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# Understanding Public Attention towards the Beautiful Village Initiative in China and Exploring the Influencing Factors: An Empirical Analysis Based on the Baidu Index

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**Abstract:** The implementation of China's Beautiful Village Initiative was an extraordinary achievement and aroused extensive public attention. However, existing research mostly focuses on the construction and seldom on public attention towards the Beautiful Village Initiative. For this reason, this paper investigated the spatiotemporal characteristics of public attention based on the Baidu index using time-constrained clustering and the spatial autocorrelation test. Our results showed that the evolutionary process can be divided into three stages: very little national attention (2011–2012), injection of a strong impetus (2013–2015), and rooted in the people's minds (2016–2020). Spatially, provincial public attention demonstrated obvious spatial differentiation and stable spatial autocorrelation, with Low–Low clusters in Northwest China and High–High Clusters in East, Central, and North China. Spatial econometric models were further utilized to quantify the effects of socioeconomic factors on public attention. The results of the SEM model proved the existence of spatial spillover effects and indicated that the urbanization rate, population density, education level, and network popularity rate all positively affected public attention. The relationship between Beautiful Village construction and public attention was uncoordinated and, in most provinces, advances in public attention were ahead of the construction level. Our findings contribute to the understanding of public attention towards the Beautiful Village Initiative, and policy suggestions we proposed would be applied to increasing public awareness and participation.

**Keywords:** Beautiful Village Initiative; public attention; spatiotemporal evolution; influencing factors; China

## 1. Introduction

Since the 1980s, China has experienced unprecedented industrialization and urbanization. During this period, rural areas have made great contributions and sacrifices, including rural hollowing [1,2], ecological and environmental deterioration [3], and increased rural poverty [4]. To solve these urgent issues, the Chinese central and local governments launched a series of campaigns in order to facilitate comprehensive, coordinated, and sustainable development over vast rural areas [5,6]. In 2008, Anji County in Zhejiang Province, a typical mountainous area that is known as the back garden of metropolises such as Hangzhou and Shanghai, took the lead in putting forward a Beautiful Village Initiative. The proposed goal was to become a new model for the Chinese countryside, with beauty, entrepreneurship, harmony, and happiness at its core [7,8]. In 2010, Zhejiang

Province vigorously promoted the Anji project and upgraded the Beautiful Village Initiative to include provincial-level policies. This example is seen as the “leading goose” in beautiful countryside construction [8,9]. In 2013, “striving to build beautiful villages” was clearly stated in the No. 1 Central Document [10], and the pilot program was launched in seven provinces. This emphasized the construction of beautiful villages as a concrete objective and an important part of the Beautiful China Initiative; it became a policy decision and a joint action at the national level [11–13]. In 2017, the 19th National Congress of the Communist Party of China proposed the implementation of the rural revitalization strategy [14]. This did not represent the abandonment of the Beautiful Village Initiative, but a higher requirement for the construction of beautiful villages, i.e., the cornerstone of rural revitalization [15–17]. The aforementioned development process effectively accelerated the implementation of the concepts in the Beautiful Village Initiative. On the basis of the existing literature, the Beautiful Village Initiative refers to coordinated economic, political, cultural, social, and ecological development in rural areas. Moreover, beautiful villages should be characterized by scientific planning, high productivity, a rich and civilized way of life, protection and inheritance of culture, good sanitation, democratic management, and environmental livability [18–22]. The “Beautiful Village Initiative” in China and the “Sustainable Development in Rural Areas” in the UK have the similar function and effect [23]. As a comprehensive scheme, the beautiful village construction follows the principle of adapting measures to local conditions, pursuing regional features, rather than “thousands of villages look the same”; meanwhile, the construction requires overall planning and consideration, pursuing all-round development, rather than just buildings. (Please see the images in Appendix A).

The Beautiful Village Initiative has been developing for over 10 years and is a fast-growing field for multidisciplinary research. Scholars have conducted exploratory research on the Beautiful Village Initiative from different perspectives, integrating theories and methods from geography, economics, management, and sociology. These studies include evaluating the level of construction and the effect by the Beauty Index System [5,24,25]; the characteristics of spatial distribution using GIS and statistics methods [18,26,27]; the inheritance of rural culture [28–30]; the implementation of rural industrial revitalization, such as tourism [11,31–33]; the interaction between the Beautiful Village Initiative and other schemes, such as the Beautiful China Initiative [34,35]; and so on. Despite this, more than just administrative action and scholarly research is required for the construction of beautiful villages. The Beautiful Village Initiative cannot be viewed separately from the Chinese public and its sense of responsibility, as citizens make up the main body and are the builders of China [36]. Therefore, it is important to understand how the Chinese public views the Beautiful Village Initiative. At present, there are few studies focusing on the public perspective of the Beautiful Village Initiative, and the spatiotemporal pattern of public attention and the related influencing factors remain unclear.

The online search behaviors of network users reflect their offline concerns regarding certain issues. Thus, researchers can use these data to quantify perspective characteristics [37–40]. For example, Google Trend data are frequently utilized to measure and assess perspectives on Olympics [41], disasters [42], COVID-19 [43], the stock market [44], and so on. In China, Baidu is the most commonly used search engine, with over 80% of the market share [45], and the Baidu Search Index is suitable for use in research and is easily obtained. Currently, many studies are based on the Baidu index, which are mainly related to air pollution [46], greenhouse gases [37], homeland security [36], COVID-19 [47], Internet celebrity scenic spots [48], and other topics; however, public perspectives on the Beautiful Village Initiative are not considered, which is not conducive to understanding public opinion and concern to this end.

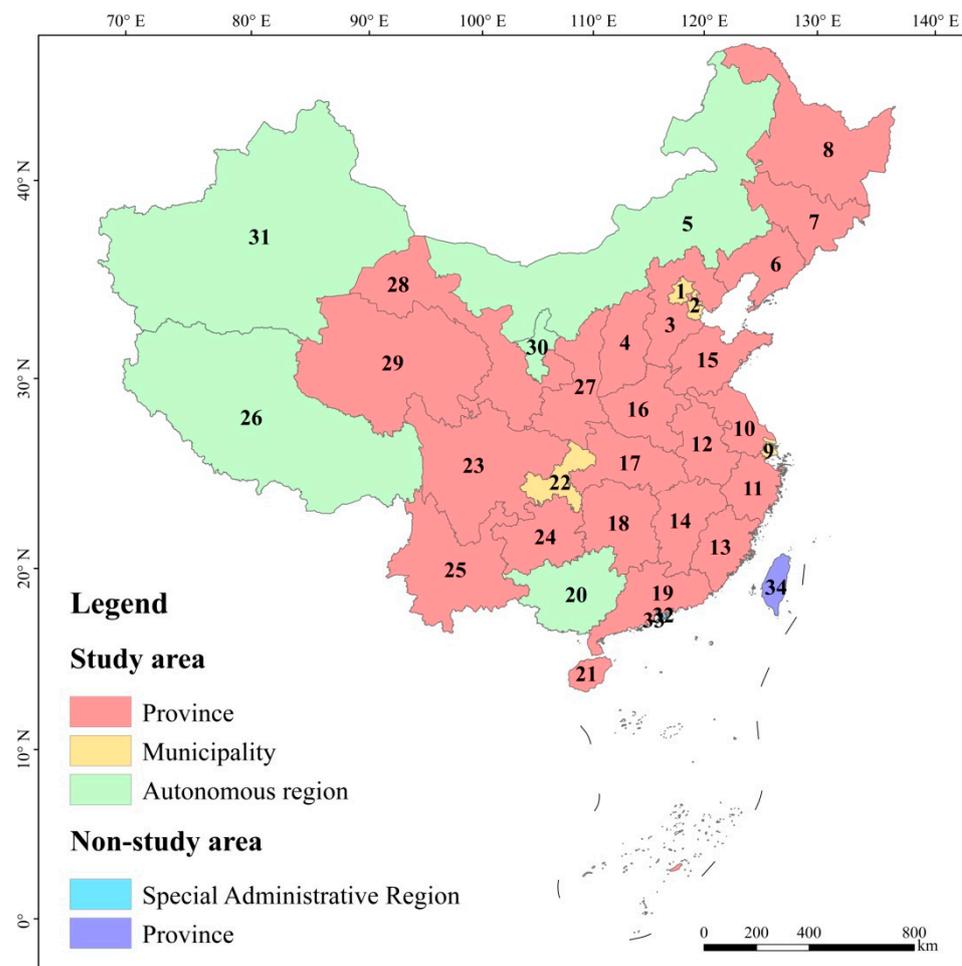
Considering the above situation, this research attempted to fully quantify the scale, spatiotemporal characteristics, and evolution of public attention towards the Beautiful Village Initiative, and explore the influencing factors and mechanisms involved therein. The findings are of vital benefit for understanding public concern towards the Beautiful

