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Measurement of tourism eco-efficiency, spatial distribution, and influencing factors in China

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Promoting sustainable development in the tourism industry is a common challenge faced globally. Enhancing tourism eco-efficiency (TEE) has become the key to addressing this challenge. Exploring the driving factors through spatiotemporal distribution patterns is an important approach. This research focuses on the period from 2011 to 2020 and examines 30 provinces in China (excluding Tibet, Hong Kong, Macau, and Taiwan) as the research subjects. Multiple spatiotemporal analysis methods are comprehensively employed, and the geodetector with optimal parameters (OPGD) is used to explore the primary driving factors behind the spatiotemporal distribution patterns. The following conclusions are drawn from the study: TEE in China as a whole has exhibited a "bimodal" development trend, with efficiency values initially increasing and then decreasing. The eastern region has higher efficiency than the western and central regions do, and the interprovincial imbalance initially decreases and then increases. The spatial distribution of TEE in China shows a "northeast–southwest" pattern, which is consistent with the eastern and central regions. However, the western region has a "northwest–southeast" distribution. Consequently, the TEE of Chinese provinces has transitioned from a "cluster and belt distribution" with high and low values to a "block distribution." The factors contributing to spatial differentiation in TEE are related primarily to external environmental and technological aspects, with regional innovation capability being the strongest factor. The intersection of technological and environmental development has the most stable influence and the highest explanatory power on TEE. The findings of this research have important theoretical and practical implications for understanding the spatial distribution and enhancement mechanisms of TEE in China.

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Introduction

Tourism, as a tertiary industry that emerged in the post-industrial era, was initially often referred to as the "smokeless industry." However, with the maturation of the tourism industry and the deepening of related research, an increasing number of studies have noted that although tourism has significant economic benefits, its operation also consumes large amounts of energy and generates additional carbon emissions (Lenzen et al. 2018). The United Nations World Tourism Organization (UNWTO) reported that tourism accounts for 5% to 14% of global carbon emissions from human activities (UNWTO 2009). From 2009 to 2013, the tourism industry generated 8% of global greenhouse gas emissions (Lenzen et al. 2018). This demonstrates the growing contradiction between the significant economic benefits of tourism and the environmental pressures it creates.

TEE was proposed by Gössling in 2005 (Gössling et al. 2005). It aims to maximize the economic value of tourism while minimizing environmental pressure. Owing to its strong alignment with the goals of sustainable development, this indicator has become an important standard for measuring destination quality. Research in this field focuses on three main aspects: the core concept of TEE, how to measure TEE, and how to improve TEE. TEE is used to represent the ability of the tourism industry to generate economic benefits (such as total tourism revenue and GDP contribution) under certain levels of resource and environmental input while reflecting the trade-off between resource consumption and environmental burdens (such as energy consumption, carbon emissions, and ecological damage). (Jiang and Wang 2024). In terms of measurement, scholars have focused mainly on single indicator methods, composite indicator methods, and data envelopment analysis (DEA) models. These methods involve data related to production functions to measure TEE (Gössling et al. 2005; Guo et al. 2022; Xu et al. 2022).

When TEE is considered as attribute data, it is reasonable to apply geographic paradigms to examine its spatial distribution (Guo et al. 2022; Song et al. 2020). It can effectively help researchers uncover spatial patterns and regularities and analyze regional differences and their underlying causes in detail, thereby providing support for formulating more precise and targeted policies. Therefore, the research has explored the spatial distribution of TEE at different scales, including enterprises, scenic areas, cities, provinces, and countries, and has yielded interesting findings (Gabarda-Mallorquí et al. 2017; Guo et al. 2022; Peng et al. 2017; Sun et al. 2024). Although some studies have explored TEE at the provincial level, there is still a need to further consolidate these research findings (Guo et al. 2022; Wang et al. 2022a). The centroid migration, gravity center changes, and hotspot clustering of TEE have not been well discussed. However, the spatial distribution of TEE and its directional migration can effectively capture its driving factors and patterns of change. In terms of driving mechanisms, the existing studies have focused primarily on microlevel factors such as tourist routes, tourism enterprises, and tourists (Gössling et al. 2024) while also discussing macro factors (Jiang and Wang 2024). If a tourist destination needs to improve its overall eco-efficiency, it should focus more on exploration at the macro level (Ritchie and Crouch 2003). In macroscale studies, influencing factors include urbanization (Gan et al. 2023), transportation density (Zhang et al. 2022), and government regulations (Jiang and Wang 2024). Most scholars have used linear regression analysis and traditional geographic detectors for analysis (Guo et al. 2022; Peng et al. 2017). Through a comparison with the existing studies, we identified several research gaps. First, a macrolevel driving framework for TEE is lacking in the current research. A summary of the existing shows that the influencing factors have been explored

from three main dimensions: technology, the organization, and the external environment. Therefore, we incorporate these three dimensions into a framework for systematic analysis, namely, the technology-organization-environment (TOE) framework. Moreover, the interactions among technology, the organization, and the external environment, as well as their complex relationships with TEE, have not been fully revealed. From a methodological perspective, linear regression analysis assumes independence between variables (Montgomery et al. 2021), whereas data discretization in traditional geographic detectors relies on subjective human judgment, which introduces errors in the results (Song et al. 2020). Therefore, employing optimized research methods to explore the driving mechanisms of TEE is highly important.

In summary, we conducted a study covering the period from 2011 to 2020. This period is significant because it corresponds to China's 12th and 13th Five-Year Plans, during which the tourism industry experienced rapid development and significant advancements in ecological and environmental protection policies. Owing to issues related to data availability, consistency, and statistical standards, this study focused on 30 provinces in China (excluding Hong Kong, Macau, Taiwan, and Tibet). We used the Super-SBM model, which is based on production functions, to measure TEE and employed various spatial characterization tools, such as nonparametric kernel density estimation, standard deviation ellipses, and hotspot analysis, to map the spatio-temporal patterns comprehensively. To avoid the errors introduced by traditional linear regression models and experience-based geographic detectors, we introduce OPGD method to further explore the complex relationship between TOE and TEE. The contributions of this study are reflected in the following aspects: (1) A comprehensive TOE domain analysis framework was proposed. (2) OPGD method was introduced. (3) The optimization of transportation convenience and economic development environments was conducted simultaneously.

Literature Review

Measurement of TEE. The scientific measurement of TEE is the core and foundation of this field. The measurement methods can be divided into three main categories: the single indicator method, the composite indicator system method, and the DEA method. The single indicator method assesses TEE by using the ratio of indicators representing product and service value to those representing the environmental burden (Gössling et al. 2005; Sun and Pratt 2014). The composite indicator system method involves identifying the various dimensions of TEE and summarizing them according to a weighting method (Mandić 2020; Xu et al. 2022). The DEA method is currently the most widely used method for measuring TEE (Assaf and Tsionas 2015). It has been widely applied in various fields, such as tourism efficiency (Chaabouni 2019; Saienko et al. 2021), ecological security (Xiaobin et al. 2021) and ecological efficiency (Peng et al. 2017). In terms of measurement content, the core indicators of the single indicator method and composite indicator system method are primarily "income" and "carbon emissions" (Sun and Pratt 2014). The DEA model is based on the production function. It includes labor, capital, energy, land, fixed assets, tourism revenue, tourist arrivals, and tourism-related carbon emissions. The concept of TEE is gradually evolving toward a more comprehensive approach (Roodbari and Olya 2024). We also believe that TEE represents the overall development level of the tourism industry at a destination. On the basis of the definition of the production function, this study uses input indicators that consider dimensions such as labor, capital, energy, and fixed assets. The output indicators tourism revenue, tourist arrivals, and tourism carbon

emissions are used to construct a super slacks-based measure (Super-SBM) model for undesirable outputs (Zha et al. 2020).

Distribution of TEE. The spatiotemporal pattern of TEE is a key focus of the research in this field. In terms of the research scale, scholars have focused primarily on products (Marrocu and Paci 2011), enterprises (Ben Aissa and Goaied 2016; Pérez-Granja and Inchausti-Sintes 2023; Zhang et al. 2020), scenic areas (Corne and Peypoch 2020; Gössling et al. 2005; Peng et al. 2017), urban-level analyses (Yang et al. 2023) and provincial-level analyses (Jiang and Wang 2024). Finally, at the national level, researchers such as Sun et al. have explored the ecological efficiency of global cruise tourism (Sun et al. 2024). In terms of the research methods, commonly used approaches to study TEE include static balance analysis, spatial clustering analysis, and directional distribution analysis, which are employed to reveal the distribution and aggregation patterns of TEE, its directional distribution, and data discretization. In previous studies, static distribution (Yang et al. 2023), spatial clustering (Jiang and Wang 2024; Wu and Liang 2023), and relational attribute distribution (Wang et al. 2022a) have been well explored, but the spatial directional distribution of TEE and the continuous change in its centroid trajectory have been overlooked.

Factors of TEE. There are significant differences in the spatial distribution of TEE, which depend on microlevel internal factors such as tourism enterprises, itineraries, tourism products, and tourists (Gössling et al. 2024; Kytzia et al. 2011), as well as macrolevel external factors at the regional level (Guo et al. 2022). These microlevel conclusions can effectively guide the sustainable development of the tourism industry. However, sustainable destination management needs to consider more macrolevel external influencing factors (Ritchie and Crouch 2003). On the basis of existing studies, scholars have explored mainly the relationships between TEE and technological, organizational, and external environmental factors. From a technological perspective, factors such as the application of information technology, green technology and clean energy, intelligent management and optimization technologies, and sustainable tourism technologies constitute the technological drivers for improving TEE (Gan et al. 2023; Hadjielias et al. 2022). At the organizational level, the focus has been on the degree of government support and the effectiveness of local policies (Sun et al. 2024). In general, government support is reflected in policy incentives and financial support. Government supervision typically involves environmental regulations, environmental monitoring, standardization, and related administrative penalties (Jiang and Wang 2024; Wu and Liang 2023). In the context of the external environment, the role of infrastructure is commonly emphasized (Abdullaevich and Abdulazizovich 2023). The existing research has focused mainly on specific aspects and has yet to form a mature framework of driving factors.

