scientific reports

OPEN

Spatial distribution and influencing factors of rural cultural ecosystem services: a case study of Fujian, China

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Rural cultural ecosystem services (CES) play a pivotal role in enhancing rural well-being. This paper examines the spatial distribution patterns and influencing factors of rural CES in Fujian Province using the biterm topic model and geodetector. The results reveal that rural CES in Fujian Province comprise five categories: culture, leisure, aesthetic, spirit, and science, among which leisure, culture, and aesthetic categories are the most easily perceived by the public. In terms of spatial distribution, the northwestern regions of Fujian Province exhibit better than the southeastern regions in terms of culture, while the latter excel in terms of leisure. Regarding aesthetics, there is an overall trend of extensive dispersion with localized concentrations, with high-value areas primarily located in the southwestern region and the eastern coastal region of Ningde City. The high value areas in the spirit are concentrated in the central and northern regions of Fujian Province. The spatial distribution of science is relatively scattered, with more high-value areas observed in Sanming City and Fuzhou City. Road density, light index, and per capita disposable income demonstrate strong explanatory power in rural CES. These findings can guide targeted development of regional cultural services and address resource mismatches in rural areas of Fujian Province, thereby enhancing the well-being of rural residents.

Keywords Rural ecosystem, Cultural ecosystem service, BTM, Geodetector, Spatial distribution, Influencing factors

Cultural ecosystem services (CES) refer to the non-material benefits that humans derive from ecosystems through spiritual fulfillment, cognitive development, reflection, entertainment, and aesthetic experiences[1,2]. With the increasing demand for spiritual and cultural needs, people are becoming more aware of the vital role that CES play in human life[3]. First, CES is considered a crucial component of ecosystem services, often appearing alongside other types of ecosystem services[4,5]. The generation of CES involves a combination of ecological, social, and cultural mechanisms, which are the processes or pathways through which ecosystems provide non-material benefits[6,7]. Compared to other types of ecosystem services, CES particularly emphasize the effect of individual experiences and social values within ecosystems. It is more perceptual in nature and closely linked to human well-being[8–10]. Secondly, CES serves as an important bridge between ecological science and social science, facilitating ecosystem management through an integrated approach[11]. Incorporating CES into economic valuation frameworks ensures that benefits such as culture, aesthetics, and recreation are not overlooked in policy decision-making[12,13]. Finally, the study of CES can provide information for land-use decision-making, ensuring that while material benefits are obtained, non-material benefits are protected, thereby enhancing residents' quality of life[14–16].

Many studies have demonstrated the practical significance of incorporating CES into land use planning. These studies cover a variety of spatial scales, such as small-scale spaces like individual villages or urban parks[17–19], medium-scale spaces like watersheds or provincial areas[20,21], and large-scale spaces like national or marine regions[22,23]. Among them, research on CES at medium or large scales is of significant importance for regional planning. Exploring the spatial distribution of CES at these scales can guide regions in making rational resource allocations, particularly in rural areas of China, which primarily rely on fiscal allocations from higher-level governments for infrastructure development. The amount of fiscal allocation is calculated based on indicators,

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and CES can serve as an important indicator in this process[26]. Moreover, ecosystems are complex and vast, and discussing them at the medium or large scales facilitates inter-regional cooperation and governance, promoting the maximization of resource use[27,28].

In recent years, research on CES has been increasing annually, with studies on CES at medium or large scales becoming more abundant. The quantitative methods for medium-large-scale CES mainly fall into three categories, with methods using online images being the dominant approach[29–31]. Many scholars also quantify large-scale CES using POI data or survey questionnaires[32–35]. The method of using online images for CES quantification mainly involves crawling online images with coordinate locations, associating landscape elements in these images with different cultural service types, and thereby achieving quantification[36,37]. However, the information conveyed by online images is relatively simple, representing only users' preferences for the visual elements, and it cannot express multi-dimensional perceptual information, thus having certain limitations. Most scholars use POI data for quantification, primarily by categorizing the names of POI data, classifying them into different cultural service types, and then combining their location information to achieve CES quantification and mapping[38,39]. Although this method is efficient, it shares similar limitations with online images: location names only represent different functions and cannot reflect people's deeper emotional responses. The questionnaire method is a more traditional approach, often combined with model algorithms for quantification, such as SolVES and Maxent models[40–42]. The limitation of the questionnaire method lies in its traditional data collection approach and the limited sample size. Besides the three methods mentioned above, a few studies have also quantified CES through online text data. The application of online text data can be categorized into two types. One method involves word segmentation of online text data, then using a CES taxonomy to calculate the word frequency of entries corresponding to each type of CES. This method uses word frequency as a direct quantification basis, but it does not perform in-depth analysis of the text content, limiting the depth of information mining[43]. Another common method combines machine learning and natural language processing techniques to quantify CES using word vectors[19,44,45]. This method, by deeply mining the relationships between words, can recognize the logical information behind the words conveyed by users, thus more accurately reflecting users' true feelings. Among these, studies that use the LDA topic model for CES quantification are the most prevalent, but some scholars point out that the LDA model is advantageous for processing long text content, while it is less suitable for short text content compared to the BTM topic model[46,47]. Therefore, using online comment text data and the BTM model for CES quantification can not only address the challenges of data collection at the medium or large scales but also achieve a deeper mapping of CES.

The classification of CES is the foundation for quantitative research. This concept originated in 1997, proposed by Daily and Costanza, and was later further explored and adapted by scholars such as Groot and Brown in the context of cultural service indicators. Although there have been adjustments, the basic connotation of the term remains unchanged, referring to the intangible benefits provided by ecosystems[48–51]. The classification of CES includes four main dimensions: aesthetic, spirit, leisure, and knowledge. The aesthetic dimension involves the aesthetic pleasure and visual satisfaction individuals experience in natural environments[52]. The spirit dimension focuses on the spiritual value provided by ecosystems[53]. The leisure dimension encompasses the various leisure activities in which people engage, aimed at relaxation, stress reduction, promoting health, and enhancing quality of life[54]. The knowledge dimension centers on the informational benefits that ecosystems provide to humans[55]. In addition to these four primary types of CES, each study classifies CES based on the unique characteristics of the study area. For example, Pike et al. included Spirituality and Freedom as key indicators in their CES assessment of the marine environment[56]. Rewitzer et al. emphasized the importance of Agricultural heritage in their study of CES in mountainous areas[57]. Teff-Seker et al. used Social and cultural identity as key indicators in their CES study of desert landscapes[58].

Different regions are composed of diverse natural and social environments, offering distinct ecosystem services, particularly when viewed from medium or large spatial scales. Exploring the influencing factors of CES is critical for ensuring that ecosystem management strategies fully reflect the value of cultural services. First, understanding how various factors influence people's perceptions of CES can help urban designers create spaces that enhance well-being and strengthen cultural services. Second, identifying and understanding the influencing factors of CES can facilitate integrated ecosystem management, enabling more targeted efforts to protect the value of cultural services. Furthermore, by understanding and addressing the factors that form CES, society can foster a deeper connection with nature, promote social equity, and enhance the long-term sustainability of both the environment and culture.

Rural ecosystems, as an important component of ecosystems, are closely related to human well-being. China's rural areas are vast, resource-rich, and culturally deep, serving as the foundation of the Chinese nation. Investigating rural CES helps to fully leverage the ecological and cultural advantages of rural areas. In recent years, under the national strategy of rural revitalization, rural areas in Fujian Province have developed rapidly. However, there are significant issues in project implementation and fund utilization. Some projects are poorly aligned with local resource endowments, industrial foundations, and people's needs. In some cases, projects are created simply for the sake of creating projects, without considering actual needs or project effectiveness, failing to fully utilize the projects' potential to drive and radiate benefits. Regarding funding allocation, some funds are scattered, lacking focus and direction, and have not been used effectively to meet the most pressing needs for rural development, nor have they leveraged the full potential of the funds[24,25]. Therefore, this study focuses on rural Fujian as the research object. By mapping the spatial distribution of rural CES, the study explores the influencing factors of rural CES and provides a theoretical foundation for improving rural CES functions in Fujian Province, thereby promoting high-quality rural development. To achieve this goal, three research questions are proposed: (1) How can online comment texts be used for CES evaluation in medium or large spatial scales? (2) What are the influencing factors of CES? (3) How can rural CES be enhanced? The expected results of this study will contribute to government policy-making for rural development and provide guidance for the allocation of rural financial resources, thus promoting the enhancement of rural cultural services.