Village Initiative, and thus increasing public awareness and participation, and providing scientific support to compile a reasonable and differentiated schedule of scheme advancement. The paper is structured as follows: Section 2 outlines the study area, data, and methods. In Section 3, the results are demonstrated and described. The discussion is presented in Section 4. Finally, the conclusions and policy suggestions are offered in Section 5.

## 2. Materials and Methods

### 2.1. Study Area

The study area consisted of 31 provincial-level administrative units in China (excluding Hong Kong, Macao, and Taiwan), including 22 provinces, 4 municipalities, and 5 autonomous regions, which are presented in Figure 1.



**Figure 1.** Map of the study area showing spatial locations and data adequacy. These areas are coded by numbers as follows: North China: 1—Beijing, 2—Tianjin, 3—Hebei, 4—Shanxi, 5—Inner Mongolia; Northeast China: 6—Liaoning, 7—Jilin, 8—Heilongjiang; East China: 9—Shanghai, 10—Jiangsu, 11—Zhejiang, 12—Anhui, 13—Fujian, 14—Jiangxi, 15—Shandong; Central-South China: 16—Henan, 17—Hubei, 18—Hunan, 19—Guangdong, 20—Guangxi, 21—Hainan; Southwest China: 22—Chongqing, 23—Sichuan, 24—Guizhou, 25—Yunnan, 26—Tibet; Northwest China: 27—Shaanxi, 28—Gansu, 29—Qinghai, 30—Ningxia, 31—Xinjiang; nonstudy area (regions with no data): 32—Hong Kong, 33—Macao, 34—Taiwan.

### 2.2. Data and Its Sources

#### 2.2.1. Baidu Index

The Baidu index is a big data indicator that can be utilized to measure and characterize the online search behavior of large numbers of netizens. It uses search volume as the

statistical basis with which to calculate the weighted sum of the search frequency of a specific keyword on Baidu web pages, and displays it in the form of a graph, reflecting netizens' acquisition and access of information for an issue during a specific period of time [37,46].

Considering the merits of scientificity, conciseness, and operability, we choose "Beautiful Village" (in Chinese "美丽乡村") as the keyword to search for on the Baidu index platform (<https://index.baidu.com/v2/index.html#/>, accessed on 19 August 2021). The reasons are chiefly as follows: The keyword should reflect and characterize the users' searching behavior to the greatest extent, and is expected to have a robust representativeness, a large search amount, and a wide cover-range of searching content. Different from other small-scale research (such as provincial and municipal scale) wherein each pilot can be selected as the keyword to search for, this research was conducted at the national scale with tens of thousands of beautiful village pilots; using all of these as keywords to search would be impractical. The word "Beautiful Village" (in Chinese "美丽乡村") has gradually developed into a generalized concept accepted by the public throughout China, and it contains both pertinence and richness of content behind it. When a netizen is eager to know the goals, implementation effects, and construction significances of abstract "Beautiful Village Initiative", and when he is willing to know the specific situation of a certain or some beautiful village construction pilots, the "Beautiful Village" is the first word that comes to mind to search for on the Baidu platform. Therefore, we admit that choosing "Beautiful Village" as the only keyword may have limitations, but it is currently the most appropriate way. Furthermore, based on this explanation, we believe that the Baidu index obtained in this way is capable of representing the degree of Chinese public attention towards the Beautiful Village Initiative.

The search index over a specific period and area was provided. It is an important data source for researchers. It made it possible for us to analyze the current search volume trends of Chinese Internet users on the specific topic of "beautiful village" and the spatiotemporal distribution characteristics of public attention. A greater index value indicates more attention to the searched keyword.

The Baidu index value since 2011 can be obtained on the Baidu platform. The search period in this study was from January 2011 to December 2020, but the values for each province in 2011 and 2012 were too small to be provided accurately. Hence, the annual daily average Baidu index from 2011 to 2020 on the national level and 2013 to 2020 at the provincial level was used to represent public attention towards the Beautiful Village Initiative, and which was selected as the dependent variable for the spatial econometric models.

### 2.2.2. Socioeconomic Data

The public attention towards the Beautiful Village Initiative was influenced by the integrated effect of social and economic conditions. On the basis of the existing literature [41–44,46–50] and data availability, in this study, we selected seven socioeconomic factors as the explanatory variables with which to quantitatively identify the impact on public attention. These are introduced in Section 3.2.1. The provincial-level datasets were obtained from the China Statistical Yearbook (2013–2020) and the Statistical Yearbook in provinces (2013–2020).

## 2.3. Methods

### 2.3.1. Time-Constrained Clustering

Time-constrained clustering was introduced to reveal the discriminative characteristics of the research object while dividing it into time stages [51,52]. It is an improvement of stratigraphically constrained clustering and can ensure the continuity of the sample clustering results. The algorithm process follows:

$$D_i = \sum_{p=1}^{n_i} \sum_{q=1}^m (x_{ipq} - \bar{x}_{iq})^2 \quad (1)$$

where  $D_i$  is defined as the sum of square deviations within the  $i$ th category,  $n_i$  is the number of samples included in the  $i$ th category,  $m$  is the number of variables,  $x_{ipq}$  is the observed value of the  $q$ th variable of the  $p$ th sample of the  $i$ th category, and  $\bar{x}_{iq}$  is the mean value of the variable  $q$  in the  $i$ th category.

$$D = \sum_{i=1}^j D_i \quad (2)$$

where  $D$  represents the sum of square deviations after dividing the sample into  $j$  categories.

The adjacent categories were merged in sequence until the increment of the sum of square deviations was the smallest.

### 2.3.2. Geographic Concentration Index and Disequilibrium Index

The geographic concentration index and disequilibrium index were employed to judge the spatial characteristics of the public attention in China.

The geographical concentration index is an important indicator reflecting the concentration degree of the public attention at national scale [53,54]; it is given by the following formula:

$$G = 100 \times \sqrt{\sum_{i=1}^n \left(\frac{x_i}{T}\right)^2} \quad (3)$$

where  $G$  represents the geographic concentration index of the Baidu index, ranging between 0 and 100;  $x_i$  refers to the Baidu index of the  $i$ th province;  $T$  refers to the sum of Baidu indexes of all provinces; and  $n$  is the number of provincial-level units.

The geographical disequilibrium index was used to reflect the degree of unbalance in public attention between different provinces [53,55,56]. It was calculated using the Lorenz curve method, and its formula can be written as follows:

$$S = \frac{\sum_{i=1}^n Y_i - 50(n+1)}{100 \times n - 50(n+1)} \quad (4)$$

where  $S$  denotes the geographical disequilibrium index of the Baidu index, between 0 and 1;  $n$  is the number of provinces; and  $Y_i$  represents the cumulative percentage of the Baidu index in the  $i$ th province sequenced in descending order.

### 2.3.3. Spatial Autocorrelation Test

In this paper, the spatial autocorrelation test was utilized to analyze the similarity and spatial association patterns of the public attention in neighboring regions.

