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# Spatio-temporal pattern and driving factors of tourism ecological security in Fujian Province

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ABSTRACT

The scientific assessment of tourism ecological security holds significant theoretical and practical importance in promoting the sustainable development of the tourism economy and the ecological environment in the region. This study focuses on 84 counties within Fujian Province as its research scope. By utilizing the DPSIR model and integrating the remote sensing ecological index (RSEI), we have established an evaluation index system for assessing tourism ecological security in the region. The tourism ecological security index was quantitatively determined using the SBM-DEA model. Subsequently, a combination of methods, including spatial autocorrelation, exploratory regression analysis, and the GWR model, was employed to explore the spatial and temporal evolution patterns, as well as driving factors affecting tourism ecological security from 2010 to 2019. The findings reveal the following insights: (1) Overall, the level of tourism ecological security within Fujian Province is low, with a decreasing disparity in the security index across different regions. The tourism ecological security mainly falls within the "unsafe" and "relatively unsafe" categories; however, regions with higher security levels are exhibiting an expanding trend. Moreover, the tourism ecological security of each county is improving, with Southern and Central Fujian outperforming other regions. (2) Notably, there is significant spatial correlation among the tourism ecological security of each county in Fujian Province, indicating pronounced agglomeration characteristics. (3) Key drivers contributing to the spatial–temporal disparities in tourism ecological security encompass tourist-related disturbances, income levels of local farmers and herders, tourism-generated income, and government interventions. Among these factors, higher income levels for farmers and herders, increased tourism income, and proactive government intervention have a positive impact on tourism ecological security, whereas tourist disturbances exert a negative influence. Additionally, the impact of each factor on tourism ecological security displays noticeable spatial heterogeneity.

## 1. Introduction

Tourism, known as the "smoke-free" and "green" industry, is characterized by its dependence on the environment and resource consumption (Liu and Yin, 2022), with strong links to the ecological environment. In recent years, tourism has grown rapidly globally, according to the "2019 International Tourism Highlights" released by the United Nations World Tourism Organization (UNWTO), the number of international tourists increased by 5 percent in 2018, reaching 1.4 billion, and export revenues from tourism reached $17 trillion. The positive impact generated by the tourism industry is undeniable. However, as the number of international tourists and revenue continue to rise, the negative consequences of the tourism industry has also grown. These adverse effects not only impact the quality of life for the residents in tourist destinations but also exert pressure on the local ecological environment, potentially posing a severe threat to the long-term sustainability of the tourism industry (Ruan et al., 2019). Sustainable tourism development has garnered global attention, with a particular emphasis on the environmental impact of both short-term and long-term tourism expansion (Tepelus and Córdoba, 2005). A healthy ecological environment is essential for the development of tourism industry and severs as an important foundation for the sustainable economic development of nations (Tang, 2015).

As the world's largest developing country, China's tourism industry

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is undergoing a phase of robust development, and despite the severe impact of the COVID-19 epidemic in recent years, tourism still plays a distinctive and vital role in the economic and social system in general (Collins-Kreiner and Ram, 2021). The 2022 report from China's 20th National Congress featured tourism-related content for the first time, emphasizing China's commitment to the tourism sector. The rapid development of tourism, driven by government policies, has heightened the complex interaction between tourism and the ecological environment (Xiaobin et al., 2021). Specifically, the rapid tourism growth has led to improved urban infrastructure, increased local employment rates, enhanced living standards, and fostered urban GDP growth. Conversely, as a result of environmental and resource consumption caused by tourism (e.g. expropriation of ecological land, loss of biodiversity, etc.), the ecological safety problems of tourist destinations have been increasingly highlighted (such as high emissions of waste, waste gases, sewage, natural disasters, and environmental degradation, etc.) (Cai et al., 2022; Pulido-Fernández et al., 2019). This is very detrimental to the sustainable development of tourist destinations. A significant strategy for the construction of an ecological civilization has been established by the Chinese government in response to the negative issues associated with tourism. The strategy's implementation and refinement have made significant progress, and the government remains committed to the vision of creating a "beautiful China" with "clear water and green mountain". To leverage the benefits of tourism in the development of an ecological civilization, local governments in China have made it the primary instrument for building this civilization, resulting in a rapid phase of tourism development. Fujian Province stands as China's foremost provincial ecological civilization pilot demonstration area and national ecological civilization pilot zone, capitalizing on its ecological advantages as a competitive asset. In recent years, the province has successfully transformed these ecological strengths into economic assets. The promotion of the "Fresh Fujian" brand and the development of comprehensive eco-tourism initiatives have drawn a significant number of tourists, leading to rapid growth in the tourism sector, albeit with certain challenges related to tourism and the environment. Consequently, amidst China's dynamic tourism-driven economic growth and the ongoing assessment of resource and environmental carrying capacity, evaluating and maintaining tourism ecological security has become the focal point of Fujian Province's high-quality tourism development.

Since the 1990s, research on tourism ecological security (TES) has progressively gained significance within academic circles. Recent research has significantly advanced the conceptual interpretation, index system construction, research content, research subjects, and research methodologies related to TES. Specifically, concerning concept interpretation, the TES is an extension of the concept of ecological security and represents a vital area for measuring eco-security of tourist sites. McCool and Lime (2001) initiated an in-depth exploration of TES, focusing on the perspective of tourism carrying capacity. As research progressed, scholars delved into TES from various angles and began to emphasize the integration of the tourism industry with the social, economic, and ecological environmental systems (Liu and Yin, 2022), as well as the relationship between tourism activities and the social ecosystem (Gari et al., 2015), among other aspects. Currently, due to the lack of a standardized definition for TES, scholars have provided nuanced interpretations of its fundamental meaning. Generally, implying the preservation and non-threatening status of the tourism destination ecosystem, allowing for orderly and harmonious functioning, thus sustaining a sound and intact state. Furthermore, it should cater to human survival needs and sustainable development (Ruan et al., 2019). In constructing index systems, scholars are building indicator systems from the economic, social, and natural environment aspects. It mainly includes the classic PSR (Pressure-State-Response) Model (Yajuan et al., 2013), which reflects the interaction between humans and the environment and is often used to evaluate the health of ecosystems; CSAED (Carrying-Supporting-Attractive-Evolutional-Developing) model (Ying et al., 2022), is primarily utilized for assessing the ecosystem functions of tourism destinations; And the DPSEEA (Driver-Pressure-State-Exposure-Effect-Action) model is founded on the principle of sustainability for monitoring the long-term health benefits of tourist destinations and evaluating environmental protection (Waheed et al., 2009). DPSIR (Driver-Pressure-State-Impact-Response) Model (Liu and Yin, 2022), which reflects the relationship between resources, the natural environment, and economics, is often used to evaluate the sustainability of tourism sites. The five dimensions of Driver (D), Pressure (P), State (S), Impact (I), and Response (R) enable a comprehensive understanding of the underlying causes of the problem and facilitate the implementation of effective measures for its resolution (Kazuva et al., 2018). This model has found widespread application in various assessments, such as nature reserve evaluation (Liu et al., 2021), comprehensive water resource assessments (Borji et al., 2018; Sun et al., 2018), and ecosystem service evaluations (Ehara et al., 2018) and other areas. Recently, scholars have successfully employed this model to evaluate TES, yielding promising results. The research objects mainly include rivers, lakes, etc. (Nie et al., 2011; Xiaobin et al., 2021); The research scale involves multiple levels such as cities and nature reserves (Liu et al., 2021; Yajuan et al., 2013). In summary, the DPSIR model offers several advantages over other models. Firstly, it is comprehensive and logical (Ehara et al., 2018). In TES evaluation, this model effectively portrays the relationship between tourism and the environment. Secondly, the DPSIR model is characterized by "loops" with the five subsystems forming a "circular" relationship, including corresponding feedback between the systems (Lu et al., 2016). As scholars continue to explore the DPSIR model, it is found that the model mainly focuses on the developmental status of various stakeholders in regional TES, and cannot comprehensively evaluate the internal operational efficiency of tourism ecosystems or fully reflect whether the factor inputs effectively meet the ecological security requirements of tourist sites (Ruan et al., 2019). Bell (2012) suggests that the model can be effectively combined with other models to address its limitations. Research content encompasses a wide array of topics, scholars have conducted research on the evaluation of tourism and environment (Yajuan et al., 2013), the forecast analysis of TES (Tian et al., 2022), as well as analysis of the spatiotemporal patterns (Ma et al., 2022), driving mechanisms (Biswas and Rai, 2022), and dynamic early warning analysis (Bahraminejad et al., 2018) and other aspects. These research contents provide the research basis for the development of TES. In terms of research subjects, scholars have explored a wide range of scales, from small-scale coastal wetlands (Jogo and Hassan, 2010) and scenic spots (Wang et al., 2021) to mesoscale counties (Ruan et al., 2019), city clusters (Xiaobin et al., 2021), and provincial regions (Liang et al., 2023). Research methodologies include the application of improved methods like the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method (Chen et al., 2020), fuzzy element model (Han et al., 2015), and other techniques for quantifying TES value. Simultaneously, spatial autocorrelation (Xiaobin et al., 2021), and the standard deviation ellipse model (Zheng et al., 2023) are employed to depict TES's spatial evolution characteristics. In the realm of driving factors, researchers often employ tools like the geographical detector (Liu and Yin, 2022), obstacle degree model (Fan and Fang, 2020), gray correlation model (Tang et al., 2018), and other methods to uncover the principal influences of TES. The utilization of these research methods enables us to comprehend the present state of TES in tourist destinations and offers valuable theoretical guidance for the advancement of tourism. In conclusion, this study provides a comprehensive review of the literature on TES, revealing notable methodologies that integrate multiple approaches. This has resulted in the emergence of a complex interplay between tourism, ecology, geography, and other interdisciplinary domains.