From a research methodology perspective, traditional econometric methods, such as Tobit regression analysis and truncated regression analysis, generally depict the relationships between exogenous variables and TEE (Peng et al. 2017; Sun et al. 2024; Zha et al. 2020). However, these methods assume that variables are independent of each other. Previous studies have often suffered from estimation biases due to multicollinearity in the data and have been criticized for ignoring the interactions between efficiency determinants (Guo et al. 2022). Geographic detectors assume that there is no linear relationship between variables, thus avoiding the problem of multicollinearity (Wang et al. 2010). Therefore, some studies have adopted traditional geographic detector methods to explore the driving mechanisms

of TEE (Guo et al. 2022; Wang et al. 2020). However, traditional geographic detector analyses usually involve subjective and arbitrary data discretization and lack precise quantitative evaluation (Song et al. 2020). As a result, research on the optimal parameters for spatial data discretization is ongoing. Currently, this method has been applied only in neighboring fields (Wang et al. 2024) and has not yet been fully explored in the TEE field. To enhance objectivity, we introduce OPGD into the study of TEE.

Methodology and measurement

Case study introduction. The study area is selected to include 30 provincial-level administrative units in China (excluding Hong Kong, Macau, Taiwan, and Tibet). China boasts abundant resource endowments and diverse regional characteristics, with significant regional imbalances in the development of tourism across provinces. This imbalance is closely related to improvements in eco-efficiency and practical pathways toward sustainable development. As a strategic pillar industry in China, tourism not only drives economic growth but also exerts considerable pressure on the environmental carrying capacity. Since the early 21st century, China has gradually intensified its focus on the construction of an ecological civilization, transitioning from an extensive growth model to a high-quality development model. The goal of improving TEE has been explicitly stated. During the 12th and 13th Five-Year Plans (2011–2020), China's economy experienced rapid growth, and the tourism industry entered a phase of comprehensive development. This period not only marks an important transitional stage for the tourism industry, but its related data also hold significant typical and policy reference value. Therefore, this study selects 30 provincial-level administrative units in China as the research subjects, with the research period spanning from 2011 to 2020. This period is both highly typical and representative. The specific locations of the case study areas are shown in Fig. 1.

Methodology

Technical roadmap. First, TEE was measured using the super-SBM model, which considers undesirable outputs. To describe its time series and spatial distribution characteristics, various methods, including the Theil index, nonparametric kernel density estimation, standard deviation ellipse analysis, and hotspot analysis, were subsequently applied. Finally, an impact framework for TEE, namely, the TOE framework, was constructed. OPGD was introduced to explore the driving effects of both single and multiple factors within the TOE framework. The detailed process is shown in Fig. 2.

Super-SBM model for unexpected outputs. Owing to the limitations and biases caused by radial and angular selection in traditional DEA models, Tone proposed an improved DEA model, namely, the SBM model (Tone 2001). However, the aforementioned model cannot handle the comparison and ranking of provinces (cities) with relative efficiency values of 1. To address this issue and further optimize the model, the super-efficiency SBM model was proposed. We selected 30 provinces (municipalities directly under the central government) as decision-making units. Provinces are economically and statistically independent, making it easier to obtain comprehensive and reliable input and output data (Charnes et al. 1997). One of the advantages of the super-efficiency SBM model is its capability for 'multiple inputs and outputs'. According to the production function's input–output indicators, labor input, fixed asset investment, energy consumption in tourism, and tourism revenue all satisfy the requirements for normal production activities, and
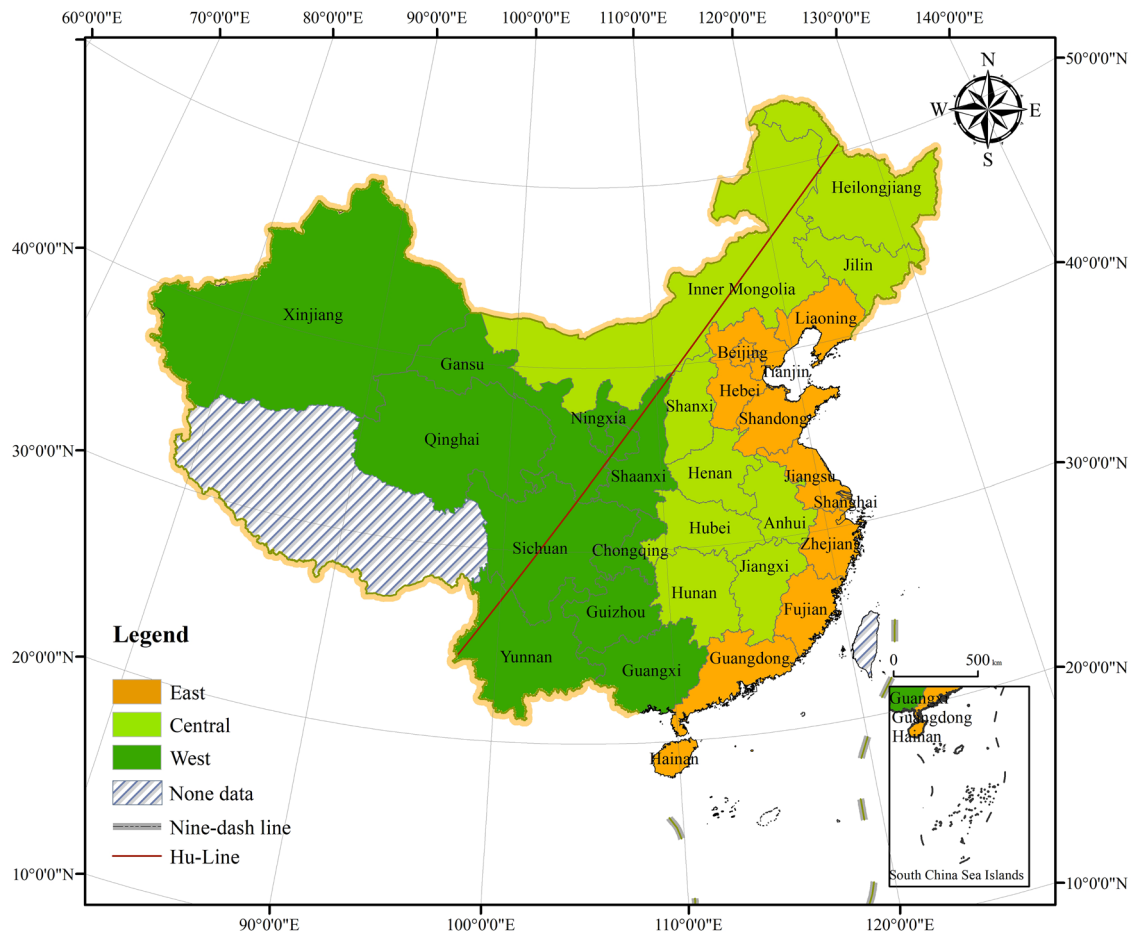
Fig. 1 Overview of the Case Study Area.

each of these indicators can represent the conditions of the province. The model is as follows:

$$\min \rho = \frac{\frac{1}{m}\sum_{i=1}^{m}(\bar{x}/x_{ik})}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\overline{y^d}/y_{sk}^d + \sum_{q=1}^{r_2}\overline{y^u}/y_{qk}^u\right)}$$

$$\begin{cases} \bar{x}\cdots\sum_{j=1,\neq k}^{n}x_{ij}\lambda_j; \overline{y^d} \ \sum_{j=1,\neq k}^{n}y_{sj}^d\lambda_j; \overline{y^d}\cdots\sum_{j=1,\neq k}^{n}y_{qj}^d\lambda_j; \bar{x}..x_k; \overline{y^d} \ y_k^d; \overline{y^u}\cdots y_k^u; \\ \lambda_j\cdots 0, i=1,2,\cdots,m; j=1,2,\cdots,n, j\neq 0; s=1,\cdots,r_1; q=1,2,\cdots,r_2; \end{cases}$$

$$(1)$$

The model assumes that there are N decision-making units (DMUs) and that each DMU is composed of inputs, m, desired outputs, r_1, and undesired outputs, r_2, x, y^d, and y^u represent the elements in the corresponding input matrix, desired output matrix, and undesired output matrix, respectively. ρ represents the TEE value. λ is a column vector.

Standard deviation ellipse. The standard deviational ellipse reveals the spatial distribution characteristics of various elements(Wang et al. 2022c). It quantitatively describes the spatial distribution features of observed variables by calculating parameters such as the centroid, orientation, major axis, and minor axis of the ellipse, which represent the spatial distributions of geographic elements.

$$\overline{X}_w = \sum_{i=1}^{n}w_i x_i / \sum_{i=1}^{n}w_i; \overline{Y}_w = \sum_{i=1}^{n}w_i y_i / \sum_{i=1}^{n}w_i \qquad (2)$$

$$\tan\theta = \frac{\left(\sum_{i=1}^{n}w_i^2\tilde{x}_i^2 - \sum_{i=1}^{n}w_i^2\tilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n}w_i^2\tilde{x}_i^2 - \sum_{i=1}^{n}w_i^2\tilde{y}_i^2\right)^2 + 4\sum_{i=1}^{n}w_i^2\tilde{x}_i^2\tilde{y}_i^2}}{2\sum_{i=1}^{n}w_i^2\tilde{x}_i\tilde{y}_i}$$

$$(3)$$

$$\sigma_x = \sqrt{\sum_{i=1}^{n}(w_i\tilde{x}_i\cos\theta - w_i\tilde{y}_i\sin\theta)^2 / \sum_{i=1}^{n}w_i^2} \qquad (4)$$

$$\sigma_y = \sqrt{\sum_{i=1}^{n}(w_i\tilde{x}_i\sin\theta - w_i\tilde{y}_i\cos\theta)^2 / \sum_{i=1}^{n}w_i^2} \qquad (5)$$

where (x_i, y_i) are the spatial coordinates of the observed variables; w_i is the spatial weight; $(\overline{X}_w, \overline{Y}_w)$ is the weighted mean center; Θ is the orientation of the standard deviational ellipse; $\tilde{x}_i$ and $\tilde{y}_i$ are the coordinate deviations from the weighted mean center; and σ_x and σ_y are the standard deviations along the x- and y-axes, respectively.