Research methods

Study region

Fujian Province is situated on the southeastern coast of China. It falls under the administrative authority of Fuzhou, Xiamen, Zhangzhou, Quanzhou, Sanming, Putian, Nanping, Longyan, and Ningde, organized into nine districts and cities, including the Pingtan comprehensive experimental area. The province comprises 11 county-level cities, 31 municipal districts, and 42 counties (including Jinmen County). Fujian boasts abundant mountainous terrain and an extensive coastline, endowing it with rich mountain and sea resources. It is famously referred to as 'eight mountains, one water, and one field' (Fig. 1). Fujian Province is abundant in rural resources and exhibits distinct cultural characteristics. As of 2023, the province has designated 494 villages as traditional Chinese villages, 19 townships as Chinese historical and cultural towns, and 57 villages as Chinese historical and cultural villages. Additionally, Fujian Province boasts a forest coverage rate of 65.12%, ranking first in China, earning its reputation as the 'greenest' province in the nation, thereby endowing Fujian villages with abundant ecological resources.

Data collection and pre-processing

The study data comprises two components: text data necessary for BTM modeling in the spatial distribution analysis, and geographic data essential for geodetector in exploring influencing factors. For the BTM model, text data selection is based on application scenarios, audience characteristics, and comment volume across various online platforms. Dianping.com, renowned for its local business search, user-generated reviews, detailed business information, discounts, group buying, and other services, serves as the primary data source, supplemented by Mafengwo and Ctrip. Network text data is retrieved using Python. Two representative villages were selected as research sites within each county-level area of the provincial region. County-level areas include county-level cities, districts, counties, and comprehensive experimental zones, hereinafter referred to as counties. Following the methodology of Nguyen et al.[59], the selection of representative villages was based on the number of online reviews. Online reviews serve as an effective indicator of audience interest and experience. Villages with a higher number of online reviews are typically those with greater regional recognition and higher levels of tourist engagement, making them representative of the higher level of rural development in the region and serving as typical samples of rural development within the area[60,61]. Owing to regional development patterns and the constraints posed by the quantity of network comments, one representative village was chosen in 12 counties, including Taijiang District of Fuzhou City, Shaxian District of Sanming City, and Xiangcheng District of Zhangzhou City. A total of 156 representative villages were selected as research subjects across 84 counties. To ensure the quality of network text data, the data selection process follows these steps: (1) If the number of comments on Dianping.com is less than five, supplementary comment data or travel notes from Mafengwo and Ctrip are added; (2) Comments from sites with the same name, such as Beigang Village and Beigang Stone House in the Pingtan Comprehensive Experimental Area, are merged into a single entry, Beigang Village. By November 12, 2023, a total of 27,574 comments had been crawled (Fig. 2). The jieba Chinese text processing function is employed for preprocessing the comment data: (1) Proper name lists are loaded as per research requirements to prevent algorithmic misjudgments in word segmentation; (2) Non-Chinese characters are filtered out; (3) Comment data is segmented into words; (4) Stopwords are imported and removed from the data.

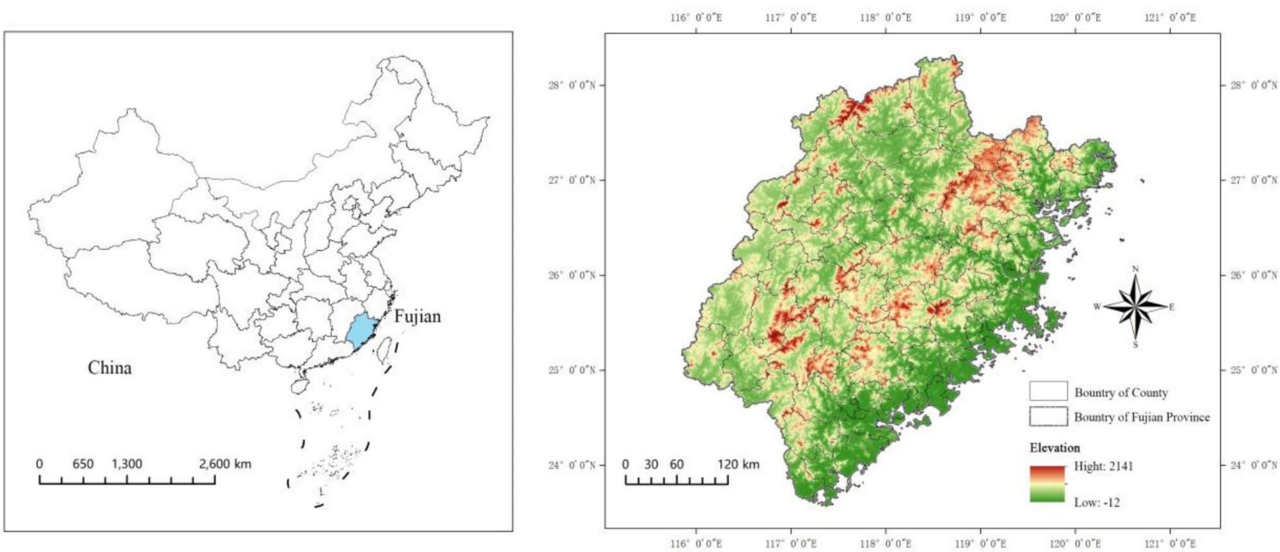

Fig. 1. Location and elevation map of Fujian Province.