Currently, the pertinent research findings on TES provide a crucial foundation for subsequent studies, but several shortcomings still warrant further investigation: (1) Regarding the construction of the index system and measurement aspects, the recent integration of the DPSIR model into the TES index system construction has supplemented the driver (D) and impact (I) subsystems of the PSR model, resulting in a more comprehensive framework. However, existing studies often superficially characterize the ecological state (S) subsystem of the DPSIR model by utilizing relatively simple indicators like green garden area, forest coverage rate, and green coverage rate of built-up areas (Liang et al., 2023; Zhao and Guo, 2022). A more comprehensive approach should involve big data to explore more objective and scientific indicators. The Remote Sensing Ecological Index (RSEI) is introduced based on extensive remote sensing image data, considers not only vegetation cover but also vital ecological elements for human survival, such as heat, humidity, and aridity. By comprehensively reflecting the evaluation outcomes (Xu et al., 2019), it more accurately portrays the overall status of the ecological environment within the research area. On the measure front, certain scholars have applied data envelope analysis (DEA) to gauge TES, yielding promising outcomes. Among these, the SBM-DEA model, in contrast to the traditional DEA model, effectively addresses unexpected outputs, thus advocating for the amalgamation of the SBM-DEA and DPSIR models for a more scientific TES measurement (Ruan et al., 2019). However, few studies have adopted the SPSIR and SBM-DEA models in a comprehensive manner. (2) In selecting research objects and sample units, most ongoing studies adopt provincial or urban areas as sample units, with a lack of investigations focusing on county-level or more localized units. Moreover, a limited number of county-level studies employ cross-sectional data from various periods for comparative analysis, neglecting to capture TES's continuous evolutionary patterns. (3) Concerning research methods, the predominant approach to examining TES's spatial and temporal patterns revolves around conventional spatial autocorrelation methods, typically relying on default GIS system threshold distances. These distances often lack the ability to delineate spatial clustering thresholds based on distance relationships between different sample units. Similarly, the prevailing studies exploring TES's driving factors frequently rely on global regression models like the ordinary least squares (OLS) model. However, the OLS model, being a "single universal" spatial regression analysis technique, overlooks TES's geographical element of "spatial non-stability" (Lin et al., 2021). Alternatively, the Geographic Weighted Regression (GWR) model, founded on local regression principles, quantifies the heterogeneity of driving factors across different sample units while visually depicting their spatial influence levels (Lin et al., 2019b; Lin et al., 2021).

Based on the statement above, the specific research objectives of this study are as follows: (1) Innovation of TES index system and establishment of TES evaluation model. (2) Exploring the spatial and temporal evolutionary characteristics of TES. (3) Identify key factors of TES and portray the driving mechanisms of TES. Moreover, the research results are anticipated to provide new insights for the study of TES and offer scientific references for the coordinated development of Fujian Province's tourism economy growth and ecological environment protection.

## 2. Study area and data sources

### 2.1. Study area

Fujian Province is situated in the southeast of China (23°31′N ~ 28°18′N, 115°50′E ~ 120°43′E), bordering Zhejiang Province, Jiangxi Province, and Guangdong Province, while also facing Taiwan Province. It falls under the jurisdiction of nine prefecture-level cities, including Fuzhou, Xiamen, and Quanzhou, encompassing 85 districts and counties (see Fig. 1). The total land area of Fujian Province spans 124,000 km2. The province boasts a distinctive Danxia landform and numerous islands, creating a captivating natural landscape. With its historical significance as the birthplace of the Maritime Silk Road, Fujian Province possesses a rich cultural heritage. The Mazu, Minnan, and maritime administration cultures have flourished here, contributing to profound cultural resources. Presently, Fujian Province boasts 463 A-level tourist attractions (as of December 31, 2022). These distinct and abundant


**Fig. 1.** Study area.

tourism resources have attracted a significant influx of visitors. In the year 2019 alone, Fujian Province welcomed a total of 536.5536 million tourists, generating tourism revenue of 810.121 billion yuan. The remarkable tourism economy has brought about a substantial population flow, placing immense pressure on the ecological environment of densely populated Fujian Province. This pressure has resulted in several ecological security concerns, such as deforestation, loss of biodiversity, accumulation of tourist waste, excessive development of scenic areas, and coastal erosion, and more. In the context of Fujian Province's active efforts to establish comprehensive eco-tourism and amid the dual pressure of the urgent need for rapid tourism economic growth and the constant challenge of resource and environmental carrying capacity concerns, it becomes imperative to thoroughly and systematically explore the spatial relationship of TES within Fujian Province. This exploration is crucial for providing a scientific foundation to achieve harmonious coexistence between the tourism economy and the ecological environment.

### 2.2. Data sources

In this study, 84 counties (excluding Kinmen County) were selected as the sample units in Fujian Province. Due to the significant impact of the COVID-19 epidemic on China's tourism industry over the past three years, leading to substantial fluctuations in tourism economic data, it is challenging to observe the general patterns of spatial and temporal changes in TES. Consequently, the study period was finalized as 2010–2019. The primary sources of panel data for relevant indicators in the counties of Fujian Province from 2010 to 2019 are as follows: Tourism-related economic statistics primarily originate from the annual "China Environmental Statistical Yearbook", "Fujian Statistical Yearbook", as well as regional publications such as "Fuzhou Statistical Yearbook", "Xiamen Statistical Yearbook", "Quanzhou Statistical Yearbook", "Zhangzhou Statistical Yearbook", "Sanming Statistical Yearbook", "Longyan Statistical Yearbook", "Putian Statistical Yearbook", "Ningde Statistical Yearbook", and "Nanping Statistical Yearbook".

Additionally, official websites, such as national economic and social development statistical bulletins and government work summaries from district and county governments in Fujian Province, were consulted. For cases of missing data, linear interpolation was applied using existing data. The RSEI index was calculated using Landsat TM / OLI / TIRS images provided by the United States Geological Survey Center (USGS). High-quality remote sensing images were selected through the GEE platform, and image collation was completed accordingly.

## 3. Methods

### 3.1. Construction of theoretical framework and index system

#### 3.1.1. DPSIR-DEA model

The "Driver-Pressure-State-Impact-Response" (DPSIR) model is an integrated model constructed by the European Environment Agency (EEA) on the basis of the Pressure-State-Response (PSR) model and the Driver-State-Response (DSR) model, with the main purpose of solving environmental problems (Tscherning et al., 2012). Comprising five distinct subsystems, each with distinct categories of indicators, the DPSIR model is capable of precisely describing the causal relationship between the environment, economy, and society as well as demonstrating the effects of socioeconomic development on the environment (Ehara et al., 2018).

Data Envelopment Analysis (DEA) is a modeling approach rooted in linear programming and distance functions. It serves to evaluate the relative efficiency of multiple comparable Decision Making Units (DMUs) with multiple inputs and outputs (Li and Shi, 2014). The model includes the radial distance function CCR and BCC models, as well as the non-radial Slack-Based Measure (SBM) model. In contrast to the traditional CCR and BCC models, the SBM model effectively addresses input relaxation and undesirable output issues in the input or output, mitigating deviations due to varying radial and angular selections (Cecchini et al., 2018). Building upon this, Tone introduced the Super-SBM model to further refine the SBM model. The resultant optimized model (SBM-DEA) offers enhanced discrimination of the efficiency among relatively efficient DMUs (Tone, 2001).

In the complex system of TES, it represents a comprehensive effect of the inputs and outputs of the tourism economy, tourism activities, and the ecological environment, rather than the result of the inputs or outputs of a single element (Ruan et al., 2019). The efficiency evaluation can reflect the comprehensive effect of the input and output of the economic and ecological environment, along with other elements of tourism activities, which is the best way to measure the input and output of resources (Zha et al., 2019). Therefore, an extensive assessment of the operational effectiveness of various tourism ecological safety systems is necessary in order to delve further into the comprehensive situation of the input and output of TES. In this study, the strengths of the DPSIR and DEA models are synergistically harnessed to establish the theoretical framework for evaluating TES in Fujian Province (Fig. 2). The approach involves the following concepts: The DPSIR model encompasses five subsystems, namely Driver (D), Pressure (P), State (S), Impact (I), and Response (R), while the SBM-DEA model encompasses input and output elements. The Driver (D) and Response (R) are categorized as input elements, whereas Pressure (P), State (S), and Impact (I) are considered output elements. Alterations in input elements influence the dynamic variations in output factors, and the conditions of output elements reciprocally impact input elements, triggering relevant responses. This proposed framework embodies a cyclical and sustainable system. Throughout this cycle, the Driver system initiates the process, with economic development levels and urban development status serving as primary drivers of TES issues. The rapid growth of tourism propels related industries, elevating the income levels of local inhabitants. Nevertheless, extensive tourism development begets challenges such as increased tourist density. Urban expansion also heightens the tourism spatial index, impinging upon residents' living space. These predicaments exert substantial pressure on the ecosystem of tourist destinations, thereby influencing the ecological quality of said areas. A-class tourist attractions encounter carrying capacity thresholds, and the proliferation of star-rated hotels yields positive and negative impacts on tourist destinations. While boosting residents' income and promoting tourism, this development concurrently diminishes arable and forest land, affecting agricultural and pastoral incomes. In response to these dynamics, local authorities implement affirmative measures including increased environmental investment and enhanced household waste management. As the terminal point in this cycle, the Response system engenders a "closed-loop" effect. This constructive response triggers a chain of feedback encompassing Driver, Pressure, State, and Impact aspects. Consequently, these factors can be adjusted and optimized within the system, fostering a virtuous cycle within the TES framework.