Hotspot analysis. The Getis-Ord Gi^* statistic is used to identify clusters of high and low values within a spatial region and reveal the spatial distribution patterns of hot spots and cold spots (Van der Zee et al. 2020). It calculates a standardized Z score, where higher values indicate hot spot areas and lower values indicate cold spot areas. A Z value approaching zero indicates that the spatial clustering characteristics of the region are not significant. The formula is as follows:

$$Gi^* = \frac{\sum_{j=1}^{n}W_{i,j} - \bar{X}\sum_{j=1}^{n}W_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n}W_{i,j}-\left(\sum_{j=1}^{n}W_{i,j}\right)^2}{n-1}}}, \bar{X}=\frac{\sum_{j=1}^{n}X_j}{n}, S=\sqrt{\frac{\sum_{j=1}^{n}X_j^2}{n}-(\bar{X})^2}$$

$$(6)$$

The equation represents the Getis-Ord Gi^* statistic, where X represents the attribute value of spatial feature j, W_{ij} represents the spatial weight between feature i and feature j, n represents the total number of spatial features, $\bar{X}$ represents the mean of the
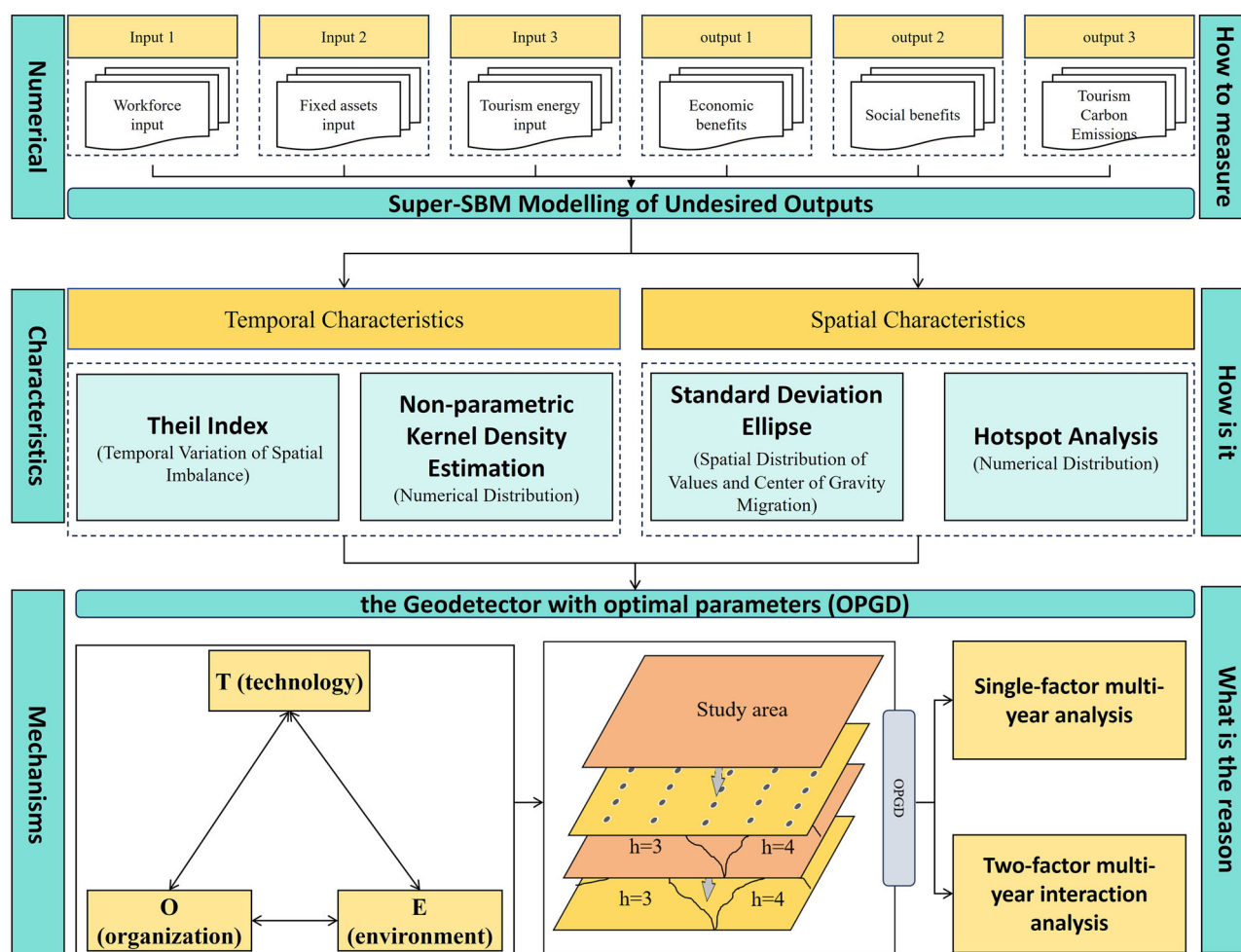
Fig. 2 Technical Route Diagram.

attribute values of the spatial features, and S represents the standard deviation of the attribute values of the spatial features. The Gi^* statistic corresponds to the z score. A higher z score indicates tighter clustering of high attribute values among the spatial features, whereas a lower z score indicates tighter clustering of low attribute values.

Geodetector analysis for optimal parameters. The OPGD model is derived from the geographic detector model by incorporating additional parameters. Parameter optimization can detect the scale and zoning effects of spatial data, which helps improve the quality and accuracy of research results. Determining the optimal scale of spatial stratification heterogeneity through spatial data discretization is a key step in applying a geographic detector. The effectiveness of discretization classification can be evaluated on the basis of the magnitude of the q statistic from the geographic detector. Using the GD package in R, methods such as *Equal Breaks*, *Natural Breaks*, *Quantile Breaks*, *Geometric Breaks*, and *Standard Deviation Breaks* are applied, with the number of classification levels set between 3 and 7 classes. The optimal parameters are the best combination of spatial data discretization methods, the number of breakpoints, and spatial scale. By calculating the q values for different combinations, the combination with the highest Q value is ultimately selected as the optimal parameter. In this study, since the research scale is fixed, the optimal parameters were determined based on the discretization method and the number of breakpoints calculated using the R language package (Song et al. 2020). Building

upon the selection of optimal parameters, the geographic detector method is employed to reveal the driving forces behind the spatial distribution characteristics of TEE in China (Wang et al. 2010). A larger value indicates a stronger explanatory power of the driving factors on the changes in TEE. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \quad (7)$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2, SST = N\sigma^2 \quad (8)$$

where q denotes the explanatory power of the factor with a value range of [0, 1], with values closer to *1* indicating greater explanatory power; h represents the stratification (strata) of the explanatory or interpreted variables; N_n and N represent the number of cells in stratum h and the whole region; σ_n and σ_2 represent the variance of the Y values in stratum h and the whole region, respectively; and SSW and SST represent the sum of the intrastratum variance and the total region-wide variance, respectively.

The interaction detector determines the characteristics of the interaction between two variables by comparing the q values of a single factor with those of the interaction of two factors. The interaction of driving factors is identified by examining the q values of the detection results to determine whether the combined effect between driving factors increases or decreases the explanatory power of the analyzed variable (**see** Table 1).

Table 1 Interaction Detection.

Factor relationships	Mean
$q(X_1 \cap X_2) < \text{Min}(q(X_1), q(X_2))$	**Weaken-nonlinear:** Effect of a single variable is nonlinearly weakened by the interaction of two variables.
$\text{Min}(q(X_1), q(X_2)) < q(X_1 \cap X_2) < \text{Max}(q(X_1), q(X_2))$	**Weaken-univariate:** Effect of single variables are univariably weakened by the interaction.
$q(X_1 \cap X_2) > \text{Max}(q(X_1), q(X_2))$	**Enhance-bivariate:** Effect of single variables are bivariably enhanced by the interaction.
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	**Independence:** Effect of the variables are independent.
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	**Nonlinear enhance:** Effect of the variables are nonlinearly enhanced.

Table 2 Measurement Indicators for TEE.

Indicator dimensions	Specific target	Data resources
Workforce input	Number of the tertiary sector workforce	China Statistical Yearbook
Capital input	Number of star-rated hotels	China Tourism Statistics Yearbook; Provincial Statistical Yearbook; Provincial Statistical Bulletin
	Number of travel agencies	
	Number of weighted scenic spots	
Tourism energy input	Tourism energy consumption	China Statistical Yearbook, China Tourism Statistics Yearbook; Provincial Statistical Yearbook
Economic benefits	Total tourism revenue	China Tourism Statistics Yearbook
Social benefits	Total number of visitors received	China Tourism Statistics Yearbook
Tourism carbon emissions	Tourism carbon emissions	China Statistical Yearbook, China Tourism Statistics Yearbook; Provincial Statistical Yearbook

Measurement

TEE measurement. The measurement indicators of TEE vary depending on the research context and data availability, but they always include input and output indicators. Considering the new requirements of ecological civilization construction for high-quality tourism development, this study refers to existing research indicator systems (Guo et al. 2022; Wang et al. 2022a) and proposes the following indicator system (see Table 2).