First, to test and measure in general the spatial autocorrelation and heterogeneous relationship of public attention in adjacent areas, the global Moran's  $I$  index was adopted [47,57,58], which can be expressed as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sigma^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (5)$$

where  $n$  is the number of provinces;  $x_i$  and  $x_j$  represent the Baidu index of province  $i$  and  $j$ , respectively;  $\bar{x}$  is the average of the Baidu index of all provinces;  $\sigma^2$  is the variance; and  $w_{ij}$  indicates the spatial weight matrix.

Equation (6) presents the Z-test statistic, which was used to test the significance of the Moran's  $I$  index:

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \quad (6)$$

The values of the global Moran's  $I$  index range from  $-1$  to  $1$ . When  $I > 0$  ( $I < 0$ ), it indicates that there is a positive (or negative) spatial autocorrelation of the Baidu index; when  $I = 0$ , there is no spatial autocorrelation.

The global Moran's  $I$  was used to describe the overall spatial agglomeration of the Baidu index; however, it cannot determine the detailed location of agglomeration and isolation areas. Hence, the local Moran's  $I$  was employed to grasp the spatial aggregation and differentiation characteristics [59,60]. It was calculated as follows:

$$I_i = z_i \sum_{i \neq j}^n w_{ij} z_j \quad (7)$$

where  $I_i$  is the local Moran's  $I$  for the province  $i$ ,  $z_i$  and  $z_j$  are the standardized values of the Baidu index of province  $i$  and  $j$ , and  $w_{ij}$  indicates the spatial weight matrix.

A local Moran's  $I$  with a positive (or negative) value implies that provinces with similar (or different) values can be assigned to one of four cluster types: A High–High cluster, Low–Low cluster, High–Low cluster, and Low–High cluster.

#### 2.3.4. Spatial Econometric Models

In order to analyze the influences of socioeconomic factors on public attention, in this study we employed spatial econometric models.

Firstly, the ordinary least squares (OLS) technique was utilized to quantify the effects of seven independent socioeconomic variables on public attention [61–63]; the model can be written as follows:

$$y = \beta_0 + \beta_i x_i + \varepsilon \quad (8)$$

where  $y$  denotes the dependent variable, i.e., the Baidu index; the parameter  $\beta_i$  indicates the undetermined coefficients of all independent variables  $x_i$ , and all the variables are defined as natural logarithms;  $\beta_0$  is the intercept term; and  $\varepsilon$  is the error term.

The OLS model ignores the spatial correlation between variables, which may lead to estimation bias. Hence, to solve this problem, the spatial error model (SEM) was adopted to analyze the factors influencing public attention.

SEM separates the spatial autocorrelation from the error term and transforms them into the spatial error term with the form of a spatial adjacent matrix [61–63]; the SEM model can be expressed as follows:

$$\begin{cases} y = \beta_0 + \beta_i x_i + \varepsilon \\ \varepsilon = \lambda W \varepsilon + \mu \end{cases} \quad (9)$$

where  $\lambda$  denotes the spatial error coefficient, which expresses the spatial autocorrelation of the spatial error terms, which, in turn, reflects the impact of the residuals of nearby provinces on the residuals of this province; and  $\mu$  is a random error vector with normal distribution. The definitions of other variables and parameters are the same as in the OLS model.

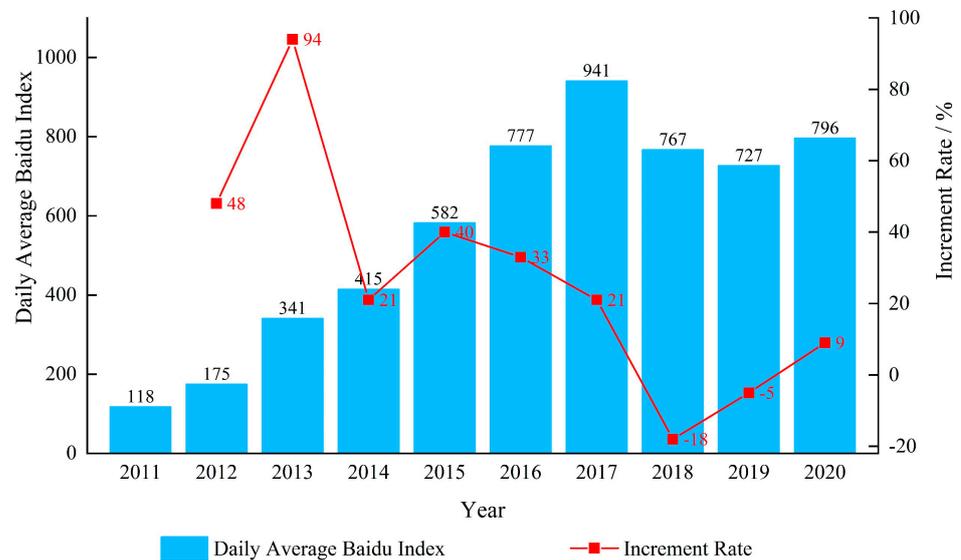
### 3. Results

#### 3.1. Spatiotemporal Pattern and Evolution of Public Attention towards the Beautiful Village Initiative

##### 3.1.1. Temporal Dynamic Evolution Characteristics

Figure 2 shows the annual daily average Baidu index for “Beautiful Villages” (hereinafter referred to as the Baidu index) and the increment rate on the national level from 2011 to 2020. During this period, the public attention towards beautiful villages (hereinafter referred to as the public attention) increased year by year from 2011 to 2017. The increment rate in 2013 was 94%, indicating that public attention in 2013 was almost double that in 2012. This may have been due to the fact that Document No. 1 of the Central Committee was released that year, which pledged “To promote the construction of rural ecological civilization and strive to build beautiful villages”. This may have triggered widespread attention. In 2018–2020, the Baidu index was characterized by a fluctuating trend, with a

decrease of 18% in 2018 and an increase of 9% in 2020, although, overall, the Baidu index remained high, indicating strong momentum regarding public attention.



**Figure 2.** China’s national-level daily average Baidu index for “Beautiful Villages” during 2011–2020.

Specifically, the evolution of public attention from a provincial perspective can be observed in Figure 3. There are obvious differences in the public attention of the 31 provinces (autonomous regions and municipalities). The Baidu indexes of all provinces in 2011 and 2012 were too low to generate accurate statistics; therefore, the analyzed time series began in 2013. The provinces and autonomous regions with the lowest public attention throughout were Tibet (the daily average Baidu index varied from 1 to 12), Ningxia (varying from 5 to 36), and Qinghai (varying from 6 to 33) in 2013–2020. The public attention in all other provinces in the study area (except Liaoning) demonstrated a trend that first increased and then decreased, which is roughly consistent with the evolution at the national level. The period from 2017 to 2018 was peak for public attention, and the inflection point of attention evolution appeared here. The provinces with the highest public attention were Zhejiang (the multiyear daily average Baidu index value was 163), Shandong (159), Beijing (149), and Guangdong (147). Moreover, in the earlier stages, Henan and Fujian, and in the later stages, Jiangsu, were also provinces that demonstrated high attention.

Furthermore, time-constrained clustering was introduced to objectively divide the time stages of public attention evolution and summarize temporal characteristics. The results from 2013 to 2020 are shown in Figure 4. We can see from Figure 4 that the optimal number of clusters was two. During 2011–2020, Chinese public attention towards beautiful villages could be divided into three stages, i.e., the first stage from 2011 to 2012, the second stage from 2013 to 2015, and the third stage from 2016 to 2020. The first stage is where the foundation was laid. In this stage, the construction of beautiful villages had only started in Zhejiang and Fujian, which did not attract national public attention, and thus, the Baidu index for each province was very low. In the second stage, the introduction of national policies and the practice of building beautiful villages in various places had increased public attention, and the Baidu indexes rose rapidly. In the third stage, the positive impact of beautiful countryside construction was being felt, and the associated concepts had become rooted in people’s minds; thus, the Baidu index remained at a high level.