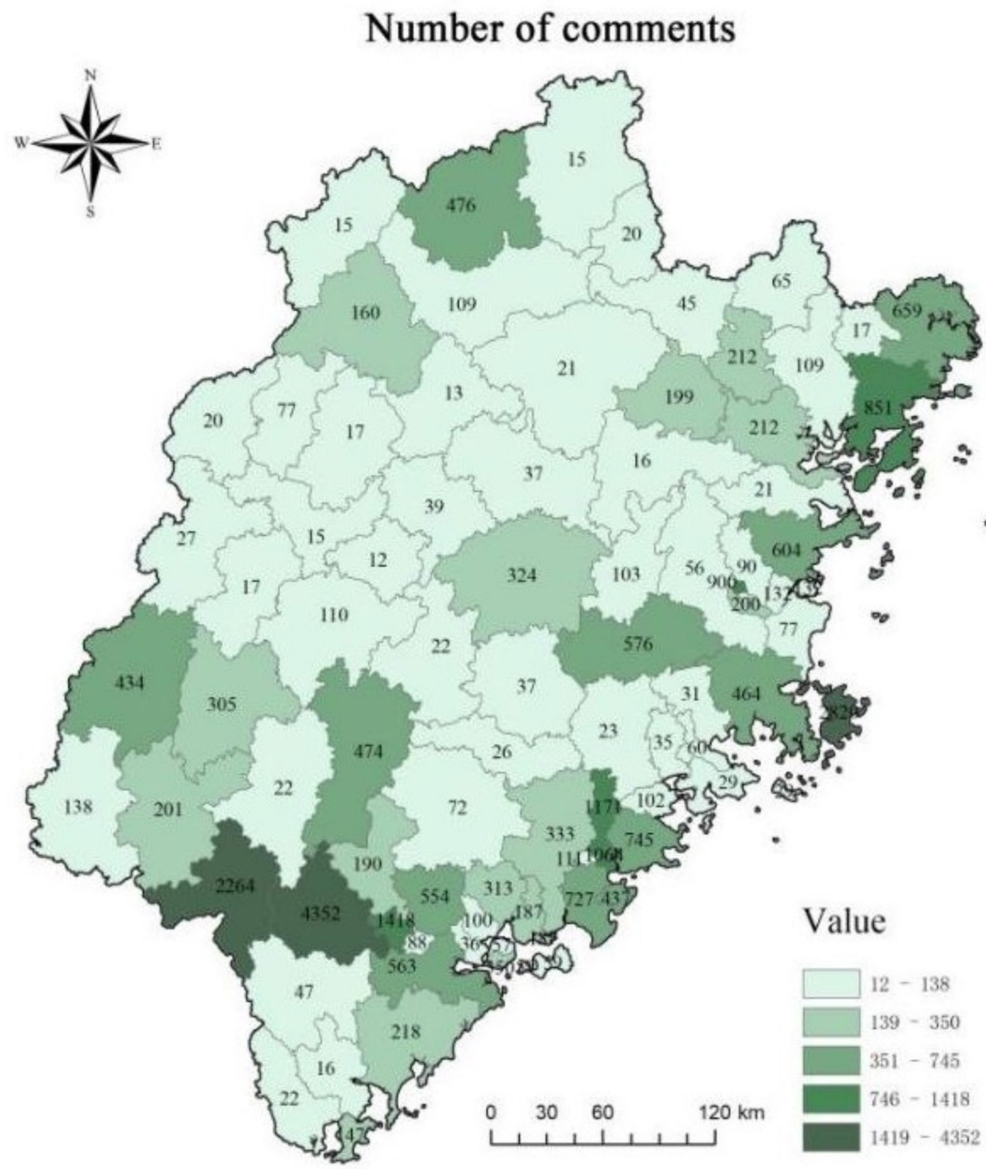

Fig. 2. Number of comments for Fujian village.

Referring to the related results on the influencing factors of CES by Vigl et al.[62], Li et al.[63], Yan Xiaolu et al.[64], and Zhong Jingqiu et al.[65], and considering the data processing characteristics of the units in this study, this paper selects three indicators—altitude, forest coverage, and river system—as influencing factors of natural ecology level. These three indicators can to some extent reflect the natural ecological pattern of the region. Altitude reflects the topographical variation of the region, which has a significant impact on ecosystems and human activities, thereby influencing the cultural services provided by ecosystems[63]. Forests are an indispensable component of natural ecosystems, and the forest coverage directly affects biodiversity and cultural services[66]. River systems, as an important element of nature, can provide various values such as recreation, aesthetics, and culture to people[67]. This study selects three influencing factors of community economy level—GDP per capita, per capita disposable income, and sown areas of farm crops[68]. GDP per capita is a standard measure of economic wealth, directly influencing the supply and demand of CES. Regions with higher per capita GDP are likely to have better infrastructure, enabling more people to access areas that provide cultural services. Per capita disposable income determines the amount individuals or households can allocate to activities related to CES, thus affecting the level of CES. The area of crops sown reflects agricultural activities, which are an important part of the regional economy. Agricultural areas can shape cultural characteristics and customs, and agricultural traditions and landscapes influence the local cultural heritage and experiences. Referring to the studies of Plieninger et al., this research, in addition to the natural ecology and community economy dimensions, introduces tourism-related attractive potentiality indicators, including road density, lighting index, and rural policy index[69]. Road density reflects the accessibility of a region. A well-developed road network improves people's ability to reach natural and cultural sites, thereby enhancing the potential to attract tourists[70]. The light index indicates the level of artificial lighting in a region, typically representing urbanization and nighttime visibility, serving as an important indicator of regional tourism development[71]. The rural policy index represents the government's support and attention to rural development, and rural policies play a crucial role in forming infrastructure, incentives, and protection strategies that support CES. According to the data characteristics required for geographic detection, the data were processed using the preprocessing methods shown in Table 1. In addition, some county-level data from the *Fujian Provincial Statistical Yearbook* is missing, and the missing data was supplemented with the average values of the counties under the corresponding city.

Methods

Biterm topic model

Bierm topic model (BTM) utilizes word pair co-occurrence to analyze the short text corpus comprehensively and extract the global topic distribution. Word pairing represents an algorithmic optimization of the BTM when contrasted with conventional approaches. In traditional topic modeling, data are processed at the level of individual words, with textual themes discerned through word co-occurrence[72–74]. Word pairs mitigate the issue of sparse co-occurrence among individual words in short texts, attributed to content length limitations. Word pairs, also known as disordered binary groups, co-occur within the text. For instance, the short text 'long history, beautiful scenery, pleasant climate' encompasses three word pairs: [long history, beautiful scenery], [beautiful scenery, pleasant climate], and [long history, pleasant climate], aimed at mitigating information loss resulting from short text segmentation[75,76]. The modeling process of the BTM comprises four steps (Fig. 3): (1) Constructing a word-pair corpus using the target text as the foundational data; (2) Training the model with the word pair corpus; (3) Adjusting model calculation parameters; (4) Generating the topic distribution.

The BTM calculates parameters using the Gibbs sampling method. Firstly, topics for the word pairs are randomly initialized. Secondly, the conditional probability distribution for word pairs [W_i, W_j] in the corpus is computed as follows:

$$P\left(z|z_{-b},B,\alpha,\beta\right)\propto\left(n_z+\alpha\right)\frac{\left(n_{wiz}+\beta\right)\left(n_{wjz}+\beta\right)}{\left(\sum_w n_{w|z}+1+M\beta\right)\left(\sum_w n_{w|z}+M\beta\right)} \tag{1}$$

where $P(z|z_{-b}, B, \alpha, \beta)$ represents the conditional probability distribution of each word pairs; z_{-b} signifies the subject distribution of other word pairs in the set B except the word pairs; n_z denotes the number of times the subject z has been assigned to the word pairs; $n_{w|z}$ indicates the number of times the subject z has been assigned to the word w; and M represents the dictionary size.

Utilizing the Gibbs sampling process, the distribution of word pairs and the subject distribution can be calculated using Eqs. (2) and (3), as follows:

$$P\left(b|d\right)=\frac{n_d(b)}{\sum_b n_d(b)} \tag{2}$$

$$P(z|d)=\sum_b P(z|b)P(b|d) \tag{3}$$

where $n_d(b)$ represents the frequency of word pairs b in document d.

The BTM commonly identifies the optimal number of topics using either Perplexity or Coherence metrics. Perplexity indicates the model's explanatory power, with lower values suggesting better text interpretation. Coherence measures topic quality based on word similarity, with values closer to zero indicating higher topic quality. Consequently, this study introduces topic validity (TV) as a criterion for judging the optimal number of topics. The calculation formula is as follows:

Influencing factors	Indicators	Data sources	Preprocessing	Data type
Natural ecology	Altitude (X_1)	National Center for Basic Geographic Information (NCBGI) (https://www.ngcc.cn)	Use the natural breakpoint method to categorize the data into 9 classes	Raster data
	Forest cover (X_2)	Science Data Bank (https://www.scidb.cn/en)		
	River system (X_3)	NCBGI (https://www.ngcc.cn)	Multi-ring buffering at 500-m intervals to categorize data into 9 classes	Vector surface data
Community economy	GDP per capita (X_4)	*Fujian Provincial Statistical Yearbook*	After applying the interpolation method at the county level, the data are then classified into 9 levels using the natural breaks method	Conversion of vector point data to raster data
	Per capita disposable income (X_5)	*Fujian Provincial Statistical Yearbook*		
	Sown areas of farm crops (X_6)	*Fujian Provincial Statistical Yearbook*		
Attractive potentiality	Road density (X_7)	National Earth System Science Data Center (http://www.geodata.cn)		
	Light index (X_8)	Keyword Statistics for Government Websites		
	Rural policy index (X_9)	*Fujian Provincial Statistical Yearbook*		

Table 1. Influencing factors of rural CES.