#### 3.1.2. Selection of the indicator system

Building upon the previously mentioned theoretical framework for TES evaluation in Fujian Province, and drawing from the insights of prior researchers, as well as utilizing data collected from 84 counties within Fujian Province, a total of 20 evaluation indicators were

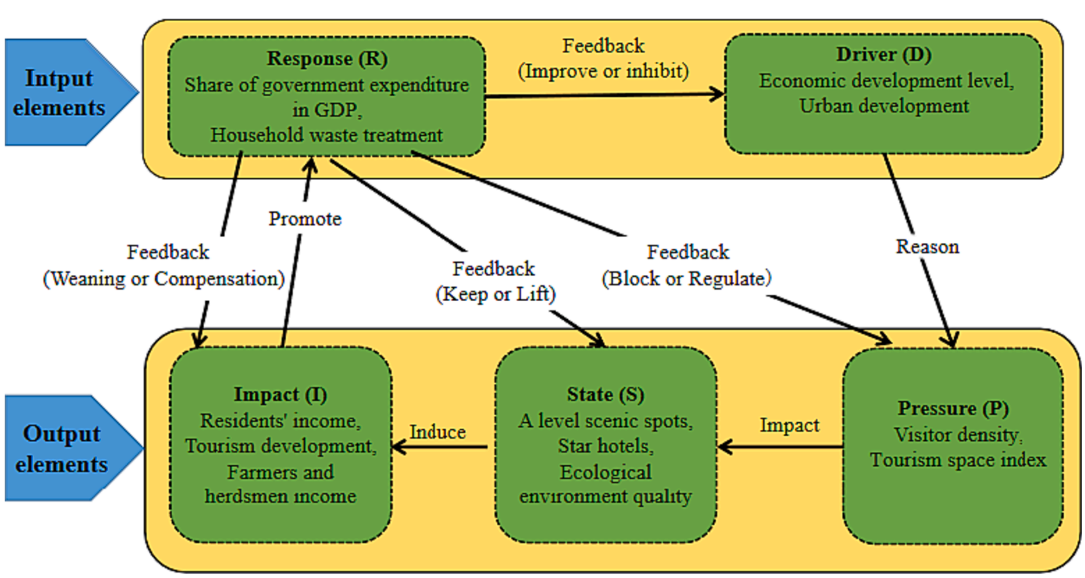


**Fig. 2.** TES evaluation theoretical framework in Fujian Province based on DPSIR model and SBM-DEA model.

ultimately selected across five subsystems. The weighting for each of these indicators was objectively determined using the entropy method (refer to Table 1).

*3.1.3. Calculation of RSEI*

In the State (S) subsystem of the DPSIR model, it is essential to assess the ecological environment status of tourist destinations. Previous studies have often relied on relatively simplistic indicators, such as green garden area, forest coverage rate, and the green coverage rate of built-up areas, to represent this status. However, these indicators do not provide a comprehensive reflection of the ecological environment at tourist destinations. In this study, an innovative approach is introduced: The RSEI leverages remote sensing information technology to comprehensively gauge the ecological environment quality. This index is composed of four ecological elements: The vegetation index, humidity component, surface temperature, and soil index. These elements correspond to greenness (NDVI), heat (LST), humidity (WET), and dryness (NDSI), respectively. These factors are intimately linked to human survival. The RSEI is integrated with each indicator by using principal component transformation, i.e., the effect of each indicator on RSEI is determined by the nature of its data itself, which overcomes the defect of subjectivity of artificial weighting (Xu et al., 2019).

The study area encompasses 84 counties in Fujian Province, which is relatively large. This scale introduces challenges in acquiring and processing satellite remote sensing image data. To address this, the study capitalizes on the capabilities of the Google Earth Engine (GEE) platform for remote sensing data processing. The GEE platform is used to select the highest quality remote sensing images within the study area. Subsequent steps include image radiometric correction, cloud removal processing, and masking. For each year, calculations are performed for NDVI, LST, WET, and NDSI. Since each indicator possesses distinct units and value ranges, normalization is applied to these four indicators before performing Principal Component Analysis (PCA). Upon normalization, $PC1$ is computed through eigen analysis on the GEE platform (Jing et al., 2020). Based on $PC1$, the formula for calculating the initial $RSEI_0$ is as follows:

$$RSEI_0 = 1 - PC1[f(NDVI, WET, NDSI, LST)] \tag{1}$$

In the formula: $RSEI_0$ represents the initial remote-sensing ecological index; $PC1$ represents the first principal component in the principal component analysis; and $f$ indicates that the indicator has been normalized. NDVI represents the level of greenery, WET signifies humidity, NDSI corresponds to dryness, and LST denotes heat.

*RSEI* was computed using the normalization method applied to $RSEI_0$. $RSEI_0$-min and $RSEI_0$-max respectively refer to the minimum and maximum values of the remote sensing ecological index after normalization, with the *RSEI* range being [0, 1].

$$RSEI = (RSEI_0 - RSEI_0\text{-}min)/(RSEI_0\text{-}max - RSEI_0\text{-}min) \tag{2}$$

In the formula, *RSEI* represents the remote sensing ecological index, with a range of [0, 1]. The closer the value is to 1, the better the ecological quality; conversely, the closer the value is to 0, the worse the ecological quality.

**Table 1**
Index system of TES in Fujian Province.

| Dimension | | Index | Index meaning | Weight | Literature reference |
|---|---|---|---|---|---|
| Driver | | D1 GDP per capita (yuan) | It reflects the impact of the economic development of tourist destination on ecological environment of tourist destination. | 0.0005 | (Xiaobin et al., 2021) |
| | | D2 Number of visitors (ten thousand people) | | 0.0008 | |
| | | D3 Urbanization rate (%) | It reflects the impact of tourist urban development and population growth on ecological environment. | 0.0241 | (Zhao and Guo, 2022; Zheng et al., 2023) |
| | | D4 Population at the end of the year (ten thousand people) | | 0.0042 | |
| Pressure | Social population pressure | P1 Population density (person / km$^2$) | It reflects the degree of land area occupied by residents in tourist destinations, the ratio of permanent resident population to land area is used to represent. | 0.0033 | (Xiaobin et al., 2021) |
| | | P2 Visitor density | It reflects the disturbance of tourists to the residents' life, the ratio of the number of tourists to the population at the end of the year is used to represent. | 0.0023 | (Bai and Tang, 2010) |
| | ecosystem carrying capacity | P3 Tourism space index (person / km$^2$) | It reflects the tourist carrying capacity of the tourist destination, the ratio of the number of tourists to the local land area is used to represent. | 0.0007 | (Liu and Yin, 2022) |
| State | | S1 Number of A-level scenic spots (amount) | It reflects the tourist reception capacity of the tourist destination. | 0.0038 | (Tang et al., 2018) |
| | | S2 Number of travel agencies (amount) | | 0.0075 | |
| | | S3 Number of star hotels (amount) | | 0.0141 | |
| | | S4 Remote Sensing Ecological Index (RSEI) | It reflects the ecological environment quality condition of the tourist destination. | 0.0108 | (Hu and Xu, 2018) |
| | | S5 Tourist reception to population ratio | It reflects the service supply provided by residents of tourist destination for tourists. | 0.0614 | (Zhao and Guo, 2022) |
| Impact | | I1 Total asset income of agriculture, animal husbandry and forest (100 million yuan) | It reflects the income status of farmers and herdsmen in tourist destination. | 0.3650 | (Liangjian and Kaijun, 2021) |
| | | I2 Per capita tourism income (yuan) | It reflects the tourism income situation of tourist destination to residents. | 0.1210 | (Peng et al., 2017) |
| | | I3 Social product realizion depth coefficient | It reflects the influence of tourism industry in tourist destination, the ratio of total tourism income to total retail sales of social commodities is used to represent. | 0.2797 | (Liangjian and Kaijun, 2021) |
| | | I4 Proportion of total tourism revenue in GDP (%) | It reflects the economic contribution of tourism industry in tourist destination. | 0.0461 | (Tang et al., 2018) |
| | | I5 Proportion of the tertiary industry in GDP (%) | It reflects the macroscopic situation of tourism development in tourist destination. | 0.0097 | (Zheng et al., 2023) |
| Response | | R1 Domestic sewage treatment rate (%) | It reflects the level of environmental pollution control in tourist destination. | 0.0084 | (Fan and Fang, 2020) |
| | | R2 Number of teachers per 10,000 people (person) | It reflects the level of education and training talents in tourist destination. | 0.0135 | (Liangjian and Kaijun, 2021) |
| | | R3 Proportion of fiscal expenditure in GDP (%) | It reflects the investment strength of the tourist destination government to improve the ecological environment. | 0.0232 | (Liang et al., 2023) |