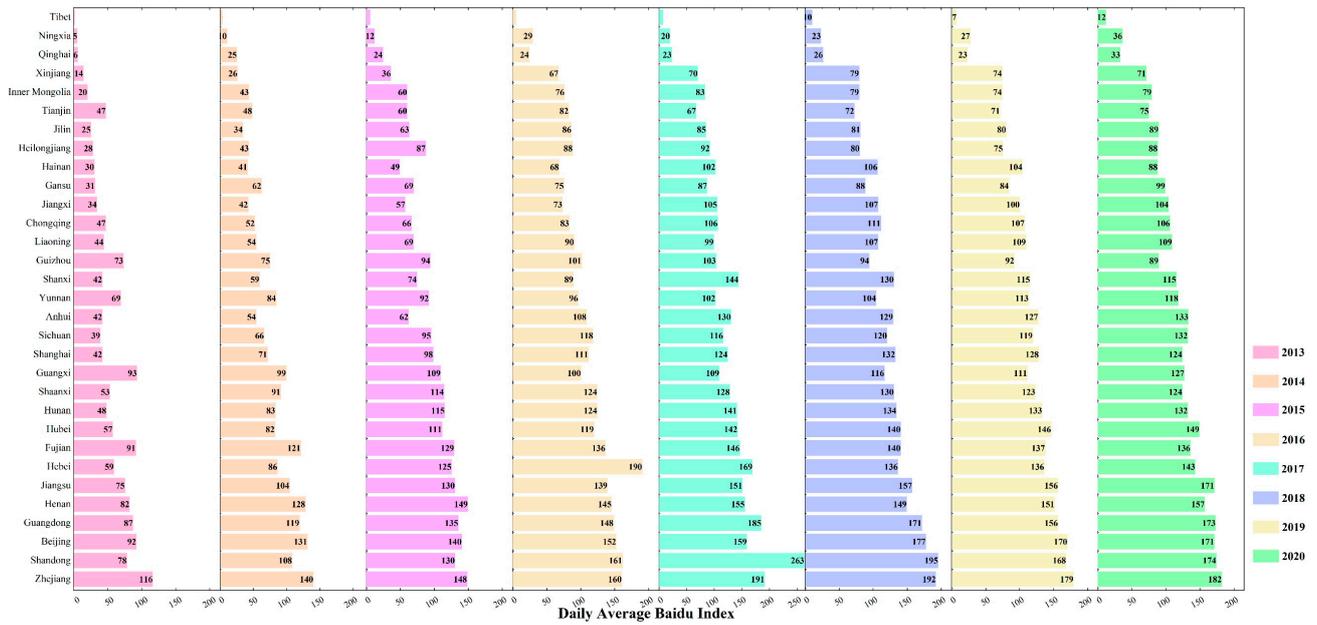


Figure 3. China’s provincial-level daily average Baidu index for “Beautiful Villages” during 2013–2020.

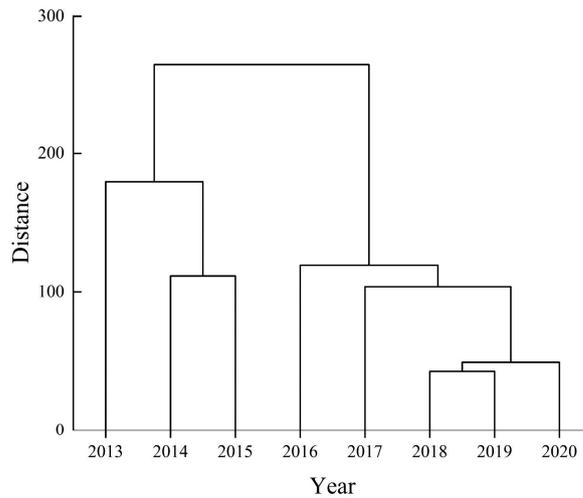


Figure 4. Annual stage division of daily average Baidu index of “Beautiful Villages” from 2013 to 2020.

### 3.1.2. Spatial Distribution Pattern Characteristics

Figure 5a shows that China’s provincial daily average Baidu index has obvious differentiation with the general pattern: East China > Central China > West China, and South China > Central China > North China. To intuitively reflect this process, Figure 5b–d details the spatial distribution of the Baidu index in 2015, 2017, and 2019, showing that the number of low-attention provinces markedly decreased, while the number of high-attention provinces clearly increased. Specifically, the area and Baidu index level in East, Central, and South China greatly increased; while the Baidu index remained low in the Northeast and Northwest China, including Heilongjiang, Jilin, Inner Mongolia, Xinjiang, and Qinghai.

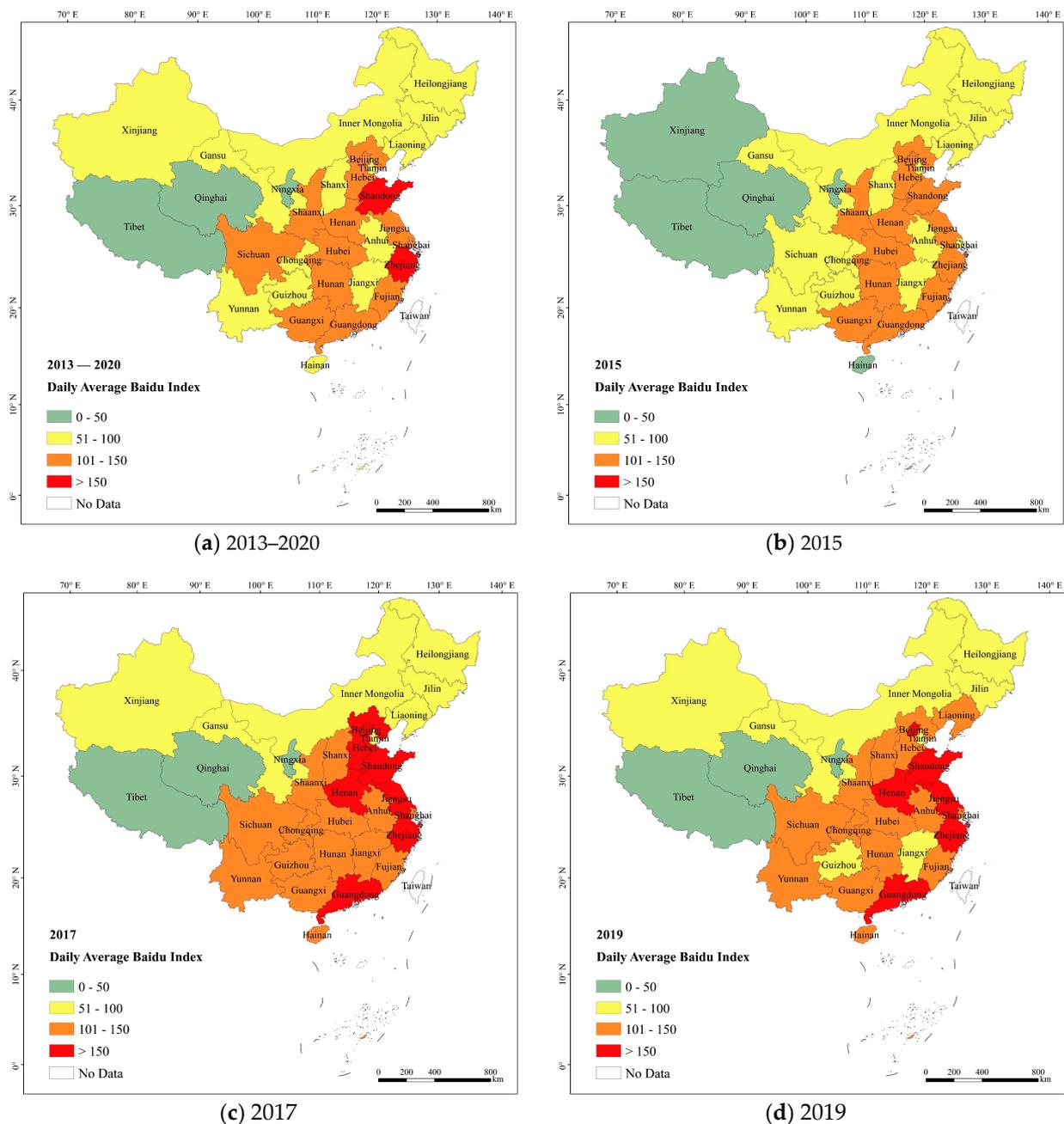
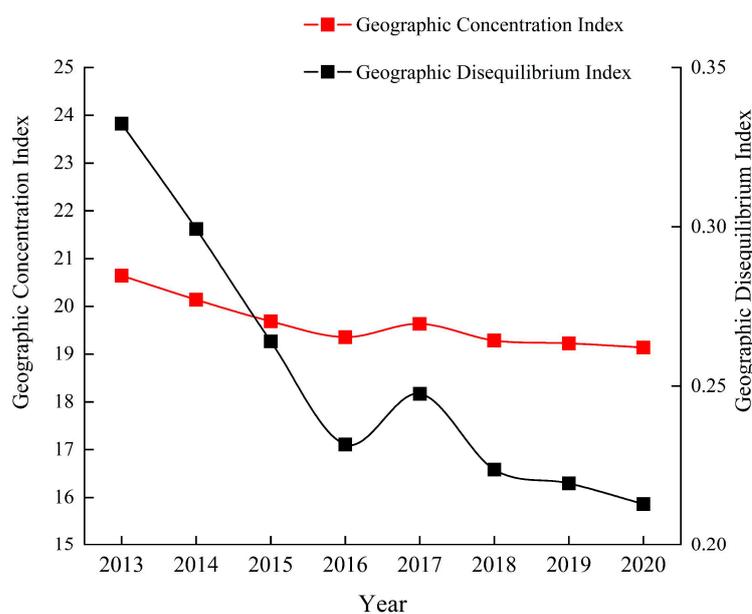