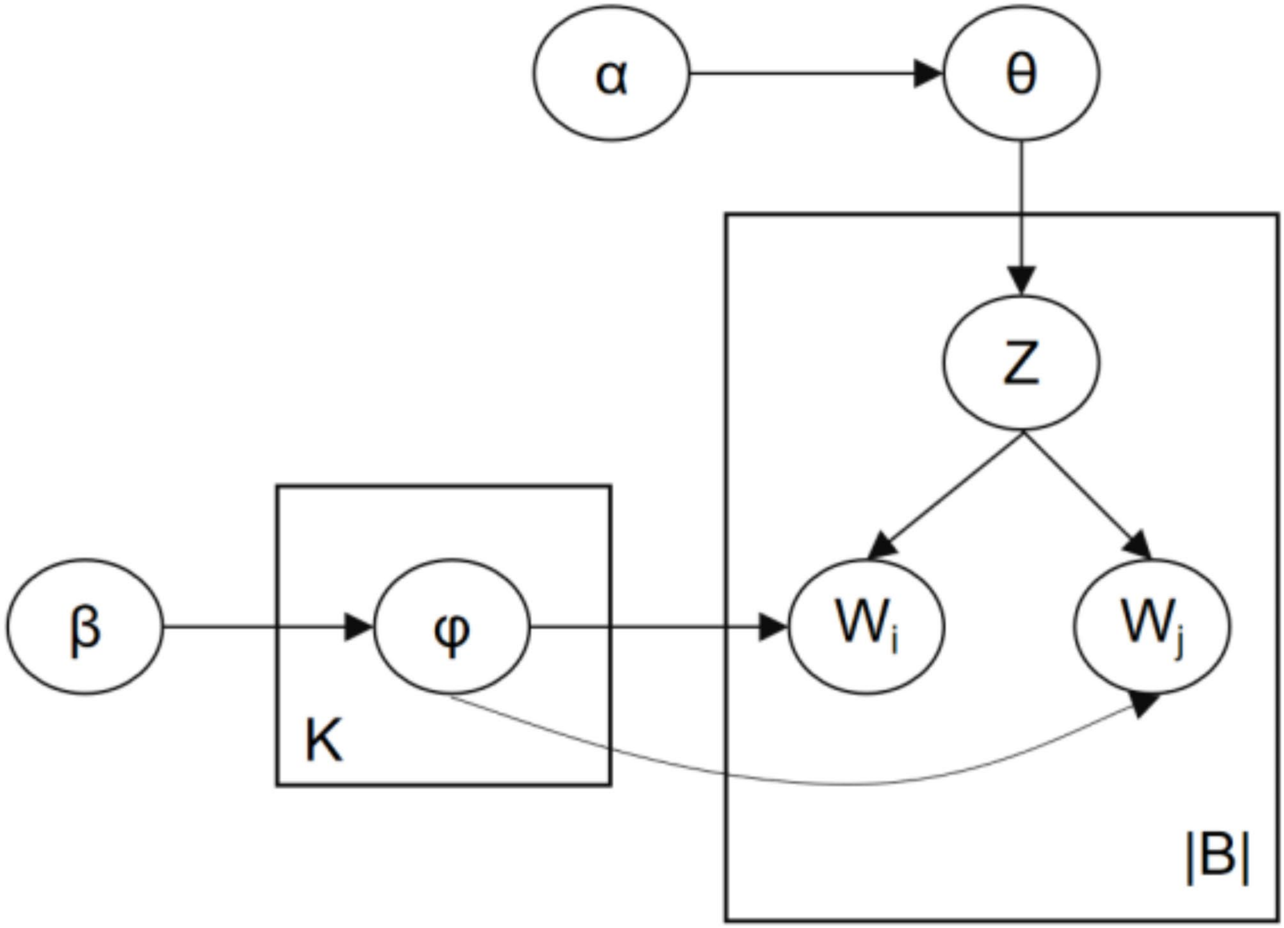

Fig. 3. Principle flow of BTM. Where α and β represent Dirichlet prior parameters, θ denotes the probability parameter of the potential topic within the word pair corpus, Z signifies a potential topic within the corpus, and φ indicates the probability of the word pair appearing in the topic. The corpus contains K topics and $|B|$ word pairs, with the words W_i and W_j forming word pairs $[W_i, W_j]$.

$$TV = TP * TC \tag{4}$$

where TV represents the topic validity, TP represents the topic Perplexity, and TC represents the topic coherence. The closer the TV value is to zero, the better the model's interpretation ability, and the farther the value is from zero, the poorer the model's interpretation ability becomes.

Set the range of the number of topics K from 2 to 30, with an interval of 1, and run the topic model to calculate the TV value of each topic (Fig. 4). At 28 topics, the TV value is closest to zero, leading to the selection of 28 as the number of topics for this study. Therefore, K = 28; typically α = 50/K, β = 0.01, with 2000 iterations for iterative learning, and running the BTM model.

The 28 topics are displayed in the form of a word cloud, with the top 20 words selected from each topic based on word probabilities to form the word cloud. The size of the words represents the probability of their occurrence within the topic (Fig. 5). From the figure, the thematic content can be visually matched with the intangible benefits for people. Two experts, three PhD students, and five Master's students were invited to classify the 28 topics into CES categories, considering the meaning of rural CES and the characteristics of the comment data, while referring to relevant literature. Based on the previous discussion, CES is mainly divided into four types: aesthetic, spiritual, recreational, and knowledge. Considering the heritage characteristics of rural environments, the knowledge aspect is further divided into culture and popular science. Hubatova et al. share a similar view, treating culture and popular science as essential components of rural CES[77]. Van et al., in their CES evaluation of rural agricultural landscapes, also discussed culture as an important category[78]. The CES value corresponding to each county is calculated based on the average value of the topic values included in the network texts of that county. The topic value for each network text is simulated by the BTM model through word vector computation, with a portion of the original topic values provided (Table 2). Based on this, the CES proportion of rural samples in each county is averaged and analyzed using interpolation, which results in a spatial distribution map of rural CES in Fujian Province.

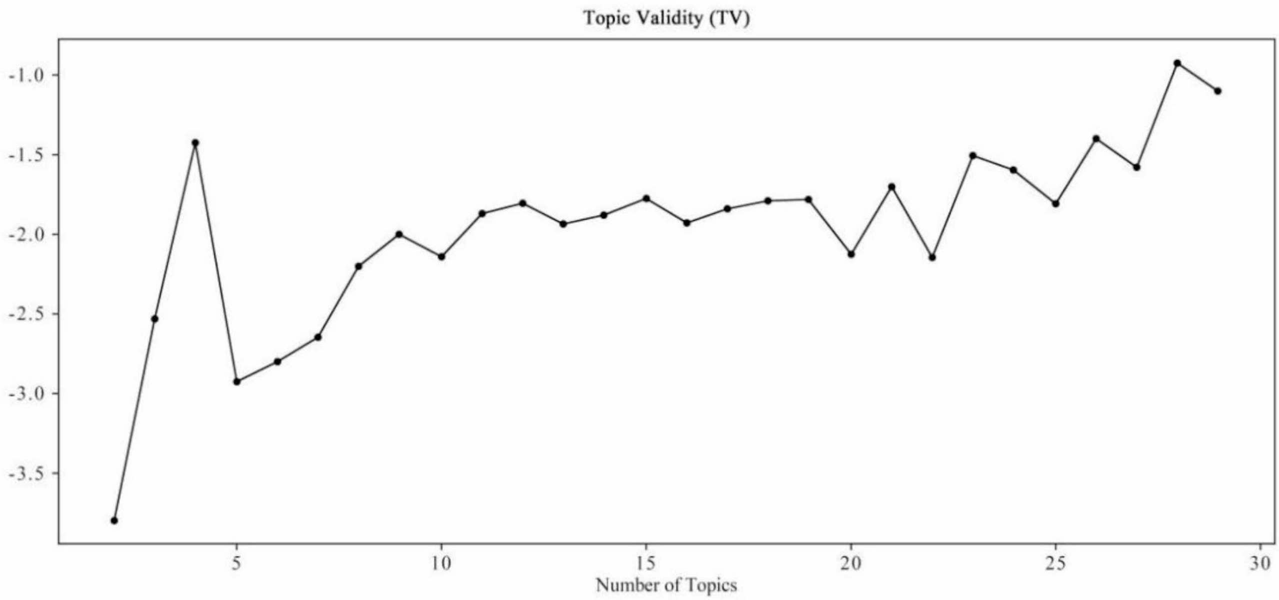

Fig. 4. Topic validity values under different number of topics.