### 3.2. Measurement of the TES index

In this study, we employed the optimized DEA (SBM-DEA) model to assess the relative efficiency of TES in Fujian Province. Subsequently, the TES index was derived based on the outcomes of the optimized DEA model. The mathematical expression formula is as follows:

$$\rho^* = min\rho = min\frac{1-\left(\frac{1}{N}\sum_{n=1}^{N}\frac{S_x^n}{x_n^k}\right)}{1+\left[\frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{S_m^y}{y_m^k}\right)+\sum_{i=1}^{I}\frac{S_j^b}{b_i^k}\right]}$$

$$s.t.\begin{cases}\sum_{k=1}^{K}z_k^y y_m^k - s_m^y = y_m^{k'}, m = 1,\cdots,M;\\ \sum_{k=1}^{K}z_k^y y_i^k + s_i^b = b_i^{k'}, i = 1,\cdots,I;\\ \sum_{k=1}^{K}z_k^x y_n^k + s_n^x = x_n^{k'}, n = 1,\cdots,N\\ z_i^k \geq 0, s_m^y \geq 0, s_i^b \geq 0, s_n^x \geq 0, k = 1,\cdots,K\end{cases} \tag{3}$$

In the formula: $\rho$ represents the value of TES efficiency, where $N$, $M$, and $I$ stand for the quantities of input, expected output, and undesired output, respectively. $(s_m^y, s_i^b, s_n^x)$ refers to the input–output relaxation variables, $(z_k^y, x_k^x)$ refers to the weight of each input–output value, and $(y_m^k, b_i^k, x_n^k)$ refers to the input–output values of the production unit $k$ at time $t$. $\rho^*$ represents the objective function, which strictly decreases with the input–output relaxation variable. It holds true that $0 < \rho^* \leq 0$. When $\rho^* = 1$, it indicates that the production unit is fully effective; $\rho^* < 1$ indicates that the production unit has an efficiency loss (Cecchini et al., 2018). A higher value of $\rho^*$ indicates a higher level of TES. According to the above model framework (Fig. 2), output elements include subsystems of pressure, state and impact, while, output factors are further divided into expected output factors and undesired output factors. State and impact are respectively considered as expected output factors, and social population pressure and ecological bearing pressure are taken as undesired output factors. As such, the internal attributes of the SBM-DEA model are established, leading to a comprehensive and scientific measurement of TES in Fujian Province.

### 3.3. Spatial autocorrelation analysis

The method of Exploratory Spatial Data Analysis (ESDA) is primarily employed to investigate the spatial distribution characteristics of the research subjects and unveil any underlying spatial correlations or anomalies. The core technique involves measuring and testing spatial correlation using the spatial autocorrelation method (Lin et al., 2019b), which mainly includes global spatial autocorrelation and local spatial autocorrelation. In this study, global spatial autocorrelation is applied to analyze the spatial correlation of TES in Fujian Province. For details of the specific formula, please refer to (Zhao et al., 2022). To further enhance the accuracy of the spatial autocorrelation analysis results, this study introduces the variable distance strategy of incremental spatial autocorrelation, building upon the original spatial autocorrelation analysis to optimize the spatial autocorrelation analysis method. Incremental Spatial Autocorrelation (ISA) refers to the changes in the degree of spatial autocorrelation and spatial clustering changes resulting from varying threshold distances. This is based on alterations in $Z$-scores and Moran's $I$ values. Ultimately, the optimal threshold distance is selected (Halls et al., 2018). Generally, $Z$-scores increase with escalating spatial distance, indicating an intensified agglomeration effect. The maximum peak score indicates optimal spatial agglomeration at that distance (Alho and de Abreu e Silva, 2014).

### 3.4. Exploratory regression analysis approach

Exploratory Regression Analysis (ERA) is a tool used to assess the optimal combination of influencing factors. The optimal combination of key factors can be determined by inputting multiple influencing factors, setting threshold conditions for these influencing factors, and attempting to explore suitable combinations of different influencing factors. In this study, the TES value was treated as the dependent variable, while 20 indicators (as shown in Table 1) were considered as independent variables, and the exploratory regression tool within the ArcGIS software was introduced for screening. To enhance the explanatory power of the regression model and prevent multicollinearity among variables, the exploratory regression tool within the ArcGIS software was employed to identify the most influential independent variables combination. The main screening principles are as follows: (1) Combinations of independent variables that yielded a substantial adjusted R-squared value of 0.6 were assessed; (2) Maximum Variance Inflation Factor (VIF) values were well below 7.5; (3) The Akaike Information Criterion (*AICc*) value for the chosen combination of independent variables was minimized.

### 3.5. Geographically-weighted regression model

Unlike ordinary least squares (OLS) model, geographically weighted regression (GWR) model incorporate spatial relationships into the analysis, allowing them to describe the relationship between the dependent and independent variables while reflecting spatial heterogeneity among the variables. GWR is a spatial statistical method capable of exploring spatial non-stationarity (Huang et al., 2020). TES is influenced by social, economic, and environmental factors, and the relationship between these influencing factors varies across different geographic locations, leading to a spatially non-stationary relationship. The GWR model is a valuable tool for exploring this relationship (Lin et al., 2019a). Therefore, this study used GWR model to investigate the spatial heterogeneity of the main influencing factors of tourism ecological safety in Fujian Province. Its mathematical formulation is presented as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p}\beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{4}$$

In the formula: $y_i$ represents the dependent variable, namely the TES index; $\beta_0(u_i, v_i)$ represents the constant term of the $i$-th observation point; $u_i, v_i$ represents the geographic coordinates of the $i$-th observation point; $x_{ik}$ represents the observed value of the independent variable $x_k$ in position $u_i, v_i$; $\beta_k(u_i, v_i)(k = 1, 2, \cdots, p)$ represents the regression parameter of the observation point at the center of mass in region $i$; $\varepsilon_i$ represents the random error term of the $i$-th observation point.

## 4. Results

### 4.1. Spatio-temporal changes of TES

#### 4.1.1. Temporal change characteristics of TES

The TES index of 84 counties in Fujian Province was calculated using the Max-DEA software for the years 2010 to 2019. The temporal trend of the TES index was then analyzed visually. As shown in Fig. 3, the mean TES value in Fujian Province exhibited minimal overall change from 2010 to 2019, fluctuating slightly around 0.31. The disparities in TES among different regions within Fujian Province gradually diminished.

To delve deeper into the temporal change characteristics of TES in Fujian Province, kernel density estimation analysis was performed for the years 2010, 2013, 2016, and 2019 (Fig. 4). The position of the kernel density curves shifted leftward during 2010–2016 and rightward during 2016–2019, indicating a decreasing trend followed by a subsequent growth in TES. The shape of the kernel density curve's right tail was characterized by concentration and extension, suggesting that TES values for each county in Fujian Province congregated in low-value

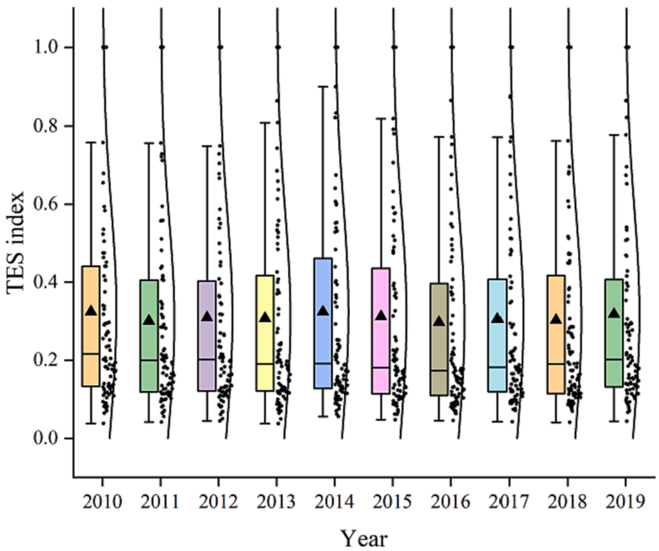


**Fig. 3.** Box map for TES in Fujian Province from 2010 to 2019.

areas. Notably, the right tail of the 2019 curve was higher than that of the other curves, indicating an expansion of TES areas in Fujian Province. Moreover, the peak value of the kernel density curve exhibited a gradual and stable increase, reflecting an overall upward trend in TES. In conclusion, although the TES index of Fujian Province shows less fluctuation and areas with better TES are expanding in 2019, the overall index value remains relatively low. Even areas with excellent TES may face critical or unsafe conditions. Therefore, it is essential for relevant government officials to strengthen the monitoring and feedback of TES in Fujian Province.

### 4.1.2. *Spatial change characteristics of TES*

To explore the spatial trends of TES within Fujian Province, the TES data were classified using ArcGIS software. The TES in Fujian Province was categorized into five levels using the natural breakpoint method (see Fig. 5): Insecurity ($0 < TES \leq 0.140$); Relative Insecurity ($0.141 < TES \leq 0.236$); Critical Security ($0.237 < TES \leq 0.405$); Security ($0.406 < TES < 0.678$); Extreme Security ($0.679 < TES \leq 1$). The TES in Fujian Province was categorized into five levels using the 019. Among them, the count of insecurity sites remained constant at 26 places during this period. The number of relative insecurity sites increased from 19 in 2010 to 22 in 2019, dispersed throughout various regions of Fujian Province. The count of critical security sites decreased from 16 in 2010 to 15 in 2019, situated between relative insecurity and security areas, primarily found in the central region of Fujian Province. The number of security sites declined from 14 in 2010 to 10 in 2019. In 2010, these were predominantly concentrated in Anxi County, Yongchun County, and Dehua County of Quanzhou City, as well as Hanjiang District, Chengxiang District, and Xianyou County of Putian City, etc. In 2019, Shaxian County and Sanyuan District of Sanming City were additionally included. The count of extreme security sites increased from 9 in 2010 to 11 in 2019. In 2010, these were mainly distributed in Wuyishan City, Siming District, Fengze District, Jinjiang City, Shishi City, Hui'an County, Gulou District, Jin'an District, Taijiang District, and Zherong County, among other areas. In 2019, Anxi County, Nan'an City, and Xiuyu District were also added.