Figure 5. Spatial distribution of daily average Baidu index during 2013–2020.

In the evolution of spatial distribution, the geographic disequilibrium index was between 0.332 and 0.213 (Figure 6), i.e., characterized by a downward trend, indicating that polarization of Baidu index was prominent, although it weakened. The average geographic concentration index was 19.638, with values displaying a decreasing trend. If the Baidu index had been evenly distributed in all provinces, the geographical concentration index would be 17.961; however, the actual geographical concentration index was consistently greater than this value, revealing that the distribution of the Baidu index was generally concentrated at the provincial level.



**Figure 6.** Geographic concentration index and disequilibrium index for public attention from 2013 to 2020.

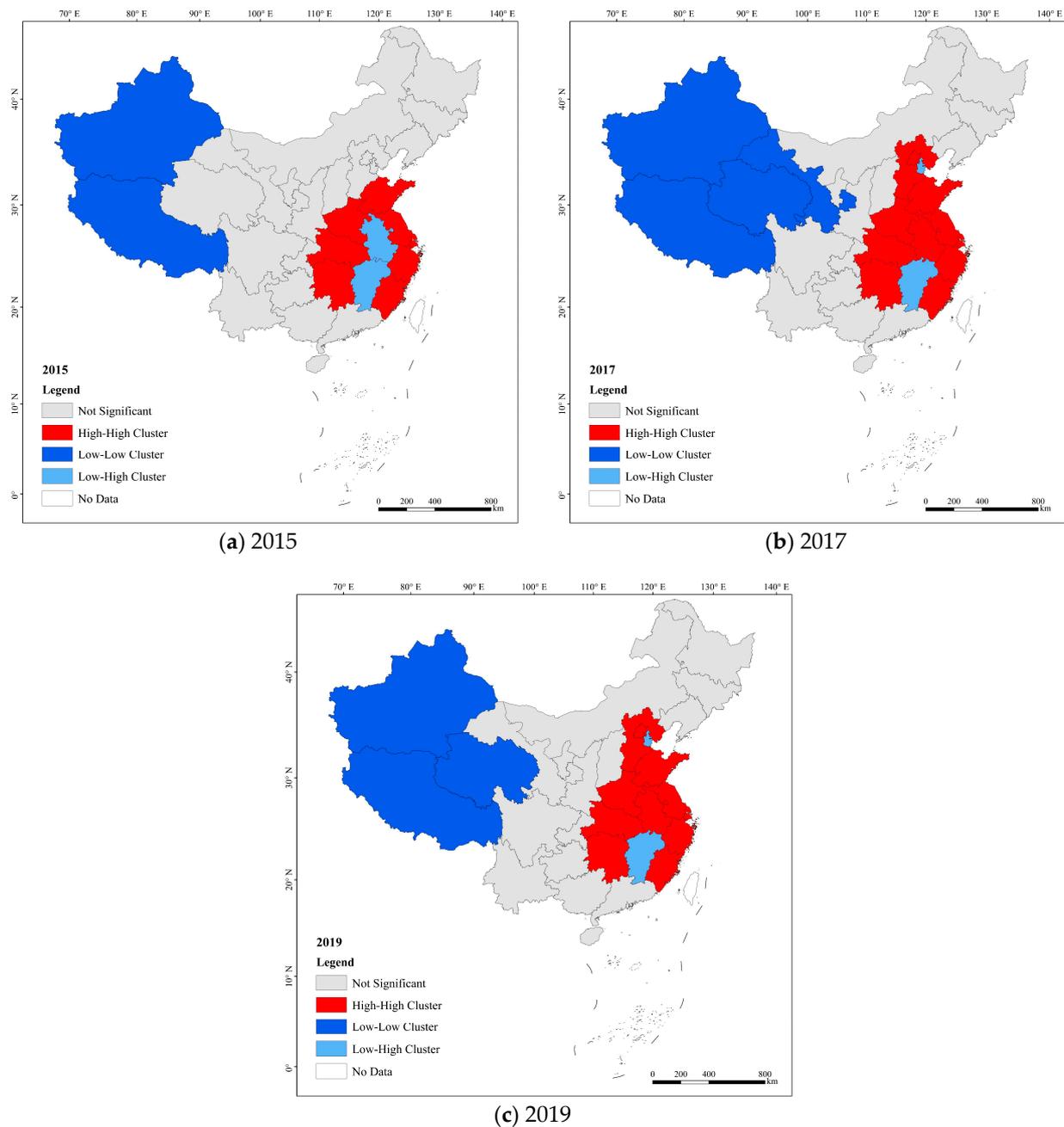
On the basis of the preceding analysis, it appears that the pattern and evolution of the Baidu index was characterized by clustering and agglomeration, i.e., the Baidu index of an area was spatially correlated with the neighboring area to a certain extent. Therefore, we examined the autocorrelation and relevancy characteristics.

The results of the global spatial autocorrelation of the Baidu index during the period studied are presented in Table 1. The global Moran's  $I$  index was always positive and higher than 0.30, which passed the 0.01% level significance test, indicating that there was a significant and stable spatial autocorrelation in the annual Baidu index. It can be confirmed that the Baidu index of the area was highly positively associated with neighboring values.

**Table 1.** Global Moran's  $I$  index of Baidu index concentrations during 2013–2020.

Year	Moran's $I$	Z-Score	$p$ -Value
2013	0.329	4.037	0.001
2014	0.301	3.721	0.002
2015	0.305	3.763	0.003
2016	0.336	4.336	0.002
2017	0.346	4.428	0.001
2018	0.384	4.498	0.001
2019	0.412	4.898	0.001
2020	0.378	4.408	0.001

Furthermore, the local spatial autocorrelation analysis was used to detect specific characteristics of Baidu index agglomeration, and the spatial clustering pattern is shown in the LISA map (Figure 7). The Baidu index mainly formed three categories of clustering in the regional distribution. The Low–Low clusters were situated in Northwest China, such as in Xinjiang and Qinghai, and in Tibet, which included two, five, and three provinces in 2015, 2017, and 2019, respectively. The High–High Clusters were formed in East and Central China in 2015, for example, in Jiangsu, Zhejiang, Hubei, and Hunan. We see that the High–High Clusters extended northward in 2017 and 2019 to Hebei and Beijing, which proves that the Baidu index in North China also increased to a high level, and these clusters had 8, 11, and 11 provinces in 2015, 2017, and 2019, respectively. Moreover, there was a “depression area” in Central China, i.e., a Low–High cluster, including Anhui and Jiangxi, whose Baidu index was obviously lower than that of the surrounding areas.