Fig. 5. 28 topic word clouds.

Value	Review1	Review2	Review3	Review4	Review5	Review6	Review7	Review8	Review9	Review10
Topic1	0.0132	0.0047	0.0489	0.0112	0.0187	0.0159	0.0410	0.0179	0.0503	0.0006
Topic2	0.0021	0.0015	0.0017	0.0014	0.0011	0.0013	0.0044	0.0064	0.0013	0.0000
Topic3	0.0074	0.0341	0.0046	0.0019	0.0051	0.0009	0.0065	0.0109	0.0040	0.0000
Topic4	0.0622	0.0105	0.0369	0.0164	0.0208	0.1106	0.0252	0.0131	0.0148	0.0000
Topic5	0.0208	0.0111	0.1012	0.0052	0.0859	0.0000	0.0169	0.0058	0.0720	0.0000
Topic6	0.1762	0.1553	0.0534	0.0391	0.0388	0.0751	0.2054	0.0955	0.1058	0.0186
Topic7	0.0257	0.0137	0.0308	0.0368	0.0067	0.0091	0.0434	0.0429	0.0043	0.0005
Topic8	0.0810	0.0146	0.0255	0.2414	0.0381	0.1522	0.0332	0.0746	0.1126	0.0071
Topic9	0.0009	0.0114	0.0078	0.0004	0.0013	0.0001	0.0017	0.0111	0.0012	0.0000
Topic10	0.0252	0.0142	0.0081	0.0356	0.0316	0.0727	0.0850	0.0387	0.0145	0.0000
Topic11	0.0084	0.0079	0.0096	0.0224	0.0931	0.0146	0.0111	0.0289	0.0132	0.0000
Topic12	0.0059	0.0029	0.0655	0.0012	0.0031	0.0070	0.0090	0.0045	0.0123	0.0000
Topic13	0.0235	0.0315	0.0095	0.0219	0.0081	0.0800	0.0401	0.1173	0.0116	0.0000
Topic14	0.0070	0.0047	0.0157	0.0111	0.0162	0.0014	0.0054	0.0339	0.0048	0.0000
Topic15	0.0161	0.0083	0.0196	0.0172	0.0496	0.0333	0.0055	0.0046	0.0060	0.0004
Topic16	0.0241	0.0096	0.0096	0.0107	0.0994	0.0295	0.0169	0.0192	0.0422	0.0000
Topic17	0.1792	0.3760	0.2129	0.0917	0.0855	0.0170	0.2658	0.1172	0.2287	0.4198
Topic18	0.0023	0.0023	0.0125	0.0018	0.0062	0.0005	0.0065	0.0097	0.0082	0.0000
Topic19	0.0459	0.0174	0.0169	0.0351	0.0299	0.0393	0.0301	0.0531	0.0141	0.0005
Topic20	0.0030	0.0026	0.0065	0.0006	0.0046	0.0024	0.0313	0.0013	0.0264	0.0000
Topic21	0.0150	0.0127	0.0200	0.0141	0.0449	0.0337	0.0192	0.0544	0.0111	0.0001
Topic22	0.0138	0.0096	0.0061	0.0073	0.0436	0.0462	0.0104	0.0153	0.0130	0.0003
Topic23	0.0736	0.1050	0.0475	0.0614	0.0449	0.0566	0.0105	0.0301	0.0090	0.0369
Topic24	0.0299	0.0169	0.0297	0.0292	0.0428	0.0146	0.0334	0.1082	0.0107	0.0011
Topic25	0.0127	0.0126	0.0321	0.0013	0.0004	0.0014	0.0021	0.0117	0.0408	0.0001
Topic26	0.0798	0.0451	0.0822	0.2608	0.1648	0.1751	0.0191	0.0487	0.1366	0.4798
Topic27	0.0232	0.0317	0.0257	0.0053	0.0111	0.0048	0.0130	0.0162	0.0117	0.0037
Topic28	0.0216	0.0322	0.0596	0.0176	0.0036	0.0048	0.0080	0.0089	0.0187	0.0306

Table 2. Raw values for review text topic values (excerpts). Excerpts from the first ten comments from Pingtan County, Fuzhou City, China.

Geodetector

Geodetector is employed to detect spatial heterogeneity, offering advantages over traditional linear correlation methods. It is a statistical method that effectively elucidates spatial drivers, particularly facilitating the exploration of nonlinear interactions between variables. This study primarily utilizes the factor detector and the interaction detector within Geodetector[79–81]. Specifically, the factor detector assesses the impact of individual factors on the dependent variable, utilizing the q value to quantify influence and the *p* value to assess significance. In contrast, the interaction detector identifies interactions between distinct driving factors by comparing q values under single and combined factor scenarios.

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2 \tag{3}$$

where N represents the total sample size; σ^2 is the total sample variance; N_h is the sample size of the h-th sub-stratum; σ_h is the within-stratum variance of the h-th sub-stratum; q is the explanatory power of the detection factor, with a value range of [0, 1]. *A* higher q value indicates a stronger spatial distribution driving force of the corresponding factor.

Results

Rural CES classification

The 28 CES topic are categorized as shown in Table 3. The Culture aspect of rural CES includes 7 topics, such as Topic 5, 7, and 12, primarily focusing on the village as a geographical and social entity conveying its unique connotations to the audience. Representative words include features, ancient houses, and ancient roads[82]. The Leisure aspect includes 8 topics, such as Topic 6, 8, and 10, mainly reflecting activities in the village, such as entertainment, leisure, and sightseeing, with representative words including attractions, transportation, and tickets[83]. The Aesthetic aspect includes 6 topics, such as Topic 1, 4, and 11, reflecting the visual appeal of the village, encompassing words such as most beautiful, grassland, and cherry blossoms[84]. The Spirit aspect includes Topic 3 and 24, referring to the spiritual satisfaction provided by the rural environment, with representative

CES category	Description	Representative words	Included topics
Culture	To offer locations imbued with cultural significance, enabling individuals to grasp the local essence	Features, ancient houses, hairpin flowers, Hakka, academies, ancient roads, etc.	Topic 5, 7, 12, 14, 18, 20, 27
Leisure	To offer recreational and entertainment opportunities, allowing individuals to unwind	Homestay, attractions, food, transportation, tickets, experience, etc.	Topic 6, 8, 10, 15, 16, 19, 21, 22
Aesthetic	To provide visual pleasure, allowing individuals to appreciate beauty	The most beautiful, grassland, cherry blossoms, tea garden, stone, scenery, etc.	Topic 1, 4, 11, 17, 23, 28
Spirit	To offer intellectual enlightenment, fostering spiritual contentment in individuals	Confucian temple, ancestral hall, confucian temple, feeling, peacefulness, life, etc.	Topic 3, 24
Science	To provide educational access, facilitating knowledge acquisition for individuals	Tour guide, interpretation, wisdom, distance, beam, built in, etc.	Topic 2, 9, 13, 25, 26

Table 3. Category of rural CES.

words like ancestral hall, feeling, and peacefulness[85]. The Science aspect includes 5 topics, such as Topic 2, 9, and 13, reflecting the process of the village transmitting knowledge to the audience, with representative words including tour guide, wisdom, and interpretation[86].