From the above analysis, it is evident that the TES of Fujian Province exhibited a gradual positive development trend from 2010 to 2019. Specifically, in 2010, the tourism economy of Fujian Province primarily followed an extensive development path. As the tourism economy expanded, an increase in tourist density and a high tourism space index led to pressures on the tourism ecosystem, potentially resulting in deteriorating TES. By 2016, the TES in Fujian Province had improved, largely attributed to the coordinated growth of the tourism economy and the ecological environment, guided by government policies. For instance, in March 2014, the State Council released Several Opinions on Supporting Fujian Province to Further Implement the Ecological Provincial Strategy and Accelerate the Construction of Ecological Civilization Pilot Demonstration Zones, elevating the development of Fujian's Ecological Province from local decision-making to a national strategy. This offered a robust foundation for the development of the ecological civilization pilot demonstration zone in Fujian Province. In April 2016, the Fujian Provincial Government issued the "13th Five-Year Plan for the Construction of Fujian Ecological Province," further advancing the comprehensive implementation of the Fujian Ecological Province strategy. By 2019, the TES situation had improved, and the ecological security of tourism in very secure and secure surrounding areas has gradually gotten better, but several counties still exhibited unsafe and less safe levels, accounting for 31 % and 26 %, respectively. It indicates that TES has a radiating effect, though the scope is not large, and there is still a risk of TES deterioration in Fujian Province. Relevant government departments should focus on counties with unsafe and less safe levels and should not overlook county areas with critically safe levels. Simultaneously, advocating the implementation of a green tourism development model in these regions is essential to minimize the negative impact on the ecological environment. In summary, the process of upgrading the ecological safety level of tourism in Fujian Province's counties is characterized by twists and turns and gradualism. It is not an overnight accomplishment but requires continuity and persistence. It also reflects

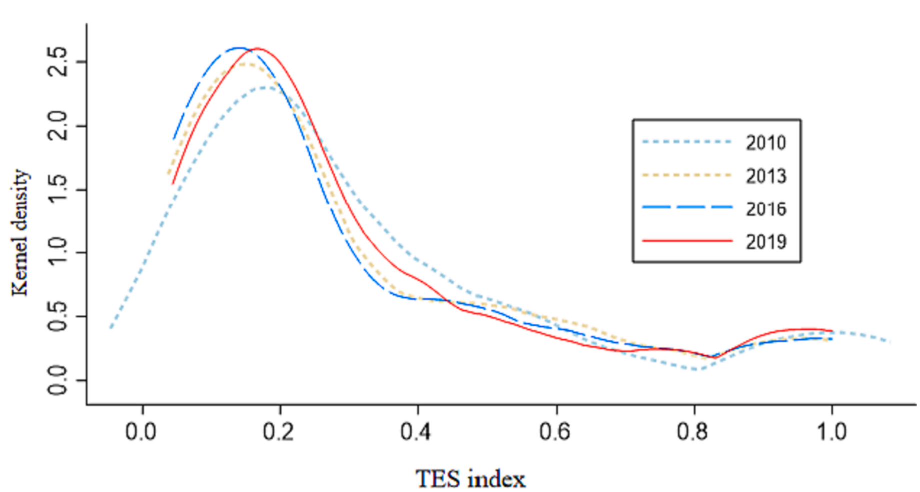


**Fig. 4.** Kernel density estimation for TES in Fujian Province from 2010 to 2019.

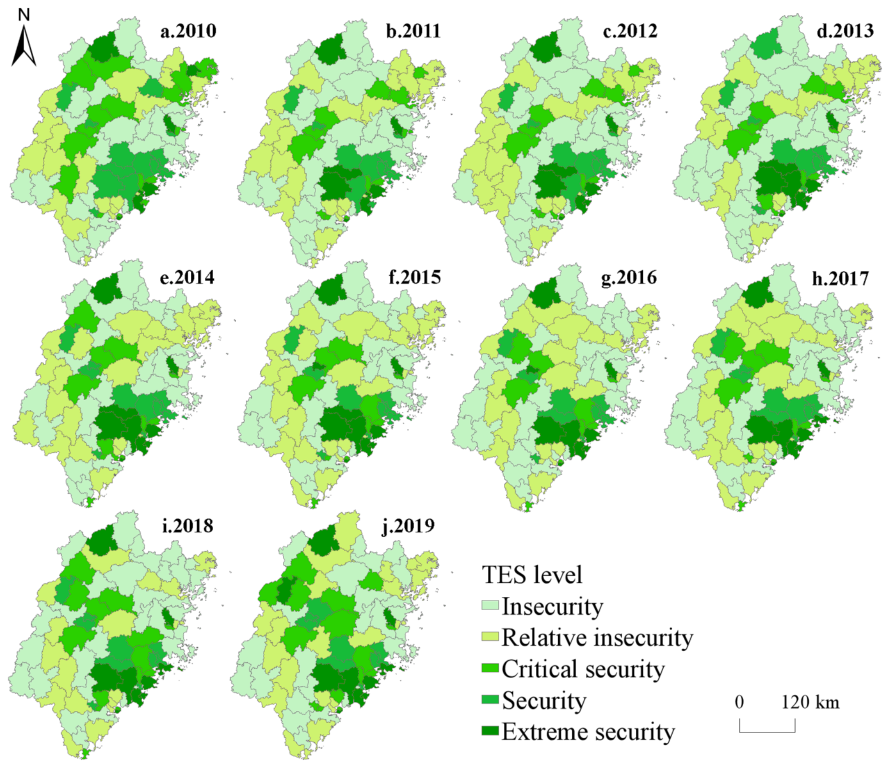


**Fig. 5.** Spatial pattern of TES in Fujian Province from 2010 to 2019.

the evolutionary law of the development of things with waves and spirals.

Considering the spatial distribution of TES, noticeable disparities have emerged among various counties in Fujian Province. To comprehensively observe changes in the TES index across different regions from 2010 to 2019, Fujian Province was divided into five areas: Eastern Fujian (Ningde City), Western Fujian (Longyan City, Sanming City), Southern Fujian (Xiamen City, Zhangzhou City, Quanzhou City), Northern Fujian (Nanping City), and Central Fujian (Fuzhou City, Putian City) (Fig. 6). Generally, substantial differences in TES were observed among these five regions, with the TES index rankings as follows: Southern Fujian > Central Fujian > Western Fujian > Northern Fujian > Eastern Fujian. When considering changing trends, Northern Fujian, Central Fujian, and Eastern Fujian displayed initial downward trends followed by upward trends, while Southern Fujian showed an initial upward trend followed by a downward trend. Western Fujian displayed a continuous upward trend. After 2018, all five regions demonstrated improved TES. The TES is higher in southern and central Fujian than in other regions can be attributed to the relatively developed economy of Southern Fujian, where Xiamen, Zhangzhou, and Quanzhou collectively

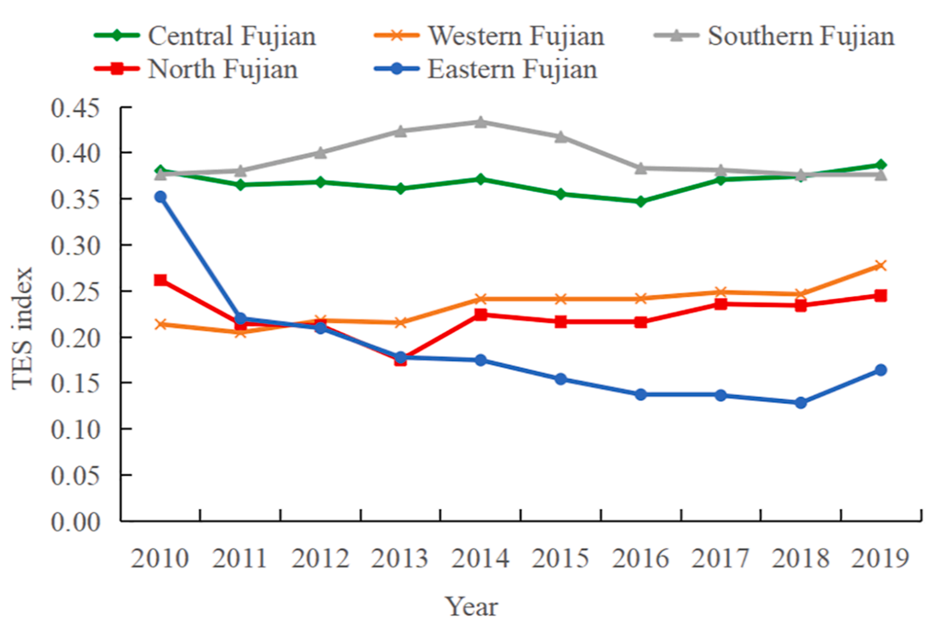


**Fig. 6.** Change of regional TES index in Fujian Province from 2010 to 2019.

form the Golden Triangle of Fujian Province. Additionally, Southern Fujian possesses rich cultural heritage and abundant cultural tourism resources. Xiamen City, relying on its advantageous location, has vigorously developed its tourism industry, attracting a significant number of visitors to the city and driving economic development in the local and surrounding areas. In response, the government needs to pay greater attention to the ecological aspects of the environment. Meanwhile, the central Fujian region, with Fuzhou as the capital city of Fujian Province, serves as the economic and cultural center of the province. It boasts richer tourism resources and more developed transportation hubs, leading to higher TES levels compared to other regions.