**Figure 7.** LISA agglomeration maps of public attention in China in 2015, 2017, and 2019.

The spatial autocorrelation analysis confirmed the existence of significant spatial agglomeration of public attention towards “Beautiful Villages” in China, which reveals that spatial correlation and spatial dependence should be considered and controlled in the influencing factors analysis.

### 3.2. Analysis of the Factors and Mechanisms Influencing Public Attention towards “Beautiful Villages”

#### 3.2.1. Explanatory Variables

Considering the existing literature [41–44,46–50] and data availability, we selected seven socioeconomic factors as explanatory variables in this study, and quantitatively explored the degrees and mechanisms of their influence on public attention towards Beautiful Villages. They follow:

**Economic Development.** The level of economic development directly affects the level of technical skills on the Internet and the abundance of Internet resources, and it is most often measured by GDP per capita.

**Urbanization.** In China, urbanization, especially “New Urbanization”, is conducive to the construction of Internet infrastructure, the cultural atmosphere, and the reshaping of spiritual life. We chose the population urbanization rate to measure the urbanization level.

**Population.** The population density influences the amount of investment from Internet companies, due to the scope economies of the Internet industry. Moreover, population density determines the scale and speed of regional information diffusion. Local residents in areas with larger population densities are more likely to transmit information about beautiful villages.

**Educational Attainment.** The educational level reflects the population literacy to a certain extent, and directly and indirectly affects the population’s ability to capture new issues. When the educational level is high, the population more effectively constructs and transmits ideas concerning ecological civilization and culture, which includes the construction of beautiful villages.

**Social Informatization.** Network popularity rate was utilized to characterize the level of social informatization. Improving the network use rate broadens resident information channels, weakens the negative impact of geographical distance, and increases the ability of local residents to search for novel initiatives and ideas through the Internet, especially rural residents. This is important for receiving information about beautiful villages.

**Beautiful Village Construction.** The construction of beautiful villages involves the interests of local residents, improves resident social wellbeing, and stimulates their attention and encourages them to participate. Beautiful countryside construction imperceptibly encourages farmers to improve their lifestyle and spiritual life, while also helping the urban population enjoy a new form of leisure and pay more attention to beautiful villages. In addition, the successful construction of beautiful villages increases reports in the news media, which also increases public searches for beautiful villages. In recent years, the Ministry of Agriculture and Rural Affairs of China has selected national-level beautiful villages based on rigorous reviews by experts. The number and ratio of these selections demonstrate the achievements of beautiful villages in various provinces.

**Historical and Cultural Protection.** Public attention towards “Beautiful Villages” is also influenced by regional historical and cultural resources. The protection and development of traditional villages greatly improves the overall environmental quality. Historical and cultural resources are an indispensable and important part of the cultural value of beautiful villages, which not only increase rural tourism, but also create a spiritual bond with the area.

The units, labels, and definitions of these independent variables are shown in Table 2. The summary statistics for the variables and the variance inflation factor values that were utilized to check the multicollinearity are shown in Table 3. These indicate that there was no unacceptable collinearity between variables.

### 3.2.2. Comparison of Model Goodness-of-Fit

The estimates of the global regression models are summarized in Table 4. For the OLS results, the  $R^2$  was 0.683 in 2015, 0.848 in 2017, and 0.816 in 2019, which suggests that this model has relatively good explanatory power. The results obtained in Lambda, with values of 0.693, 0.933, and 0.986, show that the spatial error term of SEM was significant, supporting the existence of spatial agglomeration in the Baidu index. The  $R^2$  of SEM was improved to 0.726, 0.893, and 0.889, respectively. These results indicate that the models that considered spatial autocorrelation were better than the traditional OLS model. Furthermore, the AIC statistic and Sigma<sup>2</sup> of SEM were better than those of the OLS model; therefore, SEM better explains the relationship between variables. Thus, this section mainly explores the results analyzed from SEM.

**Table 2.** Definitions and descriptions of variables.

Variables	Factors	Labels	Units	Definitions
Economic Development	GDP Per Capita	GDPP	Yuan	The gross domestic product divided by the population
Urbanization	Urbanization Rate	UR	%	The proportion of urban population to total population
Population	Population Density	PD	Person/km <sup>2</sup>	The amount of population per unit area
Educational Attainment	Education Level	EL	%	The ratio of the population with high education level to the population aged 6 and over
Social Informatization	Network Popularity Rate	NPR	%	The proportion of the household with Internet broadband access to the total households
Beautiful Village Construction	National-Level Beautiful Village	NBV	‰	The ratio of national-level beautiful village to total villages
Historical and Cultural Protection	National-Level Traditional Village	NTV	‰	The ratio of national-level traditional village to total villages

**Table 3.** Statistical description and variance inflation test of the variables.

Year		Variables						
		GDPP	UR	PD	EL	NPR	NBV	NTV
2015	Mean	53084	56.64	474.74	14.31	48.19	0.92	5.72
	Min	26165	27.74	2.70	7.11	34.00	0.16	0.27
	Max	107960	87.60	4163.79	42.34	75.00	5.03	41.93
	Std. Dev	23308.50	12.89	762.11	6.75	11.41	1.02	8.60
	VIF	6.14	9.71	2.54	4.70	4.21	1.89	1.41
2017	Mean	60856	58.98	478.65	15.33	53.35	1.94	8.87
	Min	28497	30.89	2.81	7.65	40.00	0.36	0.66
	Max	128994	87.70	4168.97	47.61	77.00	9.43	51.37
	Std. Dev	27573.46	12.01	763.25	8.18	10.06	1.89	11.02
	VIF	5.46	8.23	3.21	5.77	4.45	1.88	1.37
2019	Mean	69235	60.85	482.28	15.74	56.19	3.31	13.84
	Min	32995	31.54	2.93	8.32	43.00	0.59	1.09
	Max	164220	88.30	4186.21	50.49	78.00	16.98	59.14
	Std. Dev	32698.43	11.59	765.84	8.05	8.84	3.22	14.83
	VIF	3.98	9.03	3.19	5.37	4.81	1.68	1.33

**Table 4.** Estimation results of the impact of variables on the Baidu index.

Variables	2015		2017				2019					
	OLS	SEM	OLS	SEM	OLS	SEM						
Ln GDPP	−0.195	(−0.356)	0.008	(−0.016)	−0.496	(−1.439)	−0.379	(−1.433)	0.020	(−0.067)	−0.125	(−0.640)
Ln UR	0.875	(−0.734)	0.841	(−0.898)	1.160	(−1.422)	0.732	(−1.221)	1.340	(−1.455)	0.507	(−0.701)
Ln PD	0.314 ***	(−3.411)	0.320 ***	(−4.230)	0.310 ***	(−4.475)	0.343 ***	(−6.130)	0.240 ***	(−3.376)	0.313 ***	(−5.469)
Ln EL	0.226	(−0.428)	0.018	(−0.045)	0.589 *	(−1.718)	0.285	(−1.124)	0.278	(−0.729)	0.248	(−0.962)
Ln NPR	0.247	(−0.310)	0.068	(−0.102)	0.046	(−0.067)	0.610 ***	(−1.146)	−0.671	(−0.759)	0.114	(−0.180)
Ln NBV	−1.679	(−3.116)	−1.493 ***	(−3.480)	−1.506 ***	(−5.980)	−1.361 ***	(−7.222)	−0.865 ***	(−4.433)	−0.746 ***	(−5.641)
Ln NTV	0.225	(−1.379)	0.223 **	(−1.781)	0.204 **	(−2.143)	0.172 ***	(−2.720)	0.137 *	(−1.669)	0.148 ***	(−2.860)
Lambda			0.639 **	(−2.271)			0.933 ***	(−5.592)			0.986 ***	(−7.174)
R <sup>2</sup>	0.683		0.726		0.848		0.893		0.816		0.889	
AIC	49.119		46.396		24.024		17.259		25.695		14.817	
Sigma <sup>2</sup>	0.230		0.147		0.102		0.053		0.108		0.048	

Notes: \*\*\*, \*\*, and \* represent the 1%, 5%, and 10 % significance levels, respectively. The numbers in the parentheses are the t-statistics.