Spatial distribution of rural CES

From Fig. 6 and Table 4, it can be observed that rural CES culture levels in Fujian Province are primarily concentrated in Nanping City, and Sanming City, with a decreasing trend from northwest to southeast. The average of Culture value for the three northwestern cities is 0.3114, while the average for the five southeastern cities is 0.2279; Leisure levels show high concentration in Xiamen City, Fuzhou City, and Zhangzhou City, with Leisure values of 0.4404, 0.3809, and 0.3715, respectively. The southeastern region generally performs better than the northwestern region; Regarding aesthetics, there is an overall trend of extensive dispersion with localized concentrations. High-value areas are mainly located in the southwestern part of Fujian Province and the eastern coastal areas of Ningde City. Among these, Zhangping, Gutian, and Shanghang counties have the highest aesthetic values, which are 0.4444, 0.4184, and 0.4174, respectively; The Spirit aspect is concentrated in the central and northern parts of Fujian, with the highest value in Cangshan District of Fuzhou City, at 0.2636. The Science level, on the other hand, is more dispersed, with high-value areas more concentrated in Sanming and Fuzhou City.

The influencing factors of spatial differentiation of rural CES

Geodetector was employed to investigate the influencing factors of various CES, and the results of factor detection are presented in Table 5. Regarding the influence on the Culture level of rural CES, the three factors with the highest influence degree are road density (0.1864), sown areas of farm crops (0.0786), and rural policy index (0.0736), with road density being the most prominent. Nanping, Sanming, and Quanzhou cities exhibit strong cultural perceptions. Interestingly, Nanping and Sanming are the two cities with the lowest road density among the eight cities in Fujian Province, with road densities of 0.5052 and 0.5632, respectively. In contrast, Quanzhou has the highest road density among the eight cities in Fujian, at 1.7793. Regional road density is closely related to cultural resources. Nanping and Sanming are mainly mountainous areas, where the provincial road density is relatively low. Traffic limitations have promoted the development of rich local cultures with typical mountain characteristics. These areas possess diverse local cultures, with each region preserving unique languages, lifestyles, and traditional customs. In contrast, Quanzhou is a coastal city with the highest road density in the province and a long history of economic development. As the former largest eastern port and the starting point of the Maritime Silk Road, its cultural characteristics are both inclusive and traditional, contributing to its strong cultural vitality; The order of influence on the Leisure level is per capita disposable income (0.2280), light index (0.2198), and rural policy index (0.2021), with their influence degrees being close to each other. This is linked to the higher economic level exhibited by cities with higher recreational perceptions. High cultural perception in the recreational aspect is concentrated in coastal regions, where the geographical advantage has led to significantly better economic development compared to inland areas, resulting in higher per capita disposable income. With rapid economic growth, population concentration has created a strong nighttime lighting environment. Economic development and policy support complement each other, improving infrastructure in coastal areas and providing more comfortable tourism experiences compared to inland regions; Among the influences on the Aesthetic level, road density has the strongest influence, with q-values of 0.2755 and 0.2587, respectively. The high-value areas for rural aesthetic values in Fujian Province are found in Shanghang and Xiapu counties, which are closely related to the rapid development of rural tourism in these two regions. This also supports the influence of road density and lighting index on the aesthetic level, where regions with well-developed road networks and better nightscapes tend to have better tourism development, and tourism is closely linked to the region's scenic beauty; The light index has the strongest influence on the Spirit level, with a q value of 0.1982. The influence of each factor on the Science level is relatively low. The most influential factor is per capita disposable income, with a q value of 0.0580. Overall, factors with a greater impact on rural CES primarily focus on community economy and attractive potentiality. Per capita disposable income, light index, and road density are the most prominent among them. Factors at the natural ecology level have a low influence on rural CES, with only a certain influence observed at the aesthetic level. Notably, altitude demonstrates significant explanatory power, with a q value of 0.1295.

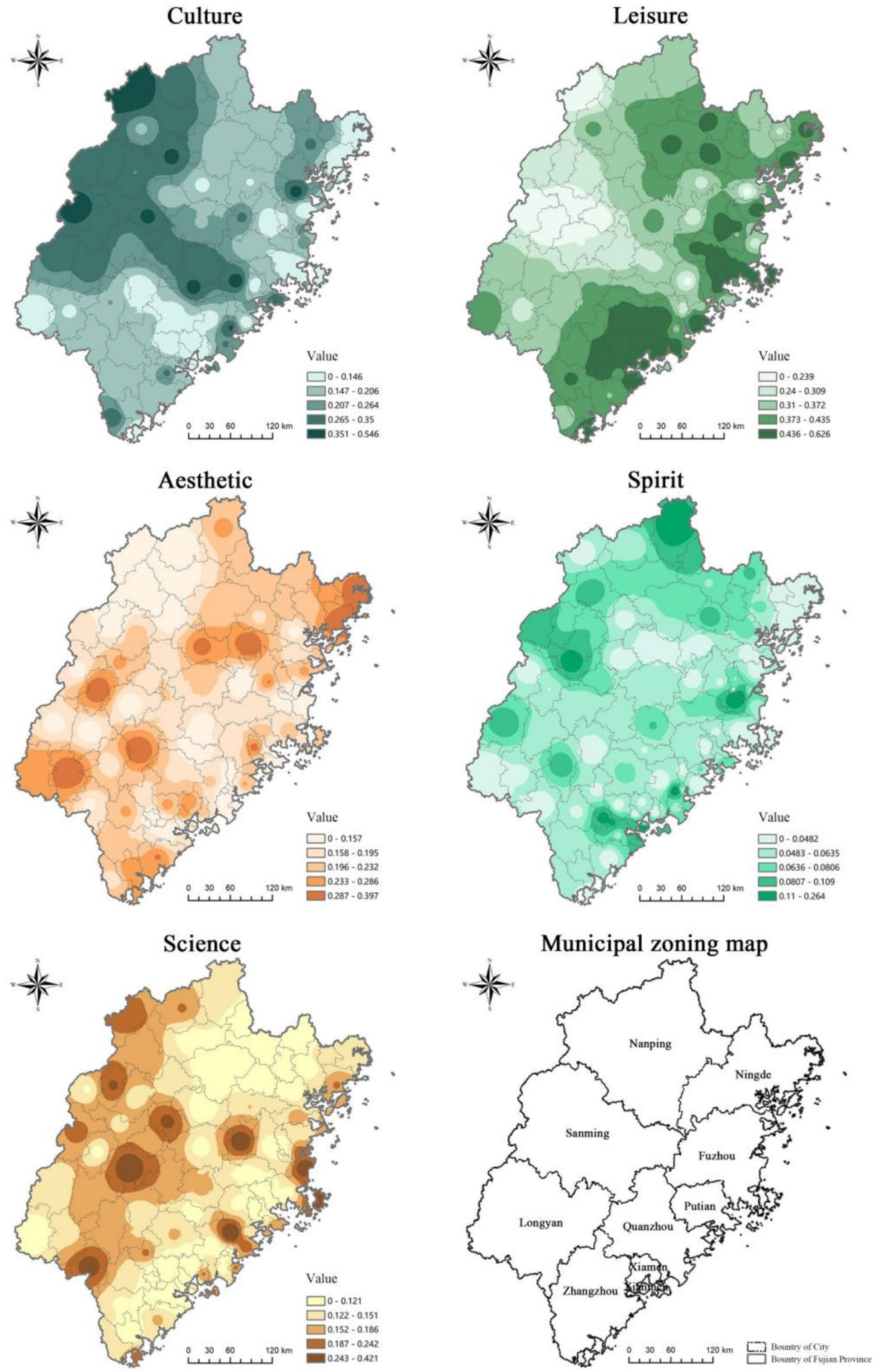

Fig. 6. Distribution map of rural CES in Fujian Province and the municipal zoning map of Fujian Province.