### 4.2. Spatial autocorrelation analysis of TES

The spatial autocorrelation analysis method was employed to conduct a spatial exploratory analysis of TES in Fujian Province, and its spatial correlation was tested using GeoDa software (Table 2). As shown in Table 2, the $Z$-values were all greater than 1.96, and the $P$-values were all less than 0.05 from 2010 to 2019, thereby passing the significance test (Ruan et al., 2019). This demonstrates the clear spatial correlation characteristics of TES across various regions in Fujian Province. The Moran's $I$ index increased from 0.194 in 2010 to 0.228 in 2019, indicating a pronounced tendency of agglomeration for TES in Fujian Province. Thus, coordination among the counties within the province is recommended for the management of TES and for collectively advancing the development of TES in Fujian Province.

Utilizing the ISA tool, we further explored the optimal threshold distance for spatial autocorrelation of TES in Fujian Province (Fig. 7 and Fig. 8). As depicted in Fig. 7, the Moran's $I$ index for each year exhibits a rapid downward trend within the 53–72 km threshold distance range, while it fluctuates within the range of 72 to 110 km, with a slower decline observed beyond 110 km. This suggests that the spatial correlation of TES in Fujian Province decreases with increasing spatial distances. Additionally, the Moran's $I$ index for each year shows peak values at 82 km and 110 km, as well as lower peak values at 72 km and 91 km. This fluctuating pattern suggests that the TES in Fujian province is characterized by "large gathering" and "small gathering". Fig. 8 illustrates that the $Z$-score values are positive for each year, following a trend similar to that of the Moran's $I$ index. In 2010, 2018, and 2019, the $Z$-score values are lower; in other years, however, they are all greater than 1.5 ($P < 0.05$). This indicates that the spatial distribution of TES in Fujian Province exhibits spatial autocorrelation at a 95 % confidence level, with notable clustered distribution characteristics. To conclude, based on the ISA analysis results, the Moran's $I$ index and $Z$-score values reached their peaks at 82 km and 110 km between 2010 and 2019, with the highest $Z$-score value recorded at 110 km. From this, we can see the optimal threshold distance for TES in Fujian Province is 110 km, signifying substantial spatial autocorrelation and distinct distribution aggregation characteristics. It indicates that the influence range of TES in Fujian Province is limited, and its impact varies as different peaks emerge with increasing distance. Therefore, government stakeholders should continually monitor the degree of TES influence, expand the scope of positive influence, and strive to reach the optimal peak in order to fully leverage the spillover effect of TES.

**Table 2**
Overall Moran's $I$ index of TES in Fujian Province from 2010 to 2019.

| Year | Moran's $I$ | $Z$ | $P$ | Year | Moran's $I$ | $Z$ | $P$ |
|---|---|---|---|---|---|---|---|
| 2010 | 0.194 | 3.1075 | 0.02 | 2015 | 0.283 | 3.7184 | 0.01 |
| 2011 | 0.27 | 3.756 | 0.01 | 2016 | 0.276 | 3.9062 | 0.01 |
| 2012 | 0.273 | 3.3471 | 0.01 | 2017 | 0.273 | 3.8998 | 0.01 |
| 2013 | 0.337 | 4.1401 | 0.01 | 2018 | 0.231 | 3.7016 | 0.01 |
| 2014 | 0.302 | 3.9403 | 0.01 | 2019 | 0.228 | 3.9011 | 0.01 |

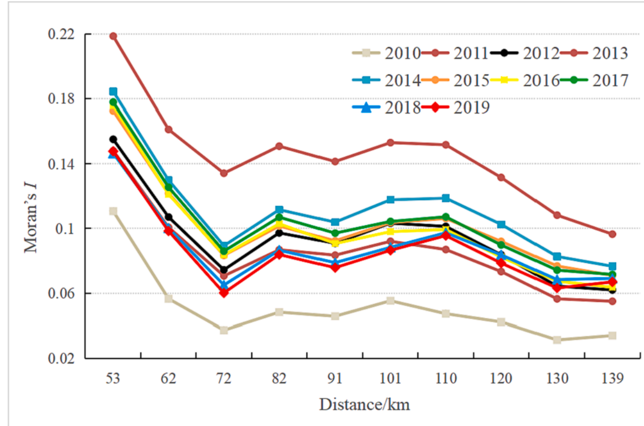


**Fig. 7.** The Moran's $I$ result of incremental spatial auto-correlation analysis about TES in Fujian Province from 2010 to 2019.

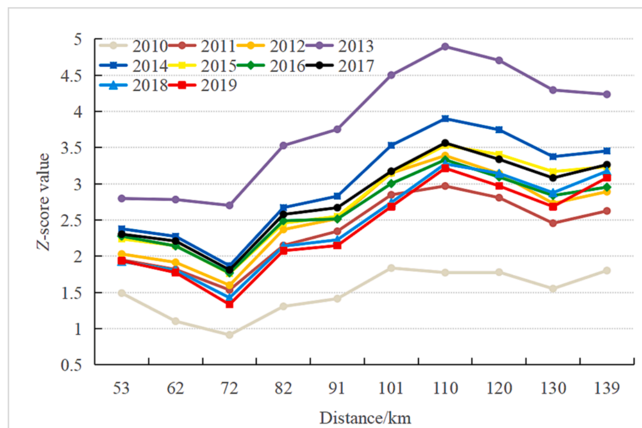


**Fig. 8.** The $Z$-score values result of incremental spatial auto-correlation analysis about TES in Fujian Province from 2010 to 2019.

### 4.3. Driving patterns of TES

#### 4.3.1. Identification of key drivers

Based on the analysis of the temporal and spatial changes in TES in Fujian Province, there is a noticeable trend of deterioration in TES. Therefore, to address the risks associated with TES in Fujian Province, it is essential to implement appropriate measures to control the ecological risk level. This involves analyzing the relevant factors affecting TES and subsequently establishing the driving mechanism of TES in Fujian Province. To avoid redundancy among factors and enhance the explanatory power of influencing factors, this study utilizes exploratory regression analysis to identify the most significant key driving factors (Table 3). As observed in Table 3, the $R^2_{adj}$ of various combinations of drivers is above 0.5, and the VIF value is less than 7.5, indicating that the combined effect of all factors is good and there is no multicollinearity issue.

Following the filtering principle mentioned in section 3.4, threshold conditions were established for the indicators, and explanatory

**Table 3**
Results of exploratory regression analysis of drivers.

| Combination of drivers | $R^2_{adj}$ | AICc | VIF |
|---|---|---|---|
| P2、I1、I2、R3 | 0.591 | 125.36 | 0.072 |
| P2、I1、I3、R3 | 0.548 | 125.71 | 0.619 |
| S5、I1、I3、R3 | 0.527 | 137.36 | 0.001 |

regression analysis was conducted to identify four independent variables with the most significant explanatory power: P2 (visitor density), I1 (total asset income of agriculture, animal husbandry, and forests), I2 (per capita tourism income), and R3 (the proportion of fiscal expenditure to GDP). According to the framework of the DPSIR model, it can be observed that tourist density represents the level of interference caused by tourists on the tourist site. The greater the interference, the higher the pressure on the ecosystem of the tourist site, which, in turn, affects the quality of the ecological environment at the tourist site, subsequently impacting the income of local residents engaged in agriculture, animal husbandry, and forestry, as well as tourism income. The protection level of TES and the quality of its supporting infrastructure are also affected by changes in resident income levels. Additionally, the percentage of government spending relative to GDP reflects the degree of government intervention in TES. Higher investment indicates the region's government's commitment to TES and the eco-security level of tourist sites. Consequently, further analysis of this indicator portfolio is warranted. Building on the results of exploratory regression analysis and considering the specific circumstances of the study area, this research explores the spatial and temporal evolution of TES in Fujian Province. The investigation encompasses several aspects: The impact of tourist disturbances (DT), income levels of farmers and herders (FHIL), tourism income levels (TIL), and government intervention (GI) (Table 4).

#### 4.3.2. Comparison of OLS and GWR model

To capture temporal changes and spatial heterogeneity in the impact of various key factors on TES, the same variables (as shown in Table 4) were selected for constructing both OLS and GWR models. These models were then compared for the years 2010 and 2019. The results of the fitting parameters are presented in Table 5. The GWR model demonstrates a smaller *Sigma* value in comparison to the OLS model, and its goodness of fit ($R^2$) surpasses that of the OLS model. Furthermore the difference in *AICc* values between the two models exceeds 3, with the *AICc* value of the GWR model being lower. These outcomes from the parameter comparison outcomes collectively indicate the superior fitting performance of the GWR model over the OLS model. Consequently, this study employs the GWR model to conduct for conducting an in-depth analysis of the driving factors behind TES.

#### 4.3.3. Spatial variations in driving patterns of TES

Based on the results of the GWR model, ArcGIS's natural discontinuity method visualized spatial distribution of regression coefficients (Fig. 9). Tourist disturbance exhibited a northeast-to-southwest decreasing trend in both 2010 and 2019. The income level of farmers and herdsmen displayed a shifting impact from negative to positive, indicating a growing influence on TES. Tourism income level had a positive effect on TES, with a stable impact over time. Government intervention showed an increasing effect with spatial heterogeneity. In 2010, the eastern region experienced greater intervention, while in 2019, this effect diminished due to effective government policies.