First, in terms of input indicators, labor, capital, and land are regarded as the basic production factors of tourism economic activities (Zha et al. 2020). During the study period, there were significant differences in the statistical standards for tourism labor, resulting in large data fluctuations. This study uses the number of people employed in the tertiary industry as a proxy indicator. Capital refers to the investment resources associated with tourism economic activities. In this study, it specifically refers to fixed asset investment. Owing to limitations in tourism fixed asset investment data and drawing from the existing research, this study uses the sum of the number of star-rated hotels, travel agencies, and weighted scenic spots as a representation of fixed asset investment. Another input indicator selected in this study is tourism energy consumption (Perch-Nielsen et al. 2010). This study estimates tourism energy consumption and carbon emissions indirectly (Becken and Patterson 2006; Perch-Nielsen et al. 2010). Land refers to the land resources used for tourism development, such as land for building scenic spots, hotels, transportation facilities, etc. However, because tourism satellite accounts do not include tourism land, this factor is not considered in this study.

Second, in terms of expected output indicators, the tourism industry aims to meet tourist demand and create social and economic output. Economic output is the ideal output indicator. This study uses total tourism revenue to represent economic output. To eliminate the impact of price fluctuations, the study uses the consumer price index (CPI), with 2011 as the base year, to convert total tourism revenue into constant prices. The total number of tourist arrivals is considered a proxy for social output. Additionally, tourist satisfaction is also an ideal indicator of output for a tourism destination, but due to data limitations, this indicator is not considered (Peng et al. 2017). In terms of

unintended output indicators, during tourism economic activities, the emission of pollutants is inevitable when using production factors to produce goods and services. Tourism carbon emissions reflect the impact of tourism development on the ecological environment, so tourism carbon emissions are considered a negative output indicator. Following the approach of previous studies (Wang et al. 2022a), this study adopts a bottom-up measurement method (see the supplemental material).

Factor measurement. We constructed a framework of influencing factors on the basis of "technology—organization—environment" (Baker 2012; Zeng et al. 2023) (see Table 3). This framework was proposed by Tornatzky and Fleischer and later applied to macro-level research (Zeng et al. 2023). Its advantage lies in the ability to simultaneously consider the comprehensive static impacts of three dimensions—technology, organization, and environment—within the TOE framework, providing a more comprehensive reflection of the complexity and diversity of TEE improvement. The technological dimension includes regional innovation capability and the digitalization level; the organizational dimension encompasses government attention and human resources; and the environmental dimension covers resource endowment, transportation convenience, and the economic development level.

(1) **Regional Innovation Capability:** The supply side of tourism can utilize technologies such as big data and blockchain to innovate cultural and tourism industry products, formats, and scenarios (Yunita et al. 2019). Technological innovation also provides strong support for innovative regulation of integrated market phenomena, favoring tourism development (Gan et al. 2023; Pascual-Fernández et al. 2021). Referring to existing research (Wang et al. 2022b), we use the knowledge creation index disclosed in the regional innovation report for measurement. Specific indicators can be found in the China Regional Innovation Capability Evaluation Report (see the supplemental material).

(2) **Digitalization Level:** The degree of digitalization promotes cross-industry exchanges and collaborations among tourism market entities on the basis of organizational innovation (Aghaei et al. 2021). The data analysis capabilities provided

Table 3 Measurement Indicators for the Independent Variables.

TOE	Variable	Representation method	Data resources
T (Technology)	Regional Innovation (RI)	"knowledge creation index"	China Regional Innovation Capability Evaluation Report
	Digitalization Level (DL)	Weighted quantity of per capita postal service expenses, per capita telecommunication service expenses, mobile phone penetration rate, internet penetration rate, per capita express delivery volume, domain names per ten thousand people, and long-distance optical cable density	EPS
O (Organization)	Government Support (GS)	The weighted sum of the number of occurrences of "tourism" in general fiscal expenditures and government work reports, along with the number of provincial-level tourism policies issued.	PKU Law and government reports
	Human Resources (HR)	Labor force engaged in the tertiary industry	EPS
E (Environment)	Transport Convenience (TC)	Weighted quantity of railway operating mileage density (km/10,000 square kilometers) and national highway mileage density (km/10,000 square kilometers)	EPS
	Economic Development (ED)	Per capita GDP	EPS

by digital technology help tourism market entities respond quickly to the precise production and market processes between supply and demand (Hadjielias et al. 2022). The level of digitalization typically involves digital infrastructure (Okafor et al. 2023) and digital service capabilities (Zhang et al. 2024). Therefore, we constructed a digitalization measurement system with seven indicators based on these two aspects: digital infrastructure and digital services.

(3) **Government Support Level:** The government can increase efforts to enhance research and financial investment to ensure regional technological upgrades (Li et al. 2023; Sun et al. 2024). A sound institutional mechanism also mitigates the rent-seeking behaviors caused by market failure (Greenwood et al. 2011).Drawing on existing research (Zhang 2025), this study measures tourism-related factors based on the frequency of the word "tourism" in government reports and the number of officially issued policies.

(4) **Human Resources:** High-quality labor is a comprehensive entity that integrates explicit skills and tacit knowledge (Tandon et al. 2023). It can apply uncoded tacit knowledge and experiential skills to the tourism development process, promoting organizational innovation, technological innovation, and tourism product innovation in the cultural and tourism sectors.

(5) **Transportation Convenience:** The transportation system facilitates the sharing of knowledge, technology, and talent across administrative regions and industries in the cultural and tourism sectors (Tang 2021). Its externality feature may accelerate the diffusion speed of production factors and provide innovative conditions for interregional and inter-industry innovation(Li and Liu 2022).

(6) **Economic Development Level:** The economic development level promotes effective resource allocation through price mechanisms and increases the aggregation of production factors such as technology and high-quality labor (Zhang 2023).

Research analysis

Spatial and temporal distribution characteristics. On the basis of the table and using the MAXDEA software, we comprehensively applied the Super-SBM model with global benchmarking for unexpected outputs to measure TEE in China. For the detailed results, please see below (see Fig. 3a).

Time series descriptive analysis. From a time series perspective (see Fig. 3b), TEE in Chinese provincial regions is unstable. Specifically, the development of TEE has gone through a cycle of a "growth period—stagnation period—decline period". The years 2011–2012 marked the "growth period". In 2011, the TEE value was 0.469, and by 2012, it had increased to 0.511, a growth of 9%. Starting in 2013, TEE entered a "high-level stagnation period", characterized by TEE values in each year being higher than the average for the research period and with minimal fluctuations between years. This phase continued until 2019. Compared with that in 2019, the TEE value in 2020 decreased by 21.4%. Based on China's three major economic regions, we explored the overall trends in each region. The TEE values showed a pattern of east > west and central. During the research period, the eastern region had abundant tourism resources and advanced industry technology. Coupled with the "siphon effect" attracting high-quality human resources and technological factors, TEE in the east consistently outperformed that in the west and central regions. To further characterize the overall differences in provincial TEE, both intergroup and intragroup differences were considered, and the Theil index was introduced. From the overall Theil index perspective, the trend of TEE balance changes showed a positive "W" shape. From 2011 to 2013, the overall Theil index decreased by 36.6%, indicating that the external effects of tourism technology promoted the overall extension of the provincial tourism production frontier and reduced efficiency differences. From 2014 to 2019, the overall Theil index remained at a low level, approximately 0.05. Since 2020, the nonuniformity of China's TEE has rebounded, with an increase of 87.6%. This may be due to the poor resilience and risk resistance of emerging tourism companies in most provinces, leading to a widening gap in TEE values. When the overall differences were decomposed into intergroup and intragroup differences, the intragroup differences accounted for 95.6% of the total Theil index. This finding indicates that the spatial nonuniformity of China's TEE mainly comes from within the three major regions.

To explore the overall distribution and variation differences of China's provincial TEE, this study used the nonparametric kernel density estimation function in Stata 17 to estimate the kernel density for the means of provincial administrative units for the years 2011, 2014, 2017, and 2020 (see Fig. 3c). In terms of temporal trends, over the research period, the TEE of provinces in China showed a time-changing trend from left to right. Overall, this trend exhibited a "bimodal" development pattern, with peaks ranging from high to low values. The first TEE peak was concentrated in the [0.3, 0.6] range, approximately 0.4, which constitutes the main level of China's TEE values. The second peak was concentrated in the [0.9, 1.2] range, approximately 1.0, indicating a significant "bimodal"
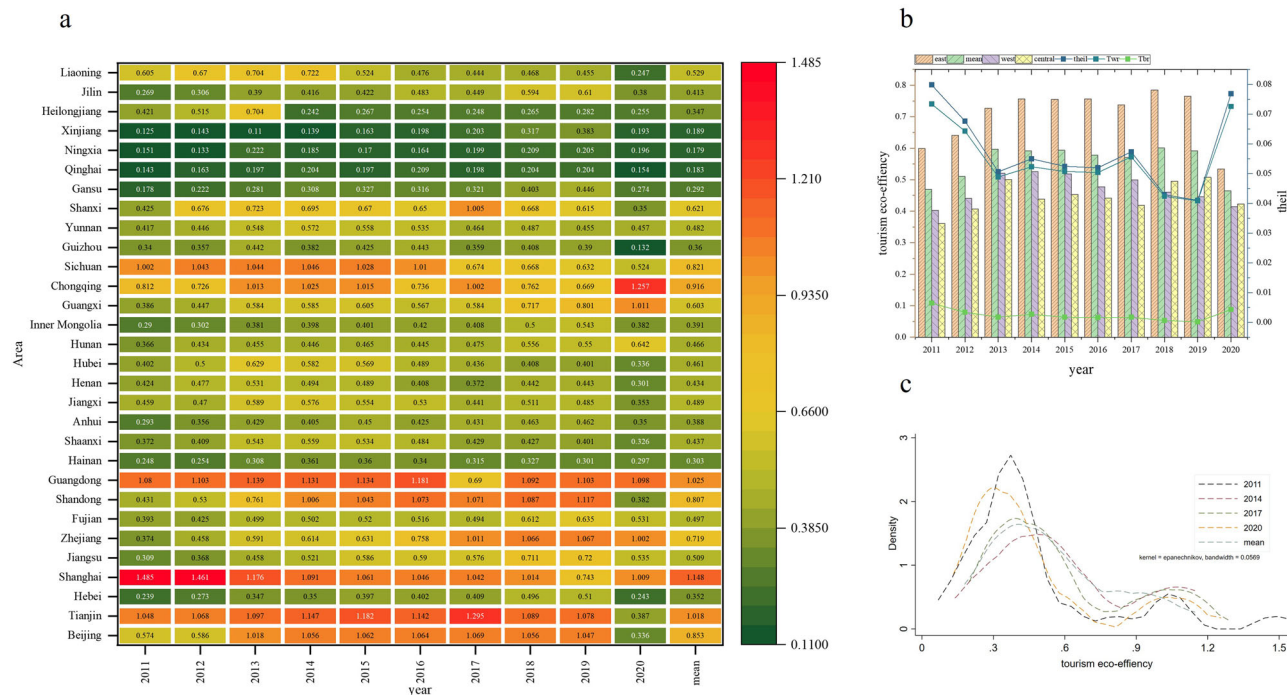
Fig. 3 TEE values and time series analysis. East, central, and west refer to the three major economic regions of China; specific lists can be found at the National Bureau of Statistics of China. "Mean" denotes the average value, "Theil" refers to the overall Theil index, "Tbr" represents the within-group Theil index, and "Twr" indicates the between-group Theil index. **a** represents the TEE values of each province during the study period, **b** represents the changes in statistical values by region and their Theil index variations, **c** represents the nonparametric kernel density variations of TEE in China.