Interaction of influencing factors

Interaction detection revealed both bi-factor and nonlinear enhancement effects among rural CES impact factors. Nonlinear enhancements were more prevalent than bi-factor enhancements, suggesting a greater impact of factor interaction on rural CES compared to single factors. The factors exhibiting the strongest interactions were identified for each influencing factor, forming the interaction detection results (Table 6). Overall, factors exhibiting strong interactions are concentrated in community economy and attractive potentiality, aligning with the factor detection results. In the Culture and Aesthetic dimensions, the interaction between road density and

City	Culture	Leisure	Aesthetic	Spirit	Science
Fuzhou	0.252450245	0.380855089	0.213443099	0.063325709	0.08967451
Xiamen	0.123288539	0.44037877	0.262954237	0.080962297	0.09057251
Putian	0.281796015	0.344807786	0.254137332	0.053569449	0.062356086
Sanming	0.406485303	0.242506122	0.217875374	0.06945535	0.063397268
Quanzhou	0.270290415	0.341064431	0.197462235	0.065158273	0.124709882
Zhangzhou	0.211803905	0.371452976	0.264774403	0.057736688	0.093313117
Nanping	0.30695558	0.324784475	0.224514628	0.073411271	0.070334046
Longyan	0.220650524	0.339137443	0.295156298	0.052797772	0.091790294

Table 4. CES values for cities.

	Altitude	Forest cover	River system	GDP per capita	Per capita disposable income	Sown areas of farm crops	Road density	Light index	Rural policy index
Culture	0.0124	0.0010	0.0023	0.0159	0.0291	0.0786	0.1864	0.0366	0.0736
Leisure	0.0857	0.0268	0.0148	0.0573	0.2280	0.1745	0.1687	0.2198	0.2021
Aesthetic	0.1295	0.0507	0.0159	0.0181	0.1687	0.0880	0.2755	0.2587	0.1260
Spirit	0.0210	0.0016	0.0041	0.0854	0.1574	0.0594	0.0488	0.1982	0.1351
Science	0.0017	0.0014	0.0004	0.0011	0.0580	0.0388	0.0388	0.0504	0.0402

Table 5. Factor detection results.

Culture		Leisure		Aesthetic		Spirit		Science	
A∩B	Q value	A∩B	Q value	A∩B	Q value	A∩B	Q value	A∩B	Q value
$X_1 \cap X_7$	0.2378(NE)	$X_1 \cap X_9$	0.3560(NE)	$X_1 \cap X_7$	0.3508(BE)	$X_1 \cap X_8$	0.2864(NE)	$X_1 \cap X_5$	0.1010(NE)
$X_2 \cap X_7$	0.1965(NE)	$X_2 \cap X_9$	0.2449(NE)	$X_2 \cap X_7$	0.2953(BE)	$X_2 \cap X_8$	0.2100(NE)	$X_2 \cap X_5$	0.0671(NE)
$X_3 \cap X_7$	0.1957(NE)	$X_3 \cap X_5$	0.2387(BE)	$X_3 \cap X_7$	0.2888(BE)	$X_3 \cap X_8$	0.2067(NE)	$X_3 \cap X_5$	0.0691(NE)
$X_4 \cap X_5$	0.3915(NE)	$X_4 \cap X_8$	0.4471(NE)	$X_4 \cap X_7$	0.4713(NE)	$X_4 \cap X_8$	0.4324(NE)	$X_4 \cap X_7$	0.1682(NE)
$X_5 \cap X_7$	0.4039(NE)	$X_5 \cap X_8$	0.6640(NE)	$X_5 \cap X_7$	0.5065(NE)	$X_5 \cap X_8$	0.6924(NE)	$X_5 \cap X_6$	0.3211(NE)
$X_6 \cap X_7$	0.4596(NE)	$X_6 \cap X_9$	0.6049(NE)	$X_6 \cap X_7$	0.5254(NE)	$X_6 \cap X_5$	0.5607(NE)	$X_6 \cap X_5$	0.3211(NE)
$X_7 \cap X_6$	0.4596(NE)	$X_7 \cap X_9$	0.6369(NE)	$X_7 \cap X_6$	0.5254(NE)	$X_7 \cap X_9$	0.6424(NE)	$X_7 \cap X_6$	0.2648(NE)
$X_8 \cap X_7$	0.3714(NE)	$X_8 \cap X_5$	0.6640(NE)	$X_8 \cap X_7$	0.5152(BE)	$X_8 \cap X_5$	0.6924(NE)	$X_8 \cap X_6$	0.2837(NE)
$X_9 \cap X_7$	0.4178(NE)	$X_9 \cap X_7$	0.6369(NE)	$X9 \cap X_7$	0.5062(NE)	$X_9 \cap X_7$	0.6424(NE)	$X_9 \cap X_8$	0.2406(NE)

Table 6. Interaction detection results. *NE* nonlinear enhance, *BE* bi-factor enhance.

other factors is the strongest. Specifically, in the Culture dimension, the interaction between the sown areas of farm crops and road density is the highest, with a Culture dimension q-value of 0.4596 and an Aesthetic dimension q-value of 0.5254. Compared to other factors, roads serve as the infrastructure for cultural exchange and tourism industry development, which is a prerequisite for perceiving intangible values, thus exhibiting stronger interaction effects in both the cultural and aesthetic dimensions. In the Leisure dimension, the most influential interaction factor is the rural policy index, with the highest interaction value between the light index and per capita disposable income, having a q-value of 0.6640. The rural policy index reflects the government's attention to local rural development, and to some extent, reflects the local government's investment in rural infrastructure, thereby influencing the local recreational value. Similarly, in the Spirit dimension, the light index shows the strongest interaction, with the highest interaction value between the light index and per capita disposable income, having a q-value of 0.6924. In terms of the science level, per capita disposable income exhibits the strongest interaction with other factors, with the highest value observed between per capita disposable income and sown areas of farm crops.

Discussions

Feasibility of using review texts for CES evaluation

Online review texts are a rich source of information about individuals' and communities' interactions with nature, heritage, and local experiences[87,88]. Users often describe their interactions with ecosystems, ranging from recreational visits to cultural rituals or daily contact with the environment. These reviews reflect a variety of values, including aesthetic appreciation, cultural identity, spiritual connections, and well-being, all of which are core elements of CES[19]. By utilizing machine learning-based topic modeling techniques, we are able to extract underlying topics and content from large corpora of user reviews, revealing public perceptions, preferences, and values related to local ecosystems[89]. One of the key challenges in CES valuation is capturing intangible and subjective aspects, such as emotional responses, cultural significance, and social well-being. The use of online review texts, coupled with complex computational models like BTM, allows us to indirectly quantify these intangible values. Topic modeling can identify recurring topics and patterns within large volumes of text, providing a systematic approach to infer how individuals assign value to specific aspects of ecosystems. Another advantage of using online reviews for CES valuation is the ability to monitor changes over time[90,91]. Digital platforms generate continuous data streams, allowing us to observe shifts in public sentiments and perceptions of the cultural and aesthetic values of ecosystems. By applying topic modeling techniques at multiple time points, we can track how people's interest in or perceived value of certain ecosystem services changes in response to external factors such as environmental changes, policy interventions, or cultural shifts. This dynamic approach enhances our ability to understand long-term trends in cultural ecosystem service valuation and provides valuable feedback for adaptive management.

Despite its potential, the use of online review texts in CES valuation is not without limitations. The subjectivity of online content can introduce biases, as reviews are often influenced by personal opinions, specific events, or individual interests[92]. Additionally, not all user-generated content carries the same informational value or relevance to CES valuation, as some reviews may focus on unrelated aspects like logistics or service quality. Therefore, it is crucial to implement appropriate data cleaning and preprocessing steps to ensure the robustness and validity of the research results.

