditional village
POI	Point of interest
OLS	Ordinary least squares
GWR	Geographically weighted regression
VIF	Variance inflation factor
LISA	Local Indicators of Spatial Association

Acknowledgements
Authors thank the National Natural Science Foundation of China ((Grant number 51908495) for the financial support of this study.

Author contributions
S.L.: Conceptualization and writing; J.G.: review and editing; M.B.: methodology, analysis and visualization; M.Y. and Z.Z.: data curation. All authors read and approved the final manuscript.

Funding
This research was funded by the National Natural Science Foundation of China (Grant number 51908495).

Availability of data and materials
All data sources have been listed in the manuscript. The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 6 February 2023 Accepted: 2 June 2023

References

1. Lavrusheva O. The concept of vitality. Review of the vitality-related research domain. New Ideas Psychol. 2020;56: 100752.
2. Icomos A. Charter for the conservation of places of cultural significance—The Burra Charter Australian ICOMOS. Burwood, Victoria, Australia: Deakin University; 1979.
3. Parkinson A, Pendlebury J. Conserving rural heritage: the cases of England and Ireland. In The Routledge companion to rural planning, Routledge; 2019. pp 398–409.
4. Li B, Luo Q, Liu P, et al. Knowledge maps analysis of traditional villages research in China based on the Citespace method. Econ Geogr. 2017;37:207–14.
5. Guo Z, Sun L. The planning, development and management of tourism: the case of Dangjia, an ancient village in China. Tour Manage. 2016;56:52–62.
6. Ying L, Huang J-k, Zikhali P. Use of human excreta as manure in rural China. J Integr Agric. 2014;13(2):434–42.
7. Bian J, Chen W, Zeng J. Spatial distribution characteristics and influencing factors of traditional villages in China. Int J Environ Res Public Health. 2022;19(8):4627.
8. Gao C, Wu Y, Bian C, et al. Spatial characteristics and influencing factors of Chinese traditional villages in eight provinces the Yellow River flows through. River Res Appl. 2021. https://doi.org/10.1002/rra.3880.
9. Liu S, Ge J, Bai M, et al. Toward classification-based sustainable revitalization: assessing the vitality of traditional villages. Land Use Policy. 2022;116: 106060.
10. Li H. Study on the hollowing of traditional villages in Hunan Province. Master dissertation, Hunan Normal University, 2015.
11. Zhu J, Zhu M, Xiao Y. Urbanization for rural development: spatial paradigm shifts toward inclusive urban-rural integrated development in China. J Rural Stud. 2019;71:94–103.
12. Fleischer A, Felsenstein D. Support for rural tourism: does it make a difference? Ann Tour Res. 2000;27(4):1007–24.
13. Gao J, Wu B. Revitalizing traditional villages through rural tourism: a case study of Yuanjia Village, Shaanxi Province, China. Tour Manag. 2017;63:223–33.
14. Chung H, Lee J. Community cultural resources as sustainable development enablers: a case study on Bukjeong Village in Korea compared with Naoshima Island in Japan. Sustainability. 2019;11(5):1401.
15. Elshof H, van Wissen L, Mulder CH. The self-reinforcing effects of population decline: an analysis of differences in moving behaviour between