differentiation in China's TEE levels. From 2011 to 2017, the center of the density function shifted to the right overall, and the "bimodal" distribution characteristics tended to weaken. This indicates that the TEE of provinces in China has generally increased, regional imbalances have decreased, and the overall balance of the tourism industry system has gradually strengthened. From 2018 to 2020, the density function shifted to the left again, and the "bimodal" distribution characteristics tended to strengthen, indicating a decrease in China's overall TEE, an increase in "bimodal" differentiation, and an intensification of imbalances.

Shift in the center of gravity and directional analysis. The shift in China's TEE center of gravity was characterized by spiraling and oscillating movement, moving from northeast to southwest, resulting in a "southwestward bias" (**see** Fig. 4). Throughout the study period, the center was mostly located in Henan Province and shifted toward Hubei Province by 2020. The directional distribution of efficiency showed a "northeast to southwest" trend, which was roughly consistent with the "Hu Huanyong Line". Specifically, looking at the spatial distribution direction of the standard deviation ellipse, the long axis was always greater than the short axis, showing a "northeast to southwest" trend overall. The shape index of China's TEE (long axis/short axis) initially increased but then decreased. While the long axis showed a decreasing trend, the short axis exhibited a growing trend, indicating a reduction in the directional nature of TEE and an expansion of the data range. Regarding the migration of the TEE center of gravity and its direction, the trajectory during the study period showed a complex spiral and oscillating movement. The continuous improvement in the market-oriented allocation and optimization of human resources in the Guangdong–Hong Kong–Macao Greater Bay Area and the Chengdu–Chongqing Economic Circle, coupled with strengthened financial capital guarantee capabilities, has promoted the maturity of tourism technology, and the structure of products and services has become

increasingly rational, leading to an increase in TEE. The abundant tourism resources and technological strength in the Beijing-Tianjin–Hebei and Yangtze River Delta urban clusters serve as engines for improvement. In terms of the trend of the directional angle, the change in the standard deviation ellipse's directional angle of China's TEE experienced two major phases: "fluctuating decline" and "rapid rise". To further delineate the regional spatial evolution trajectory of China's TEE, data from 2011, 2014, 2017, and 2020 were selected to explore the eastern, western, and central regions. The standard deviation ellipse areas in the eastern, western, and central regions all showed an increasing trend, indicating a certain level of increase in TEE within these regions. The directionality in the eastern, central, and western regions remained relatively clear, with the eastern and central regions showing a "northeast to west" direction and the western region showing a "northwest to southeast" distribution. The centers in different regions tended to shift toward the southwest to varying degrees, which is consistent with the national center trajectory.

Hotspot analysis. We employed the hot spot analysis method (Getis-Ord Gi^*) and analyzed the spatial correlation of TEE to identify regional clusters of high and low efficiency (see Fig. 5). Figure 5 presents the spatial distribution maps of China's TEE in 2011, 2014, 2017, and 2020. ArcGIS 10.8 software was used to classify the Getis-Ord Gi^* values into hot spots, medians, and cold spots using the natural breaks Jenks method. The spatial evolution characteristics were as follows: China's provincial TEE displayed spatial heterogeneity, transitioning from a "layered and zonal" distribution of high and low values to a "block-like" distribution, showing a decreasing trend from east to west. Using the "Hu Huanyong Line" as a boundary, the eastern region appeared as hot and medium areas, whereas the western region was a cold spot, showing significant spatial heterogeneity. Focusing on the spatial distribution patterns, the structure from 2011–2014 had a "layered and zonal" distribution, whereas that from 2015–2020 had a typical "block-like" distribution.
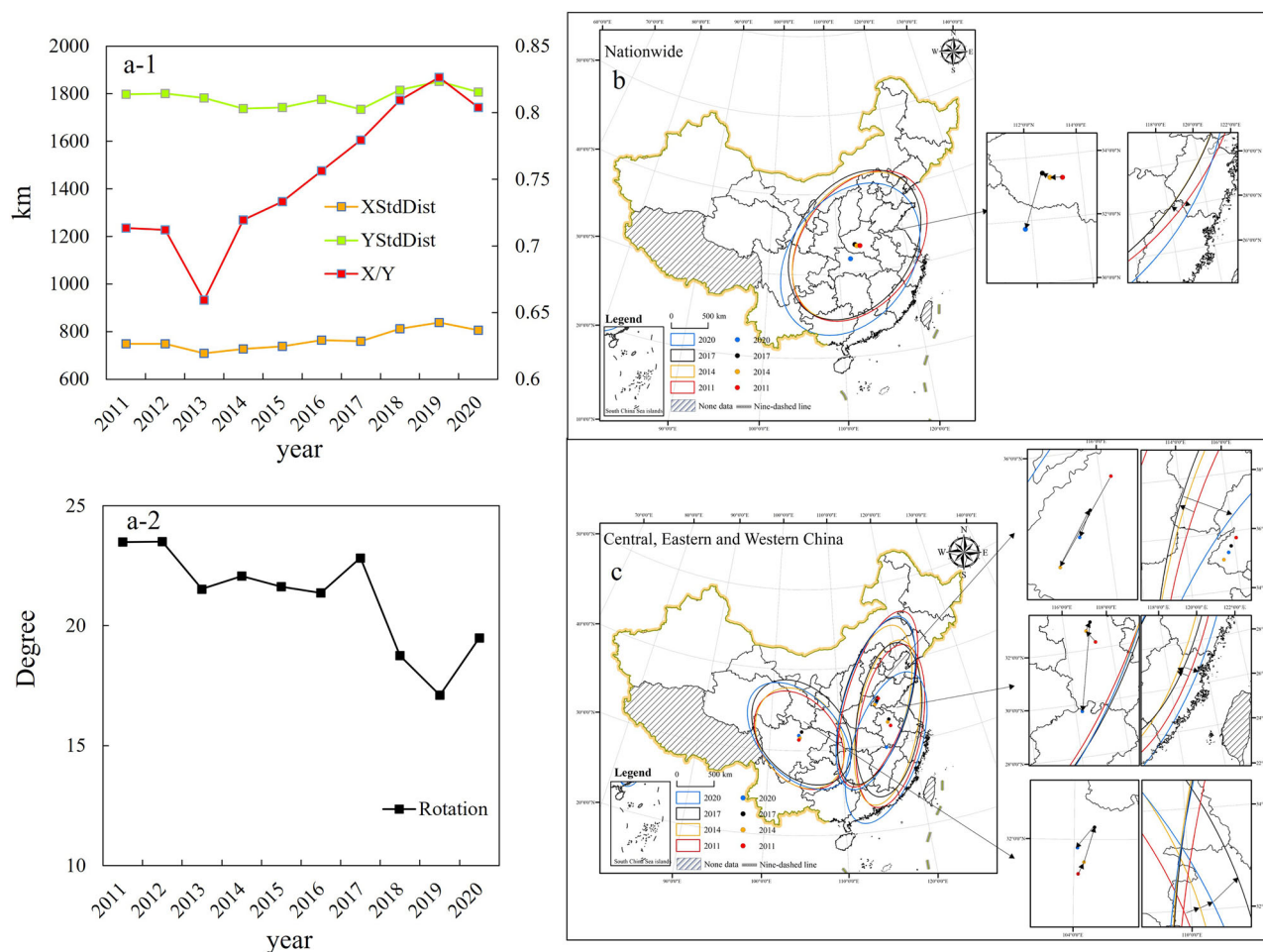
Fig. 4 Standard deviation ellipse and centroid shift trajectory. a-1 represents the long axis, short axis, and their ratio calculated using the standard deviation ellipse formula. **a-2** represents the rotation angle; **b** represents the standard deviation ellipse analysis of TEE across China and the center of gravity migration trajectory. **c** represents the specific changes in the east, central, and west regions. The generated standard deviation ellipses and their centroids are represented by different colors for each year: red for 2011, orange for 2014, black for 2017, and blue for 2020.