(1) Tourist Disturbance: As shown in Fig. 9a and 9e, in terms of concerning spatial distribution, tourist disturbance exhibited a decreasing trend with a "northeast-southwest" orientation in both 2010 and 2019. Regarding temporal patterns, the minimum regression coefficient value in 2019 exceeded the maximum value in 2010, indicating a gradual increase in the degree of tourist interference. This escalation can be attributed to the early stage of tourism destination development. At this stage, the immature tourism industry attracted fewer tourists, resulting in a limited impact on the ecological environment. However, as tourism destinations matured, their appeal grew, leading to a substantial influx of visitors and subsequently heightened disruptive effects. Consequently, managing tourist numbers and reducing their interference becomes imperative to enhance TES.

(2) Farmers and Herdsmen Income Levels: Illustrated in Fig. 9b and 9f, the regression coefficients for farmers' and herdsmen's income levels displayed both positive and negative values, initially present in northeast Fujian Province and shifting to the northwest in 2010. However, by 2019, all coefficients had turned positive. This shift from mixed polarization to positive correlation suggests an amplified influence of farmers' and herdsmen's income levels on TES in Fujian Province. This transformation can be attributed to changes in their income sources. Historically, income was earned through tree felling, which compromised the ecological environment. However, with the increasing awareness of ecological civilization and government initiatives in forest protection and management, along with the integration of forestry and tourism, emerging models like eco-tourism have attracted more tourists and boosted the income of local residents.

(3) Tourism Income Levels: Observing Fig. 9c and 9 g, the regression coefficients for tourism income exhibited a decreasing trend from southeast to northwest in 2010 and from northeast to southwest in 2019, both indicating positive correlations. This pattern underscores the positive effect of tourism income on TES. Early on, the coastal regions of Fujian Province showcased a more developed economy, robust tourism infrastructure, and higher attraction ratings for tourist sites, resulting in higher local tourism income compared to other areas. As each county's economy improved, ecological consciousness grew, and tourism resources were protected and promoted vigorously, more tourists were drawn, leading to increased tourism income at the county level and consequently, a heightened impact on TES. The relatively consistent regression coefficient values between the two periods suggest a stable influence of tourism income levels on TES.

(4) Government Intervention: Referring to Fig. 9d and 9 h, the regression coefficients for government intervention exhibited an ascending trend in both periods. In 2010, the trend was from west to east, whereas in 2019, it was reversed, indicating spatial

**Table 5**
Comparison of fitting parameters of OLS and GWR models.

| Fitted model | Dependent variable | *Sigma* value | $R^2$ | *AICc* value |
|---|---|---|---|---|
| OLS | TES in 2010 | 0.598 | 0.426 | 156.378 |
| | TES in 2019 | 0.514 | 0.579 | 131.837 |
| GWR | TES in 2010 | 0.531 | 0.604 | 142.616 |
| | TES in 2019 | 0.501 | 0.616 | 128.073 |

**Table 4**
Main variables and variable interpretation.

| Type of variable | Variable name | Variable interpretation | Average value | Standard deviation | Minimum value | Maximum value |
|---|---|---|---|---|---|---|
| Dependent variable | Tourism Ecological Security (TES) | The SBM-DEA model is used to calculate and reflect the ecological security level of tourism | 0.31 | 0.27 | 0 | 1 |
| Independent variable | Disturbance of Tourists (DT) | Visitor density (P2) | 17.41 | 15.76 | 2.70 | 84.09 |
| | Farmers and Herdsmen Income Level (FHIL) | Total asset income of agriculture, animal husbandry and forests (I1) | 46389.70 | 151152.09 | 1 | 880,619 |
| | Tourism Income Level (TIL) | Per capita tourism income (I2) | 3083.38 | 6123.79 | 103.83 | 42867.49 |
| | Government Intervention (GI) | Share of government expenditure in GDP (R3) | 10.37 | 5.71 | 1.98 | 33.69 |

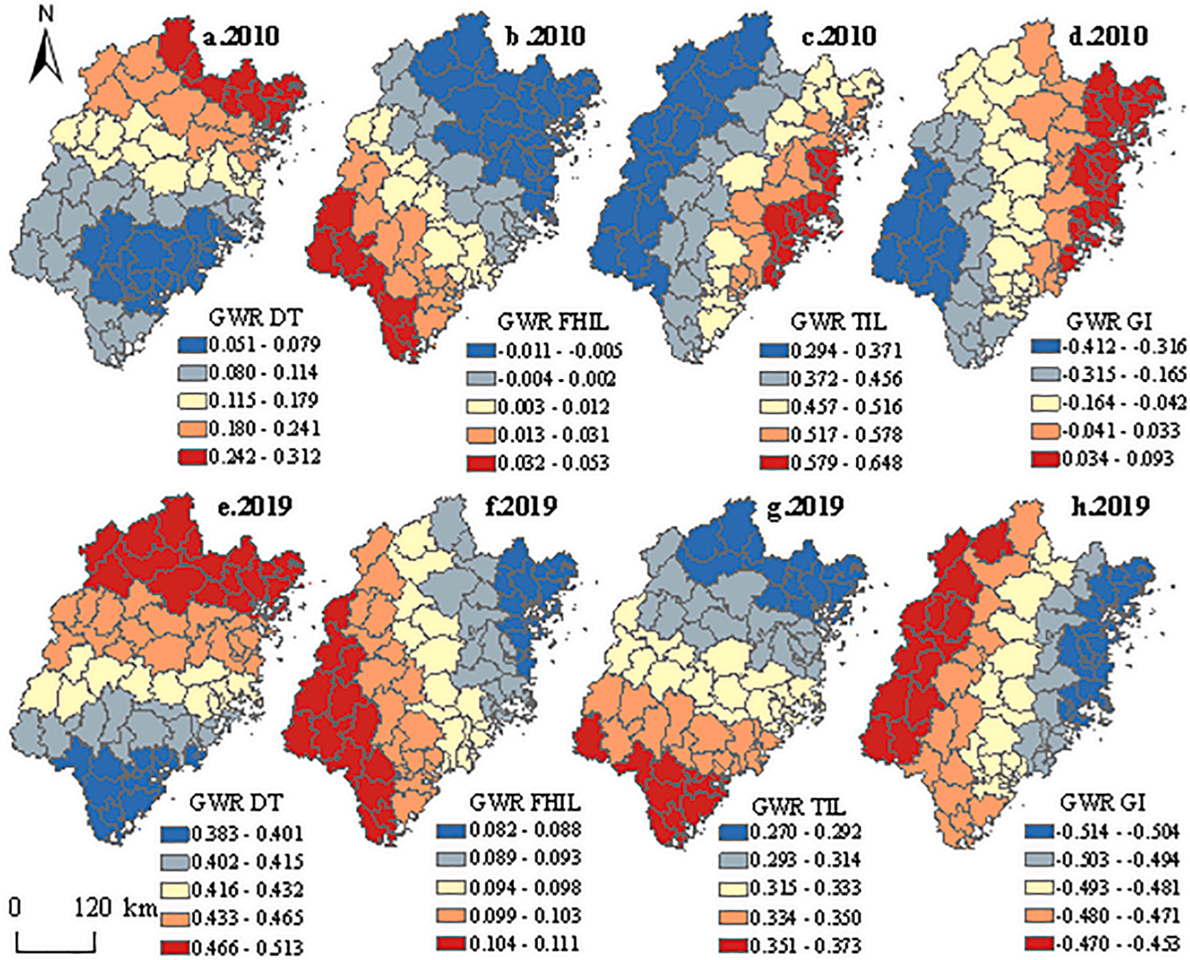


**Fig. 9.** Spatial distribution of TES and regression coefficients in Fujian Province in 2010 and 2019.

heterogeneity in the impact of government intervention on TES. This divergence can be attributed to geographical advantages, economic development, and rich tourism resources in the eastern coastal areas, leading to rapid but problematic tourism growth. Consequently, government intervention was crucial in improving TES in the eastern region in 2010. With the introduction of ecological and environmental protection policies and the concept of "all-for-one tourism", every county experienced tourism development, causing the previous high intervention in the east to be effective, resulting in a decreased impact on TES in the east by 2019. Hence, government intervention functions as an external regulatory force in TES evolution, with increased capital investment in ecological protection and environmental governance enhancing TES levels.

## 5. Discussions

Fujian Province, as the first provincial ecological civilization demonstration zone and national ecological civilization pilot zone in China, grapples with the rapid growth of the tourism industry and ongoing challenges related to the carrying capacity of the natural environment. This study delves deeply into the spatiotemporal patterns and the driving forces behind TES within Fujian Province. Its primary objective is to provide a scientific foundation for advancing the sustainable development of tourism, a goal that carries significant theoretical value and practical significance.

### 5.1. Theoretical contributions

This study constructs a theoretical framework and an index system for evaluating TES evaluation in Fujian Province, drawing on the DPSIR and SBM-DEA models. It conducts a comprehensive and scientifically-based evaluation of TES, considering a wide range of relevant indicators, including social, economic, and environmental factors, which vividly illustrate the intricate relationship between tourism and the environment (Ehara et al., 2018). Additionally, it addresses aspects that have been neglected in prior research regarding the internal dynamics and dynamic operation of the tourism ecosystem (Ehara et al., 2018). This methodology forms a fundamental and critical parts of TES research (Ruan et al., 2019) and serves as a key criterion for ensuring the sustainable development of the tourism industry. In previous studies, the majority of scholars utilized methods like improved TOPSIS and ecological footprint analysis to evaluate TES (Castellani and Sala, 2012; Chen et al., 2020). These studies predominantly adopted a "quantitative" perspective, often overlooking the "input-output" dynamics within tourism ecosystem (Ruan et al., 2019). Consequently, the principles of coordinated development within tourist ecosystems were not adequately reflected, and their dynamic changes were not accurately mapped. From an efficiency perspective, this study combines the practical realities of the various counties in Fujian Province, creating a more scientifically comprehensive evaluation method. Ultimately, it assesses the quality of TES in Fujian Province, providing essential theoretical references for subsequent studies related to urban development, land security, water ecological security, and more. Furthermore, in contrast to other provinces in China, such as Guangxi Province (Liang et al., 2023), the indexes of TES are different, even though both regions are located in the southern region of China and both are experiencing an increase in TES. Therefore, planning and management departments should consider local conditions and strike a balance between theory and practice when formulating strategies.