rural neighbourhoods with declining and stable populations. J Rural Stud. 2014;36:285–99.
16. Wu J, Lu Y, Gao H, et al. Cultivating historical heritage area vitality using urban morphology approach based on big data and machine learning. Comput Environ Urban Syst. 2022;91: 101716.
17. Huang X, Gong P, Wang S, et al. Machine learning modeling of vitality characteristics in historical preservation zones with multi-source data. Buildings. 2022;12(11):1978.
18. Zhang F, Liu Q, Zhou X. Vitality evaluation of public spaces in historical and cultural blocks based on multi-source data, a case study of Suzhou Changmen. Sustainability. 2022;14(21):14040.
19. Wang F, Liu Z, Shang S, et al. Vitality continuation or over-commercialization? Spatial structure characteristics of commercial services and population agglomeration in historic and cultural areas. Tour Econ. 2019;25(8):1302–26.
20. Accordino J, Adhikari S. Balancing act: preserving historic fabric and enhancing economic vitality in towns in the metropolitan periphery. Plan Pract Res. 2022;37(1):95–110.
21. Dhingra M, Singh MK, Chattopadhyay S. Rapid assessment tool for traditional Indian neighbourhoods: a case study of Alwar Walled City in Rajasthan. Sustain Cities Soc. 2016;26:364–82.
22. Zheng J, He J, Tang H. The vitality of public space and the effects of environmental factors in Chinese suburban rural communities based on tourists and residents. Int J Environ Res Public Health. 2022;20(1):263.
23. Mack G, Fîntîneru G, Kohler A. Do rural development measures improve vitality of rural areas in Romania. AgroLife Sci J. 2018;7(2):82–98.
24. Hancock J. The future of rural communities: the impact of farm consolidation on community vitality and individual well-being (Doctoral dissertation). 2017.
25. Saputra AA, Surjono S, Meidiana C. Vitality of Giri Kedaton site as a religious tourism attraction in Sidomukti Village, Kebomas, Gresik. J Indones Tour Dev Stud. 2015;3(3):93–104.
26. Jia Z, Gao M, Xu S, et al. Sociocultural vitality versus regulation policy and tourism development in preservation of traditional rural landscape: a case from Guizhou China. Int J Sustain Dev World Ecol. 2021;28(2):179–92.
27. Sadeghi K, Bazrafshan J, Hajinejad A, et al. Investigating the factors affecting the vitality and liveliness of rural households (case study: Fuman township). J Rural Res. 2020;11(2):250–69.
28. Li M, Liu J, Lin Y, et al. Revitalizing historic districts: identifying built environment predictors for street vibrancy based on urban sensor data. Cities. 2021;117: 103305.
29. Xiao L, Lo S, Liu J, et al. Nonlinear and synergistic effects of TOD on urban vibrancy: applying local explanations for gradient boosting decision tree. Sustain Cities Soc. 2021;72: 103063.
30. Xiaomei J, Yeqin F, Cuilan Z. Research on the territorial differentiation and influential factors of Chinese traditional villages. J Shenyang Jianzhu Univ (Soc Sci). 2015;17(05):452–60.
31. Jingyao K, Jinhe Z, Huan H, et al. Analysis on the spatial distribution characteristics of Chinese traditional villages. Prog Geogr. 2016;35(07):839–50.
32. Yingchun C, Yukun Z. Appraisal and selection of "Chinese Traditional Village" and study on the village distribution. Architect J. 2013;12:44–9.
33. Zhang M, Li W. A study on spatial characteristics and value of traditional villages in Lishui Region. J Hum Settl West China. 2015;30(05):53–8.
34. Hu Y, Chen S, Cao W, et al. The concept and cultural connotation of traditional villages. Urban Dev Stud. 2014;21(1):10–3.
35. Jenks GF. The data model concept in statistical mapping. Int Yearb Cartogr. 1967;7:186–90.
36. Gong J, Jian Y, Chen W et al. Transitions in rural settlements and implications for rural revitalization in Guangdong Province. J Rural Stud. 2022; 93:359-366
37. Liu H, Li X. Understanding the driving factors for urban human settlement vitality at street level: a case study of Dalian, China. Land. 2022;11(5):646.
38. Yi Y, Zhao C, Fu J. Research on the integration and development of modern agriculture and rural tourism based on AHP—take Yangjia town in Mianyang city as an example. Open J Soc Sci. 2019;7(7):76–87.
39. Li H, He H, Zhang J. Study on rural development evaluation and drivers of sustainable development: evidence from the Beijing-Tianjin-Hebei region of China. Sustainability. 2022;14(15):9570.
40. Wang C, Zhang Y, Yang Y, et al. What is driving the abandonment of villages in the mountains of Southeast China? Land Degrad Dev. 2019;30(10):1183–92.
41. Zeng C, Song Y, He Q, et al. Spatially explicit assessment on urban vitality: case studies in Chicago and Wuhan. Sustain Cities Soc. 2018;40:296–306.
42. Spearman C. The proof and measurement of association between two things. Am J Psychol. 1987;100(3/4):441–71.
43. Anselin L. Local indicators of spatial association—LISA. Geogr Anal. 1995;27(2):93–115.
44. Anselin L, Bera AK, Florax R, et al. Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ. 1996;26(1):77–104.
45. Fotheringham AS, Brunsdon C, Charlton M. Geographically weighted regression: the analysis of spatially varying relationships. New Jersey: Wiley; 2003.
46. Esri R, ArcGIS desktop: release 10. Environmental Systems Research Institute, CA 2011.
47. Hair JF, Black WC, Babin BJ, et al. Multivariate data analysis. 7th ed. London: Pearson New International Education; 2010. p. 1–758.
48. Brunsdon C, Fotheringham S, Charlton M. Geographically weighted regression. J R Stat Soc Ser D (The Statistician). 1998;47(3):431–43.
49. Zheng D, Wen Q, Wang Y, et al. Differentiation mechanism and reconstruction strategy of rural population hollowing in China. Econ Geogr. 2019;39(02):161–8.
50. Wang C, Gao B, Weng Z, et al. Primary causes of total hamlet abandonment for different types of hamlets in remote mountain areas of China: a case study of Shouning County, Fujian Province. Land Use Policy. 2020;95: 104627.
51. Okubo M, Mohammed AJ, Inoue M. Out-migrants and local institutions: case study of a depopulated mountain village in Japan. Asian Cult Hist. 2016;8(1):1.
52. Shehata AM. Current trends in urban heritage conservation: medieval historic Arab city centers. Sustainability. 2022;14(2):607.
53. Reyes SRC, Miyazaki A, You E, et al. Enhancing sustainability in traditional agriculture: Indicators for monitoring the conservation of globally important agricultural heritage systems (GIAHS) in Japan. Sustainability. 2020;12(14):5656.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.