From 2011–2017, the "layered structure" radiated from the Beijing–Tianjin–Hebei economic circle, influencing neighboring provinces through a mixed control mechanism of the market and government for human and technical resource allocation. Geographic proximity and technological externalities increased the TEE levels of neighboring provinces. The Yangtze River Delta urban cluster and the central Yangtze River urban cluster centered in Hunan served as engines, promoting high-quality development of tourism in coastal areas and along the "Yangtze River Basin" provinces. The scale effect caused high-quality human resources to gather in coastal areas, forming a siphon effect, leading to a change in the distribution pattern of TEE from a "layered and zonal" structure in 2011–2014 to a "block-like" structure in 2015–2020. Compared with that in 2017, the spatial pattern in 2020 strengthened, revealing a "huddle for warmth" phenomenon. Both spatial clustering and diffusion coexisted in China's provincial TEE, Specifically, the number of median-value regions decreased, while the number of cold-value regions increased. In 2011, the numbers of hotspot, median, and coldspot regions were 11, 6, and 13, respectively. In both 2014 and 2017, the three categories remained stable at 10 each. Notably, in 2020, the number of coldspot regions significantly increased to 15, while the median-value regions shrank to 5, and the number of hotspot regions remained at 10. This spatial polarization phenomenon indicates that the uneven development trend of TEE became significantly more pronounced in the later observation period. This is consistent with Fig. 3, which shows an increase in the overall Theil index from 0.0573 in 2017 to 0.0768.

Results of the geodetector model with the optimal parameters
Factor analysis. Spatial data discretization is a fundamental challenge faced by the Geodetector model, which is often determined empirically and lacked accurate quantitative evaluation in previous studies. To address this contradiction, this study employed the Geodetector model with the optimal parameters. Correspondingly, this technique is implemented mainly on the basis of the OPGD package in R language. In the application of the Geodetector model, the optimal discretization methods and number of classes for continuous variables were selected, and the number of intervals between 3 and 7 categories was set. Various discretization methods, including standard deviation (SD), geometric, equal interval, natural breaks, and quantiles, were applied to calculate the maximum q value for each independent variable influencing factor from 2011 to 2020.

Using the Geodetector model with the optimal parameters, the q values of various influencing factors at different levels were calculated, and the results are presented in Fig. 6a. These influencing factors fluctuated during the study period but showed relative stability in their sequences. Summing and averaging the q values of the influencing factors from 2011 to 2020, the ranking was as follows: **RI (0.644) > TC (0.571) > ED (0.542) > DL (0.458) > GS (0.387) > HR (0.346)**. This indicates that the primary factors leading to the temporal evolution pattern of TEE are regional innovation capability, the level of transportation development, and the economic development level. Focusing on regional innovation capability, it plays a vital role in enhancing TEE. This is achieved through the
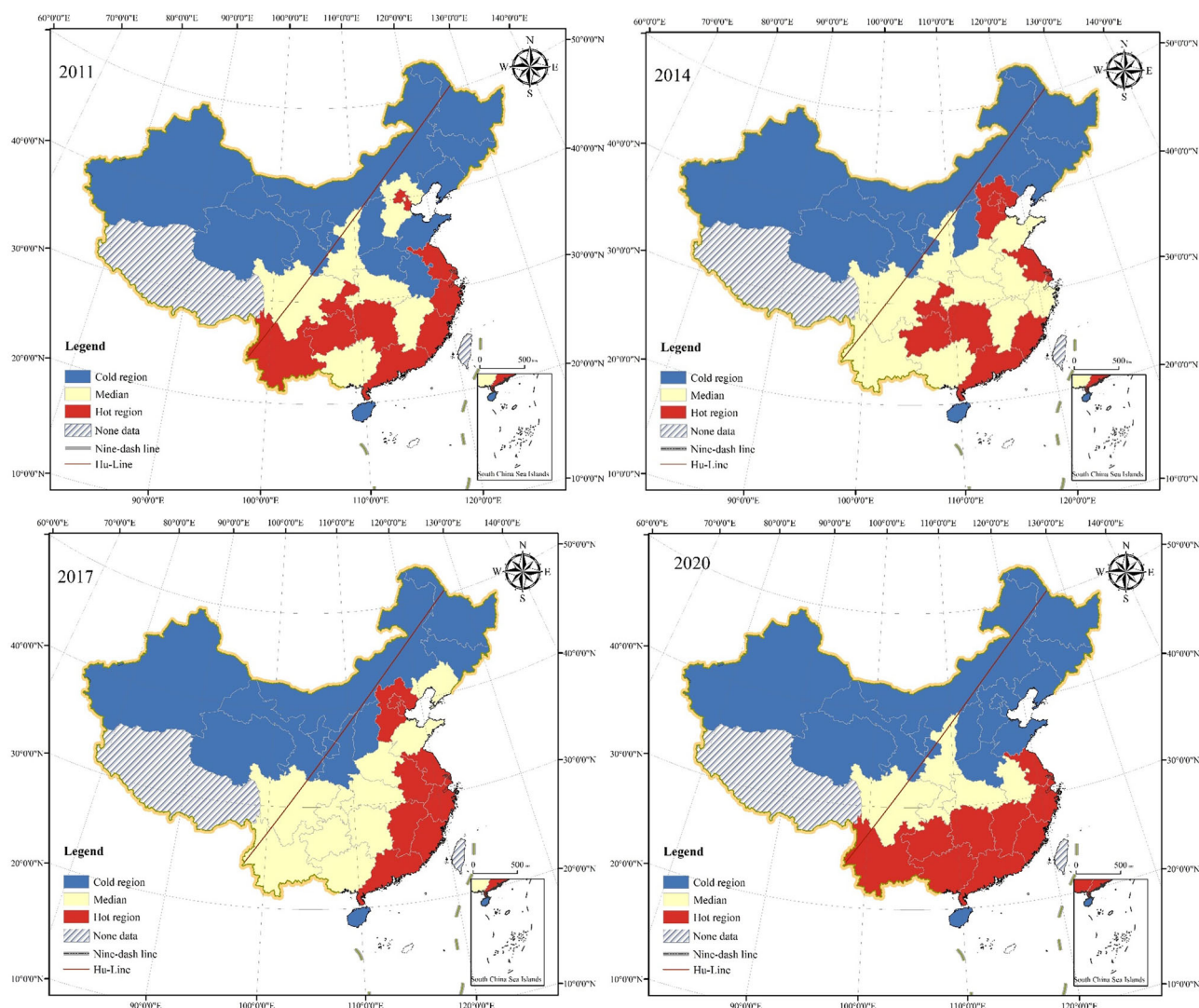
Fig. 5 Hotspot Analysis.

introduction of innovative technologies and management, the development of new products and services, the promotion of industrial collaborative innovation, and the implementation of management and policy innovations. The effective utilization of innovation capability can reduce resource consumption, minimize environmental impacts, meet tourists' demand for unique experiences, and promote the sustainable development of the tourism industry. According to the classification of the TOE framework, the main secondary dimensions were the technological and environmental dimensions. To further elaborate on the changes in different elements based on the TOE framework, this study provides a detailed description of the evolutionary process of secondary and tertiary indicators of influencing capabilities.

The evolutionary process of the impact capability across the TOE dimensions

On the basis of existing research practices, the q values of the third-level indicators of the secondary influencing factors were summed to represent the influencing factors of that secondary indicator. The trend of its capability change is shown in Fig. 6e. Overall, TEE was influenced the most by the external environment and technological dimensions, whereas organizational factors had a relatively lower impact. The trends in the technological dimension and the external environment were consistent, with a

fluctuating increase from 2011 to 2018, but a gradual decrease since 2018. It has been proven that technology is the most important means for tourism efficiency and is the fundamental reason for economic growth, greatly expanding the production frontier. Specifically, technology plays a crucial role in driving TEE improvements. Through technological innovation, tourism destinations can achieve the efficient utilization and management of resources, environmental protection, and sustainable development, provide better tourist experiences, and offer data analysis and decision-making support. The application of technology can improve resource utilization efficiency, reduce environmental impact, and enhance the attractiveness and competitiveness of tourism destinations. Therefore, emphasizing technological innovation is highly important for improving the ecological efficiency of tourism destinations. The environmental dimension also has a profound effect on TEE.

Evolutionary process of the impact capability of TOE elements

Environmental dimension (High cointegration of two factors). ① Impact Capability of TC: The impact capability first increased but then decreased. As shown in Fig. 6b, the influence of transportation convenience on TEE increased annually from 2011 to 2017 but began to decrease from 2017 to 2020. This decline could
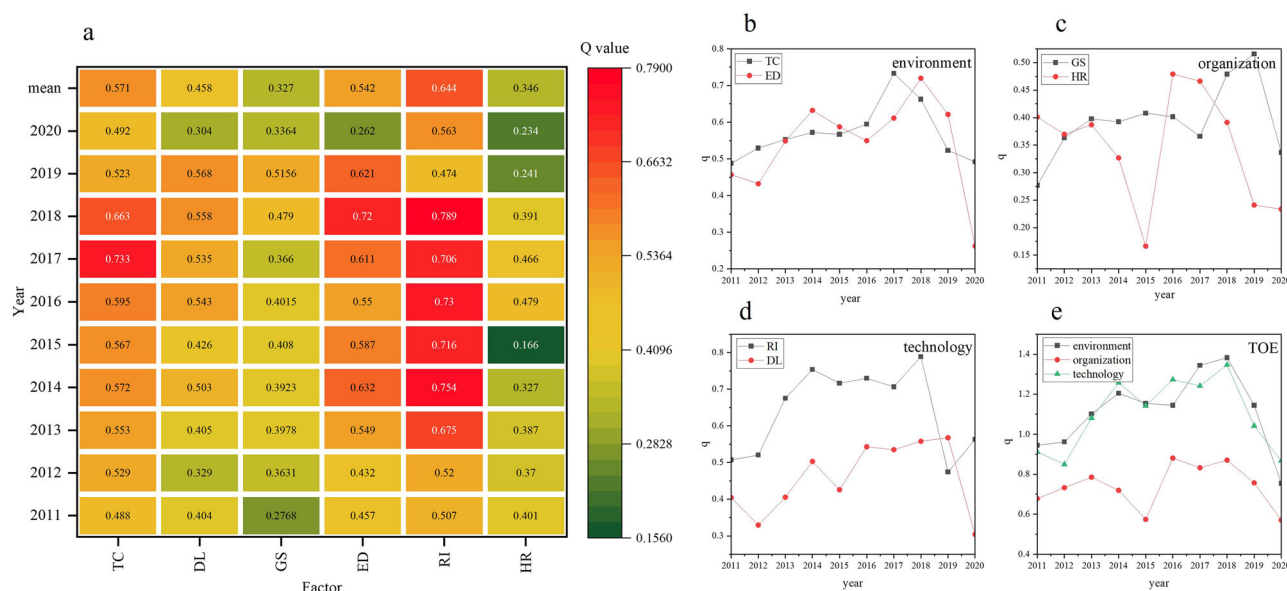
Fig. 6 Time-series results of q-Values based on the OPGD. a represents the q-values of TOE factors calculated on the basis of the OPGD during the study period. **b** represents the evolution of the q values for the environmental dimension variables. **c** represents the evolution of the q-values for the organizational dimension variables. **d** represents the evolution of the q-values for the technical dimension variables. **e** represents the evolution of the q values for the overall TOE.