### 3.2.3. Empirical Results and Interpretations

In general, the impact coefficients and significance levels of each variable had common features and obvious differences in the research time sections of 2015, 2017, and 2019.

As can be observed from the empirical results, the neighborhood effect was positive at a 1% significance level, which revealed the spatial spillover effects of the Baidu index in

China, proving that public attention towards beautiful villages was transmitted through dense economic, spatiotemporal, and cultural connections in adjacent areas.

The Ln GDPP did not return fixed positive or negative data and was not significant in any model, which was surprising. A possible reason for this is an inequality at the provincial level between the concept of ecological civilization and the level of economic development. Adjusting the regional development strategy and green governance enabled certain underdeveloped regions to achieve “overtaking by curves” in ecological civilization construction. However, in certain provinces with high-level economic development, local sustainability was ignored, and the “crowding effect” on ecological civilization was produced due to path dependence, causing the public to overlook beautiful villages and other construction projects.

The urbanization rate had a positive impact on the Baidu index, but did not pass the significance test. The influence coefficients in 2015, 2017, and 2019 were 0.841, 0.732, and 0.507, respectively, showing a decreasing trend, i.e., the intensity of the impact on the Baidu index weakened. This may have been because the research period was a stage of rapid urbanization in China, and the gap between provinces narrowed. With the implementation of targeted poverty alleviation and ecological civilization construction in China, the life of rural and urban residents has become increasingly similar, and their ability and willingness to pay attention to new issues, such as beautiful villages, has also become more alike.

The Ln PD influence coefficients remained between 0.3 and 0.4 (at 1% significance level), and the difference between years was minimal, which shows that the population density, as the fundamental material guarantee for searching and disseminating of Internet information, was one of the most vital socioeconomic factors affecting the public attention towards beautiful villages. Higher population densities led to increased attention, e.g., for every 1% increase in population density, the Baidu index increased by around 0.32%.

Although the signs of Ln EL were positive, they were not statistically significant, which was fairly unexpected. This may have been related to two aspects: First, in China’s new era of wide-ranging social, economic, and cultural development, the impact of education level on the public’s use of the Internet weakened. Second, the education data were obtained from China’s National Sample Survey on Population, which has a sampling fraction of approximately 0.8%; as a result, there may be a slight deviation in terms of describing the real educational situation.

The Ln NPR values were also positive. In 2017, the influence coefficients value was 0.610 at a 1% significance level, i.e., a 1% increase in network popularity rate was accompanied by a 0.61% increase in the Baidu index. However, this did not pass the significance test in 2015 and 2019, with influence coefficients of only 0.068 and 0.114, respectively. This may be because its influence has been explained by other relevant variables in the model, such as economic development.

The Ln NBV was negatively associated with the Baidu index at a 1% significance level in China. This seems to indicate that, statistically, the higher the regional beautiful village construction achievements, the lower the public attention. It is necessary to obtain an insight into the underlying causes, which we will discuss in detail in Section 4.

The Ln NTV was significant at a 5% significance level with a positive coefficient of 0.223 in 2015, and with values of 0.172 and 0.148 at a 1% significance level in 2017 and 2019, respectively. It was thought that the Baidu index would rise by 0.14%~0.22% when the ratio of national-level traditional village increased by 1%, as traditional village protection results in more attention being paid to them. This is because traditional villages are widely appreciated for their beautiful natural landscapes and traditional buildings, and the ecological ethics and value orientations implicit in traditional villages also appeal the public.

In general, the influence degree of seven socioeconomic factors on public attention has been quantified, the influence mechanism has been explained, and the stability of the results passed the goodness-of-fit test. Therefore, it is reasonable to believe that the empirical results of our study are robust and reliable. At the same time, we also cannot

ignore the impact of other factors, which not included in our models, on public attention towards the Beautiful Village Initiative.

#### 4. Discussion

In order to explore and discuss the relationship between beautiful village construction and public attention, we used the Baidu Index as the horizontal axis and the ratio of national-level beautiful village as the vertical axis to draw quadrantal diagrams for 2015, 2017, and 2019, as shown in Figure 8. The quadrants are divided into four: in the top right (Type I), top left ((Type II), bottom left (Type III), and bottom right (Type IV).

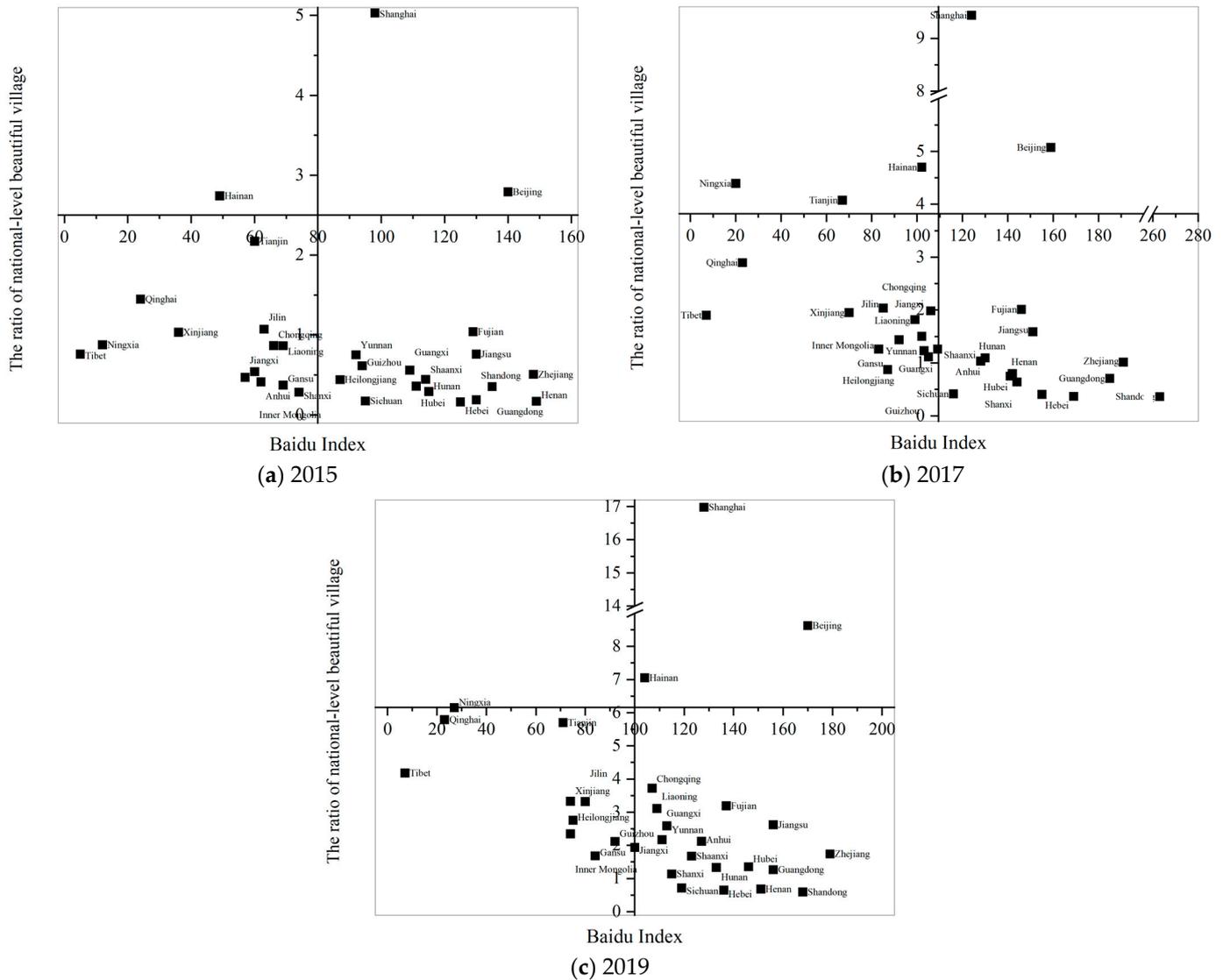


Figure 8. Quadrant diagram for the relationship between beautiful village construction and public attention.