The construction of the TES evaluation indicator system is a complex undertaking that encompasses a wide array of factors. These factors include not only social and economic elements external to the tourism ecosystem but also elements related to the tourism economy, tourism resources, and other factors within the tourism ecosystem (Zheng et al., 2023). Drawing from the five subsystems of the DPSIR model, this study has selected the corresponding factors to establish a TES evaluation indicator system in Fujian Province. Building on this foundation, the study incorporates RSEI into the state subsystem of the DPSIR framework, which can provide a more objective and comprehensive characterization of the ecological environment in the study area (Xu et al., 2019). In earlier studies, Liang et al. (2023) and Zhao and Guo (2022) utilized indicators like forest coverage and urban green space area, which lacked effective integration with scientific indicators such as big data and failed to adequately reflect the ecological condition of the study area. Furthermore, this study agrees with Liu and Yin (2022) that a single indicator cannot accurately depict the status of TES. Therefore, in this study, remote sensing image data is combined with the RSEI index and introduced into the state subsystem to characterize the overall ecological environment of the study area. This represents an innovative approach that combines satellite remote sensing image data to enhance the existing TES evaluation index system effectively.

### 5.2. Practical implications

In this study, the sample module was refined to the county level, and the spatial characteristics of TES were analyzed using the spatial autocorrelation method, confirming the existence of spatial correlation of TES within Fujian Province. On this basis, the agglomeration effect of TES in Fujian Province was further analyzed using the ISA analysis method. In comparison to previous studies (Lin et al., 2019b), most of which utilized default threshold values for spatial autocorrelation and did not further optimize the distance parameters, under different scales of study, such as provinces, municipalities, and county areas, there are large differences in spatial relevance, and this different scale of spatial relevance may produce contradictory results, the result of which will affect the scope of application and credibility of TES (Alho and de Abreu e Silva, 2014; Halls et al., 2018). This study uses the ISA analysis method to determine the optimal threshold distance for TES, improving the rationality and interpretation of the results of the spatial autocorrelation analysis, providing valuable reference for other scales of research.

Finally, this study employs the GWR model to reveal the spatial heterogeneity of the driving factors impacting TES in Fujian Province. This approach aims to address the issues associated with spatial instability in traditional methods, making it more conducive to understanding the mechanisms influencing TES (Zheng et al., 2023). Furthermore, this study enables the spatial visualization of the regression coefficients of the GWR model at the county level. These visualizations can be utilized by relevant department managers to implement measures for achieving the sustainable development of the tourism industry based on the sensitivity of TES in each county's location. This study provides a new methodology and approach (Chen et al., 2022; Yuying et al., 2022).

### 5.3. Policy implications

The coordination of tourism development with ecological environmental conservation aims to enhance the sustainable growth of tourism in Fujian Province. This research presents several feasible policy recommendations that have practical reference value for local governments, tourists and other subjects. Firstly, the provincial governments of Fujian should jointly promote the construction and development of an ecological province while reinforcing and continue to strengthen environmental governance and ecological protection efforts. Currently, as one of China's ecological provinces, Fujian Province still faces risks associated with both artificial and natural ecological factors (Cai et al., 2023; Huang et al., 2023). Decision makers should develop corresponding measures based on the status of TES and the vulnerability and sensitivity of the ecosystem in Fujian Province, and the regional synergy of tourism development cooperation in different regions (Jiang et al., 2018). Grounded in the DPSIR framework, this approach involves balancing the subsystems by not only imposing conditional restrictions on the stress system elements but also fostering the healthy development of the drivers, responses, and other system elements (Cernat and Gourdon, 2012). For instance, this can include reducing the impact of energy-intensive enterprises, promoting the development of eco-friendly businesses, and advocating for ecotourism activities.

Secondly, in areas characterized by a high level of TES and economic development along the coastal regions of Fujian Province, there should be optimization of tourism activities and improvements in tourist safety level. Enhancing the overall tourist experience and maintaining a stable source of guests is crucial. In regions where TES is low and the economy is weak, such as the southwestern and northeastern regions of Fujian Province, policies should be tilted to add and improve public tourism facilities, elevate the quality of tourist services, and attract more tourists to visit (Zheng et al., 2023). Ultimately, it will be possible to reduce the spatial differences in the level of TES with the region. The policy of favoring less developed regions has been a practice endorsed by the Chinese government and has been more effectively implemented in some other regions. This serves as a reference point for other countries and regions dealing with unbalanced development (Liu and Yin, 2022). At the same time, whether the government policy is in line with the situation in each region requires field visits by relevant personnel. Only by implementing policies according to local conditions can we strengthen exchanges and cooperation among counties and promote the drainage of passenger flow.

Finally, the results have shown that factors such as the incomes of farmers and herdsmen, the level of tourism income, and government intervention have a positive impact on TES in Fujian Province, whereas traveler disturbances have a negative impact. Therefore, in order to improve the positive effects of TES, while increasing the income of residents from tourism, the regional governments must take appropriate measures to safeguard the incomes of farmers and herdsmen, improve the tourism industry structure in tourist destinations. According to Joun and Kim (2020), the results of the study suggest that investment-based tourism may be more effective than other industries in terms of total production and employment. Therefore, tourism serves as an effective and sustainable strategy for regional economic revitalization in areas with low levels of economic development, as it mobilizes and balances the local industrial structure. In response to the negative impacts of tourist interference, the government should monitor tourist traffic during holidays and other periods, divert tourists from crowded areas, reduce the ecological pressure on tourist destinations, and maintain the ecological health of these sites (Xiaobin et al., 2021). Tourists can also plan their travel itineraries and routes rationally using big data platforms to avoid peak tourism times. Tourists play a crucial role in the TES cycle system, and the ecological pressure on tourist destinations should not be underestimated. Therefore, this study promotes green travel and ecotourism for tourists, which is of great significance in maintaining the safety and well-being of tourism destinations.

### 5.4. Limitations and future directions

The TES system epitomizes a dynamic entity. This study endeavors to unearth the spatial and temporal dynamics of TES over a span of ten years—from 2010 to 2019, and to some extent reflects the general laws of its continuous evolution. However, this study still has several limitations. Firstly, there are restrictions on data access. The statistics yearbooks of county governments at all levels have provided as much relevant indicator data as possible. However, due to the limitations of current county-level statistics, it was not possible to obtain data for longer time sequences. Secondly, to further enhance the index system for TES assessment, it will be necessary to incorporate more big data, such as tourism flows, satellite remote sensing images, and point-of-interest data for landscapes, even though representative indicator data have already been selected for the system, and how to use advanced technologies such as artificial intelligence (AI) for real-time monitoring and data acquisition of TES. Lastly, while this research establishes the essential components of TES, it does not fully consider cultural and influencing factors. For example, it doesn't thoroughly examine the extent to which festival tourism, such as that associated with Mazu and Hakka culture, affects the ecological security of local tourism. Future research should place more emphasis on these variables. Furthermore, bolstered by the establishment of a robust tourism ecological monitoring system, research can be broadened to include dynamic early warning systems and predictive analyses of future trends. This enables the concurrent development of a responsive regulatory framework for TES—a crucial element in our ongoing endeavor to delve deeper into the exploration of TES within Fujian Province.

## 6. Conclusion

This study employed the DPSIR model to develop a comprehensive index framework for TES in Fujian Province. The TES index was quantitatively evaluated for the period from 2010 to 2019 by incorporating the SBM-DEA model. Building upon this foundation, exploratory spatial analysis was employed to uncover the spatiotemporal evolution patterns of TES across each county within Fujian Province. Subsequently, exploratory regression analysis and a geographically weighted regression model were utilized to elucidate the underlying driving forces. The principal findings are outlined below:

(1) The TES index in Fujian Province exhibited a relatively modest average value from 2010 to 2019, displaying a trend of initial decline followed by resurgence. Additionally, the disparity in TES levels among counties exhibited a gradual reduction. TES levels within Fujian Province were primarily categorized as insecurity or relatively insecurity, although the count of regions deemed extreme security witnessed an increase. Overall, a positive trajectory was observed in TES development.
(2) Spatial autocorrelation analysis, indicated by the Moran's *I* index, exhibited an ascending trend from 2010 to 2019 for the TES index in Fujian Province. The TES in Fujian Province exhibits clear spatial correlation and clustering characteristics. The influence range of TES is limited, and as the distance increases, different peaks emerge, each with its own unique influence.
(3) In the realm of influencing factors, the results showed that income levels of farmers and herders, tourism income levels, and government interventions had a positive impact on TES in Fujian Province, while tourist disturbances negatively affected it. Notably, the degree of influence exerted by each factor on TES displayed spatial heterogeneity.

## CRediT authorship contribution statement

**Yuying Lin:** Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Fazi Zhang:** Conceptualization, Supervision, Resources, Project administration, Writing – review & editing. **Guo Cai:** Validation, Writing – review & editing. **Yidong Jin:** Conceptualization, Methodology, Software. **Lin Zhang:** Data curation, Funding acquisition, Validation, Writing – review & editing. **Yang Ge:** Supervision, Validation, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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