be due to diminishing returns to scale from tourism transportation. Additionally, the transportation disruptions caused by the COVID-19 pandemic in 2020 also contributed to this decrease. ② Impact Capability of the ED: The impact capability displayed a cyclical trend with an overall decrease. From 2011 to 2014 and 2014 to 2018, the economic development level alternately increased and then decreased. However, from 2018 to 2020, its impact capability consistently decreased.

Organizational dimension (Low cointegration of two factors).
① Impact Capability of GS: The impact capability shows an upward trend year by year. As shown in Fig. 6c, during the period from 2011 to 2016, the capability fluctuated, with a decline in 2017, but it later rebounded. This growth may be attributed to the government's efforts in creating a favorable tourism business environment and implementing tourism-friendly policies. Higher government attention typically indicates better government-business relations and increased government spending, which helps reduce transaction and information costs, thereby optimizing contract and price signal mechanisms. However, the impact capability began to decline from 2019 to 2020. ② Impact Capability of HR: The impact capability showed a cyclical decrease. It decreased from 2011 to 2015, increased from 2015 to 2016, and the decreased again from 2016 to 2020. The cyclical nature may be due to the profit-driven nature of tourism talent. The cyclical changes in the tourism economy lead to fluctuations in talent market saturation and contraction, resulting in cyclical impacts on TEE.

Technological dimension (High cointegration of two factors).
① Impact Capability of RI: The impact capability first increased and then decreased. As shown in Fig. 6d, from 2011 to 2018, the impact capability of regional innovation ability showed a fluctuating upward trend. However, from 2018 to 2020, it began to decrease in a fluctuating manner. On the one hand, this could be because innovative strength is too advanced, leading to products, technologies, and services that do not adapt well to the development of the tourism industry, resulting in a decrease in TEE. On the other hand, innovation capability has consumed a large

portion of the remaining public infrastructure spending, slowing the development of the tourism industry. ② Impact Capability of DL: The impact capability showed a cyclical rise and fall. This value fluctuated from 2011 to 2019, possibly because a high level of digitalization can facilitate market information acquisition and sharing. Various new digital tools and platforms have emerged, with positive impacts on TEE. However, the pandemic dealt a severe blow to the tourism industry, causing many businesses to face closures or reduced operations. This may have led to cutbacks in digital investments, thereby inhibiting further improvement in the level of digitalization and reducing TEE.

Interaction detection. Interaction detection is used to identify whether there is an interaction between the influencing factors. Specifically, it explores whether the joint effect of two factors on the spatial distribution of TEE is enhancing or weakening (see Fig. 7). The research results show that, from 2011 to 2020, the interaction between any two factors on the spatial distribution of TEE exhibited certain instability. Overall, the interaction of the two factors mostly manifested as nonlinear enhancement. In 2012, 2013, 2014, and 2018, the combination with the strongest explanatory power was TC∩ED (with q values of 0.8246, 0.8122, 0.7486, and 0.937, respectively). The TC∩ED combination appeared most frequently and had the most significant impact on the spatial distribution of TEE. This result may be due to the fact that the improvement of TEE is jointly driven by technological upgrades, industrial structural changes, and reduced transaction costs. Firstly, the level of economic development reflects the quality of the market environment. The market primarily adjusts TEE through price mechanisms, competition mechanisms, and supply-demand mechanisms. High-quality resources tend to concentrate in more efficient enterprises and regions, while inefficient tourism enterprises are eliminated, thus promoting the shift of regional tourism from extensive to intensive development. Secondly, the level of transportation development determines the flow efficiency of various production factors. In an open and free market environment, the entry costs for foreign enterprises are reduced, and the technological learning effect between local tourism enterprises and foreign enterprises is enhanced. This
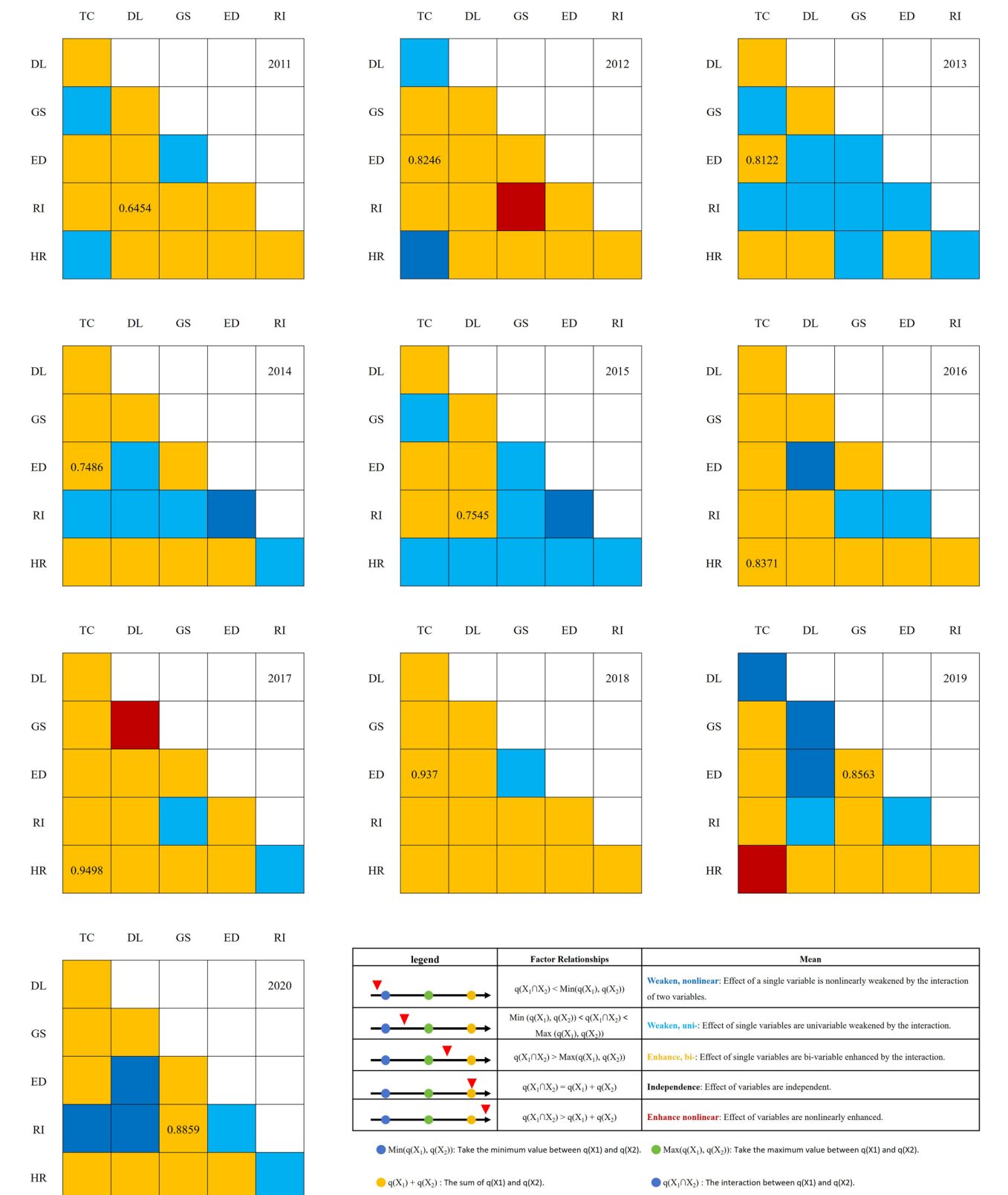
Fig. 7 Results of the interaction detection. The area of the circle represents the magnitude of the q value after the interaction between two factors.

mechanism may promote technological upgrades of local tourism enterprises and further stimulate technological and management innovations in other tourism enterprises within the region. Therefore, this study suggests that the TC ∩ ED combination can effectively promote the optimization of TEE's spatial layout.

Robustness checks. Drawing on the robustness analysis methods from previous studies (Gao et al. 2019), we randomly removed 1/10 of the samples (i.e., 3 provinces) in R and calculated the q-values and their interaction detection results. The results showed that the error range of q-values for each variable was

between 1.45% and 7.10%, and the interaction detection results remained generally consistent. Furthermore, to reduce the impact of random factors, we conducted additional validation by recalculating the q-values under different randomly selected years. The results indicated that the error rate of the q-values ranged from 0.12% to 9.54%, and the interaction detection results remained largely consistent. Therefore, we conclude that the research results are robust (see the supplemental material).