In Type I, for instance, Beijing and Shanghai, the level of beautiful village construction and public attention were both high, they were in a high-level equalization relationship, and positively stimulated each other. Type II, mainly including Ningxia and Hainan, was characterized by high-level construction and low-level public attention. It is absurd to claim that there is a negative correlation between construction and public attention, although it can be said that ecological civilization lagged behind material civilization constructions in these provinces. Type III, e.g., Tibet, Qinghai, and Jilin, was characterized by low-level balanced areas with inconspicuous construction effects and low attention. These types of

provinces require many simultaneous measures to improve the construction and to raise public attention and participation. Type IV comprised the highest number of provinces, i.e., 15, 13, and 18 in 2015, 2017, and 2019, respectively. These provinces are widely distributed in East China, Central China, and Southwest China, for instance, Guangdong, Hubei, Hunan, and Sichuan. The high Baidu index of these provinces reflects high levels of public attention to the beautiful countryside, i.e., they are highly enthusiastic and expectant about the construction. However, the current construction level is insufficient to meet the public's expectations, and the construction obviously lagged behind.

These results explain why the influencing coefficients for beautiful village construction in the estimation models were negative, which does not indicate that the construction level has a negative impact on public attention, but that the relationship between them is uncoordinated, and advances in public attention are ahead of the construction level in most provinces.

As mentioned above, the public attention towards the Beautiful Village Initiative has been rarely discussed; but, unsurprisingly, the phenomenon that the development or construction of the matter is uncoordinated with public attention has also been analyzed in related research fields. The public attention related to wastewater and the wastewater treatment has positive correlations to a certain extent [64]; however, the scarcity of water resources and the popularization of recycled water do not necessarily cause more public concern, and may even cause negative emotions, such as an aversion to using recycled water [65]. The scholars who study tourism have found that the construction quality and development level of scenic spots cannot completely determine the network attention, public preference, and demand [66,67]. In the field of public health, a variety of factors all affected the public concern of COVID-19 [47], and cases and death rates are significantly negatively associated with the public attention paid in the later stage of the epidemic [43]. This research has found similar results in different fields, which coincided with our findings, and more importantly, have also proved the significance of quantifying the impact of socioeconomic factors on public attention.

## 5. Conclusions and Policy Suggestions

### 5.1. Conclusions

The implementation of China's Beautiful Village construction over the past decade has brought about great improvements, which have attracted people's attention. In order to improve understanding of public attention towards the Beautiful Village Initiative in China, through the Baidu index, this study investigated the spatiotemporal distribution and evolution characteristics of public attention using geographic concentration, disequilibrium index tools, time-constrained clustering, and the spatial autocorrelation test. Moreover, we explored the factors and mechanisms influencing public attention using spatial econometric models, including OLS and SEM, and we assessed the relationship between beautiful village construction and public attention with quadrantal diagrams. The following conclusions were drawn:

First, the national public attention towards the Beautiful Village Initiative increased in 2011–2017, peaked in 2017–2018, and fluctuated in 2018–2020. Combining this with the variation trend at the provincial level, the course of evolution can be divided into three stages: the Beautiful Village Initiative did not attract national public attention (2011–2012), strong impetus was injected (2013–2015), and it became rooted in people's minds (2016–2020).

Second, China's provincial public attention demonstrated obvious spatial differentiation, which decreased from East to Central then to West China, and from South to Northeast China. There was a significant and stable spatial autocorrelation in public attention. Specifically, the Low–Low clusters were situated in Northwest China, and the High–High Clusters were formed in East, Central, and North China.

Third, the goodness-of-fit of the SEM model that considered spatial autocorrelation was better than that of the traditional OLS model. For the factors influencing public attention, the empirical results proved that public attention was transmitted to adjacent areas.

The urbanization rate, population density, education level, network use, and historical and cultural protection exhibited positive impacts on public attention. Economic development did not have fixed positive or negative influences due to “overtaking by curves” of ecological civilization construction in underdeveloped regions and the path dependence produced by the “crowding effect” in developed areas.

Fourth, the relationship between beautiful village construction and public attention is uncoordinated. In most provinces, advances in public attention are ahead of the construction level.

Our research on public attention towards the Beautiful Village Initiative is still in its infancy, the theoretical basis and methods are still not perfect, and certain deficiencies must be noted: (1) The Baidu index can be used as a novel and effective tool for analyzing public attention, but it does not reflect the concern of people without access to the Internet. In addition, some netizens have shifted from pure online searching to more entertaining mass media, such as Weibo and TikTok, to focus on heated issues. (2) There are a large number of beautiful village construction pilots in China, for instance, more than 2000 village pilots have been constructed Qinghai province alone, and it is difficult to specifically understand the public attention to each village in nationwide scale. Next, we will narrow the study area to understand the public attention towards specific construction pilots by adding combined offline interviews and questionnaires. (3) We only estimated the impact of the most common socioeconomic factors on public attention; the impact of other socioeconomic factors should not be ignored and deserves further research.

## 5.2. Policy Suggestions

From the conclusions drawn in this paper, we propose three policy suggestions that may be helpful to increase public awareness and participation in the Beautiful Village Initiative: (1) Intensify the construction of beautiful villages, emphasize its diversified values, popularize education about ecological civilization, and form a trend for the whole society to pay attention to and participate in the construction of beautiful villages. (2) Accelerate the construction of information infrastructures, improve Internet usage level of the mass, expand 4G and 5G network coverage, and narrow the “digital divide” between provinces and between urban and rural areas. (3) The government should broaden information collection channels to encourage the public to express their suggestions on beautiful villages. Companies can attract more people to pay attention to beautiful villages through tourism and health promotion, and NGOs can increase publicity of the Beautiful Village Initiative.

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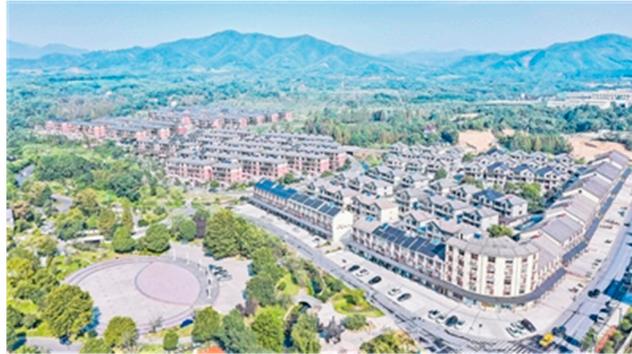
**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

Selected images of beautiful villages.



**Figure A1.** Xiaoyuan Village, Anji County, Zhejiang. Source: The People's Government of Anji County, <http://www.anji.gov.cn/>, accessed on 19 August 2021.



**Figure A2.** Xizha Village, Haidian District, Beijing. Source: Beijing Municipal Bureau of Agriculture and Rural Affairs, <http://nyncj.beijing.gov.cn/>, accessed on 19 August 2021.



**Figure A3.** An immigrant village in Xiji County, Ningxia. Source: Ministry of Agriculture and Rural Affairs of the People's Republic of China, <http://www.moa.gov.cn/>, accessed on 19 August 2021.



**Figure A4.** Dongsheng Village, Jiamusi City, Heilongjiang. Source: Ministry of Agriculture and Rural Affairs of the People's Republic of China, <http://www.moa.gov.cn/>, accessed on 19 August 2021.

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