Differences in influencing factors of different types of CES

The influencing factors of different types of CES also vary. The results of this study show that the non-material benefits at the Culture level are primarily influenced by road density, with its impact being much stronger than that of other factors. This is consistent with Winter's viewpoint, which suggests that roads facilitate cultural exchange between regions, thereby promoting the development of regional culture[93,94]. Liang Shuai and others share a similar view, finding that convenient transportation is a key factor in rural site selection, indirectly reflecting the significant role of transportation in rural history[95]. This study also found that non-material benefits at the Leisure level are mainly positively influenced by per capita disposable income and the light index. These indicators represent the development level of the region, and areas with better economic conditions tend to have more complete infrastructure, thus providing more comfortable leisure experiences. This aligns with Mandić's viewpoint, which explores the relationship between tourism infrastructure and the quality of leisure experiences, concluding that well-planned and well-maintained infrastructure significantly enhances tourist satisfaction and promotes the sustainable development of tourism[96]. Wilkes-Allemann also shares a similar viewpoint, suggesting that the development of infrastructure, such as mountain biking facilities, can improve the recreational experience in forested areas[97]. Based on the research results, we also found that non-material benefits at the Aesthetic level are primarily influenced by road density and the light index. Yuan Kehua and Miao Jie believe that road network density and the light index have a positive effect on rural tourism, with areas that have richer road networks and better nighttime lighting generally experiencing more successful tourism development[98,99]. The development of tourism is closely tied to the scenic beauty of the area[100]. Non-material benefits at the Spirit and Science levels are both primarily influenced by the light index and per capita disposable income. Good nighttime tourism resources can extend visitors' stay, allowing them to gain a deeper understanding of the area and, in turn, derive more spiritual and educational benefits. Moal-Ulvoas also reached a similar conclusion, suggesting that immersive tourism can provide various spiritual benefits[101].

Sustainable management suggestions for rural Fujian Province

Through the calculation of the topic model, the rural CES in Fujian Province can be divided into five types: culture, leisure, aesthetics, spirit, and science. Among them, leisure, culture, and aesthetics account for the highest proportion, followed by 39.0%, 20.6%, and 19.3%. It can be seen that leisure, culture, and aesthetics in rural CES in Fujian Province are most easily perceived by people. This is closely related to the data source and regional resource characteristics[38]. Most of the comments on the village in Dianping.com are published by tourist users, and the proportion of resident users is relatively small. Most tourists comment on the village from the perspective of sightseeing tourism, which leads to the public's perception of rural CES emphasizing the leisure level. Improving rural tourism supporting facilities and enriching rural tourism experiences can effectively enhance the leisure level of rural CES. Fujian Province is located on the southeastern coast of China and is mountainous. It has created characteristics of both marine culture and continental culture in Fujian's villages and has formed local culture in many areas. Additionally, due to limited transportation in the mountainous regions, inter-regional connections are restricted, resulting in numerous localized cultures. It is important to note that accessibility can also pose some limitations, preventing people from experiencing these rich cultural resources. Furthermore, the distinctive landscapes formed by abundant natural and cultural resources provide the public with aesthetic enjoyment at the visual level. Spiritual satisfaction is related to individual differences and the environmental atmosphere. Currently, most rural supporting facilities remain at a more basic level, and the rural environment is characterized by fragmented development, which cannot provide people with an overall environmental atmosphere. Therefore, the spiritual perception of rural CES is low. The level of science can be improved by enhancing science education facilities. The rich connotation of the village needs to be spread to the public through the carrier of interpretation. Currently, rural areas in Fujian are deficient in this area, which leads to the lowest perception of science[13,32].

The spatial distribution characteristics of rural CES guide the high-quality development of rural areas in Fujian Province, while the discussion of influencing factors offers development measures. Coastal areas, such as Quanzhou, Fuzhou, and Zhangzhou, should enhance rural infrastructure, optimize cultural tourism experiences, delve into historical heritage, and prevent cultural homogenization. Combining the results of the CES influencing factors, it is recommended that the governments of the coastal regions increase their investment in transport infrastructure construction in remote regions, improve transport accessibility in remote regions, and make people aware of the different cultural characteristics of the coastal regions in order to increase the perceived value of the region's cultural type services. The construction of transport infrastructure is not only the construction of municipal roads, but should also include the construction of trails, which can not only play the role of connecting space, but also play a role in enhancing the value of the landscape and promoting health. Inland areas, such as Sanming, Longyan, and Nanping, should address infrastructure deficiencies, enhance service quality, leverage cultural diversity advantages, and emphasize cultural depth experiences. The shortcomings of cultural services in inland areas are mainly focused on the leisure level, and it is recommended that these areas improve the local financial situation in combination with local speciality industries in order to increase the investment in the infrastructure part. In addition improving the local night economy is also an important channel to enhance the value of leisure. It is recommended to carry out night scenery upgrading projects in popular tourist areas and develop night experience activities to enrich people's leisure experience. Both coastal and inland areas should enhance rural scientific capabilities, refine rural interpretation systems, and innovate rural research and learning approaches. Additionally, when feasible, villages should be prioritized for holistic development to create a unified rural ambiance and to prevent waste of resources due to micro-renewal.

Limitations and prospects

Rural ecosystems, as an essential component of ecosystems, are closely linked to the well-being of the people. Due to the diversity of resource conditions, different villages exhibit significant differences in the cultural service value. Faced with the current limited resources, how to scientifically and rationally allocate resources to promote the high-quality development of rural cultural services has become a key issue that needs to be addressed. The exploration of methods to precisely quantify the spatial distribution of rural cultural ecosystem services (CES) and a deep analysis of the influencing factors behind them is both a long and challenging research path. In light of this, the following breakthroughs are proposed to further develop and improve the research, addressing the limitations of this study:

1. The generation of the CES distribution map in this study was based on interpolation methods, which are highly dependent on the spatial location of rural samples. Although the selected rural samples represent the higher level of development in the region and are typical of rural development in the area, it is important not to overlook the limitations posed by the spatial location of the samples. For future optimization, the range of online textual data could be collected at the county level, incorporating not only typical high-development villages but also ordinary villages with more moderate development, providing a more representative picture of the rural development level in the county.
2. When using online review texts for CES assessment, the data are collected from internet platforms, meaning they reflect certain user characteristics. For instance, the reviewers tend to be younger, with fewer contributions from the elderly or children. In future studies using online review texts for rural CES assessment, it would be beneficial to supplement the data with survey or interview data. This would serve as a complement to the online data, helping to overcome the limitations inherent in using a single source of data.
3. Although nine indicators in the areas of Natural ecology, Community economy and Attractive potentiality were selected to explore the influencing factors of CES in this study, these indicators can only shed light on some of the causes. It is suggested that the following research should incorporate an interdisciplinary perspective to explore in depth the socio-cultural background and economic drivers behind the changes in CES, such as ecological resource endowment, community cultural characteristics, and the demand for economic development. By incorporating interdisciplinary perspectives, future research can not only enrich the theoretical framework of CES, but also provide more targeted policy recommendations for ecosystem management in practice.

Conclusions

The results of online review text data combined with the BTM of machine learning show that rural CES in Fujian Province is divided into five types: Culture, Leisure, Aesthetic, Spirit, and Science.

According to the spatial distribution results, Sanming City, Nanping City, and Quanzhou City have a higher overall level of perception at the Culture level; Fuzhou City, Zhangzhou City, and Xiamen City show higher perception levels at the Leisure level; Ningde City, Longyan City, and Xiamen City are most readily perceived by the public at the Aesthetic level; the overall difference in perception level is not significant at the Spirit level, with relatively better perception levels in Xiamen City and Nanping City; Sanming City, Fuzhou City, and Quanzhou City have higher perception levels at the science level.

The culture level is mainly influenced by road density; the leisure level is most affected by attraction potential indicators; the aesthetic level is most correlated with attraction potentiality and is also related to regional altitude and sown areas of farm crops. The spirit level is mainly influenced by the light index and per capita disposable income; the explanatory strength of each index to the science level is weak, with per capita disposable income, light index, and rural policy index being the most influential factors. Considering spatial distribution and influencing factors, this study offers relevant recommendations for the comprehensive development of rural ecosystem cultural services in Fujian Province.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Received: 24 April 2024; Accepted: 21 March 2025
Published online: 27 March 2025

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Funding

This research was funded by the Fujian Provincial Finance Department (Grant No. 115-KLY23110XA).

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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