Conclusion

In this research, considering the global shift toward ecotourism development and the use of the Super-SBM model, which is based on unexpected outputs, we explored the spatiotemporal differentiation and intrinsic driving mechanisms of TEE across 30 provincial regions in China from 2011 to 2020. The findings are summarized as follows:

(1) The overall TEE in China showed a "bimodal" development trend, where the efficiency value experienced an initial growth phase followed by a decline. The trend changes in the three major regions (eastern > western and central) aligned with the overall national pattern. Correspondingly, regional inequalities initially decreased but then rebounded. The main reasons for this trend lie in the differences in regional development resources and technological capabilities. The eastern region, with abundant tourism resources and greater technological innovation capabilities, has driven improvements in efficiency. In contrast, the central and western regions, with weaker infrastructure and insufficient technological innovation, have experienced a widening development gap. Furthermore, unevenness in policy support, industrial agglomeration effects, the market environment, and business resilience have intensified the variation in efficiency gaps across regions. While knowledge and technology diffusion reduced the imbalance in China's TEE, the COVID-19 pandemic in 2020 hindered diffusion, leading to a gradual rebound in inequality. It is recommended to strengthen inter-provincial cooperation to promote the balanced development of TEE in China, particularly in narrowing the gap between the eastern and central-western regions. Establishing inter-provincial tourism development exchange platforms, such as seminars, forums, and workshops, can facilitate the sharing of knowledge and experiences between the eastern and central-western regions, promoting technological innovation and resource sharing. The government and relevant institutions should provide financial and resource support to encourage cross-provincial cooperation, particularly in the central and western regions, which have relatively weaker infrastructure and technology. By strengthening technological exchange and talent development, the successful experiences of the eastern regions should be promoted in the central and western regions, thereby improving resource utilization efficiency and contributing to the balanced improvement of TEE across different regions.

(2) The spatial distribution of TEE in China showed a "northeast-southwest" pattern. The eastern and central regions align with this distribution, whereas the western region follows a "northwest-southeast" pattern. Correspondingly, TEE in China's provincial regions demonstrated spatial heterogeneity, shifting from a "ring-shaped high-low value distribution" to a "block distribution," with a decreasing trend from east to west. This disparity is due primarily to differences in regional resource endowments, technological innovation, policy support, and infrastructure development. The eastern and central regions, with abundant tourism resources, relatively high economic development levels, and strong technological innovation capabilities, have driven the efficient development of the tourism industry. In contrast, the western region, which is constrained by geographical conditions, technological support, and market mechanisms, has limited the enhancement of the tourism industry, resulting in lower TEE.

(3) The factors contributing to spatial differences in TEE mainly stemmed from the external environment and technological aspects. The strongest driving factors are regional innovation capabilities, ranked as follows: RI (0.644) > TC (0.571) > ED (0.542) > DL (0.458) > GS (0.387) > HR (0.346). However, only the influence of government attention showed a cyclical upward trend, whereas the influences of other factors exhibited a cyclical downward trend. Interaction testing revealed that the combination of TC ∩ ED is the most stable and explanatory factor for TEE. First, regional innovation capability, as the core factor driving technological progress and industrial upgrading, directly enhances the overall efficiency and competitiveness of the tourism industry. The convenience of transportation is closely linked to economic development levels; transportation accessibility increases the mobility of tourism resources and promotes tourist aggregation and consumption, thereby increasing TEE. The improvement in the economic development level further provides funding and technological support for the tourism industry, promoting industrial upgrading and optimal resource allocation. Second, digitalization and human resources determine the modernization and sustainable development potential of the tourism industry to some extent, but their influence is limited by the region's implementation capacity, making their driving effect on TEE relatively weaker. Finally, the cyclical upward trend of government support suggests that, in different stages of development, the government's attention and supportive policies have increasingly contributed to the promotion of TEE, particularly by playing a key role in fostering innovation and balanced regional development.

Based on this conclusion, the government should establish differentiated ecological innovation support policies. In the eastern region, the focus should be on supporting the application of high-tech innovations such as smart tourism and digital scenic spots, as well as encouraging innovation competitions. In contrast, the central and western regions should increase fiscal support, establish ecological tourism innovation funds, and reduce the tax burden on enterprises. It is recommended to build a "government-led - enterprise-driven - university-supported" collaborative innovation mechanism, and establish industry-academia-research cooperation demonstration bases in key tourist areas. Regarding low-carbon transportation, it is recommended to implement the "Tourism Circle on Rails" plan, prioritizing the development of high-speed rail connections between major tourist cities to gradually replace medium- and short-distance flights. Promote new energy shuttle systems, with 5A-rated scenic spots achieving full coverage by electric shuttle buses, and 4A-rated scenic spots reaching an 80% electrification rate within three years. At the same time, big data should be used to optimize tourism buses, and micro-circulation systems such as shared bicycles and electric vehicles should be promoted. Considering the fiscal disparities between the eastern and western regions, it is recommended to establish a cross-regional ecological compensation mechanism. The eastern region can support the low-carbon transformation of the western region through carbon

offset purchases, targeted assistance, and other measures. The central government could set up special transfer payments to focus on supporting the construction of new energy transportation infrastructure in the western region, while encouraging social capital to participate in tourism transportation infrastructure investment through the PPP model. In terms of tourism economic development, it is recommended to implement a precise support policy of "one zone, one policy." The eastern region should support the development of new forms of tourism, while the central and western regions should increase support for the upgrading of traditional scenic spots. A national-level tourism industry fund should be established to provide low-interest loans and guarantee support for eligible projects. Additionally, the tourism talent development system should be improved, and the "East-West Talent Exchange Program" should be implemented, with tourism management talents from the eastern region being sent to the western region for annual assignments and assistance.

Discussion
Theoretical contribution.

(1) We proposed a comprehensive analytical framework for the field of TOE. As Guo stated, research on TEE seldom considers macro factors such as social and economic aspects; instead, it focuses more on microlevel entities such as tourism enterprises (Guo et al. 2022). We systematically delineated the dimensions of influencing factors and pinpointed the major macroenvironmental challenges facing the tourism industry at present. Moreover, the TOE framework has been applied to the field of TEE, aligning with research in adjacent areas such as the ecologicalization of the tourism industry (Zeng et al. 2023). Moreover, while the TOE is typically applied to the adoption behavior of enterprise information technology, we have expanded the application scope and adapted scenarios of this research framework (Baker 2012).

(2) The geographic detector analysis method with optimal parameters was introduced. Traditionally, existing scholars' research on the influencing mechanisms of TEE has focused on general linear regression models, such as Tobit (Peng et al. 2017) and the traditional geographic detector analysis method (Guo et al. 2022), which are based on a universal perspective. However, there are issues with these models, such as the linear model assuming variables are independent of each other and the traditional geographic detector method overly relying on the empirical discretization of factors. We drew on practices from neighboring research fields (Zhao et al. 2024) and introduced Song's optimal parameter geographic detector into the field of tourism efficiency (Song et al. 2020). This urges the application of the optimal parameter geographic detector to investigate the driving factors of TEE to avoid potential errors resulting from empirically determined data discretization.

(3) This statement highlights that the interactive detection results complement existing research findings. This research focused closely on exploring the dimensions and factors of the TOE framework. Initially, this study revealed that both the technological and the environmental dimensions have a significant effect on TEE. This suggests that the findings partially support the viewpoint of new economics, which posits that technological progress and externalities within the economic system are fundamental drivers of economic growth (Romer, 1986). In the factor analysis, the top three driving forces were regional innovation capability, transportation convenience, and economic development level, which aligns with the viewpoints of existing scholars (Gan

et al. 2023; Pascual-Fernández et al. 2021; Yang et al. 2023; Yunita et al. 2019; Zhang 2023). In comparison, we further derived results from the factor interaction detection, which is a research conclusion not obtained by linear models. Using the method of frequency occurrence, we determined that the combination of regional innovation capability and economic development level has the greatest impact on TEE. This conclusion can provide targeted practical insights.

Limitations and future directions. Despite the significant efforts made in this study, there are still some limitations. Firstly, the impact of three-factor interactions and higher-dimensional interactions has not been fully explored. Future research could introduce configurational analysis to reveal the mechanisms of higher-dimensional interacting factors. Secondly, this study only covers provincial-level data from 2011 to 2020. Future research could extend the time span to explore the spatiotemporal evolution characteristics of TEE over a longer time scale, in order to more comprehensively understand its development trends and influencing factors. Additionally, due to the institutional gaps in municipal-level tourism statistics, this study has not revealed the spatial heterogeneity characteristics within provincial regions. Future scholars could address this by using emerging indicators, such as introducing NPP/VIIRS nighttime light remote sensing data to infer tourism economic intensity, or combining LBS positioning data to construct tourist spatiotemporal trajectory models, to overcome the shortcomings of traditional measurement models. Lastly, this study selected relevant variables from three macro dimensions: technology, organization, and environment. Future research could further enrich this framework by introducing more refined dimensions such as basic environmental, economic, and business environments, to optimize the theoretical model and enhance the applicability and explanatory power of the research.

Data availability
Data can be made available upon written request to the author.

References
Abdullaevich AO, Abdulazizovich KUB (2023) The Importance of Infrastructure in Facilitating the Business Environment. J Surv Fish Sci 10:3695–3702
Aghaei H, Naderibeni N, Karimi A (2021) Designing a tourism business model on block chain platform. Tour Manag Perspect 39:100845
Assaf AG, Tsionas EG (2015) Incorporating destination quality into the measurement of tourism performance: A Bayesian approach. Tour Manag 49:58–71
Baker J (2012) The technology–organization–environment framework. Inf Syst Theory: Explaining Predicting Our Digital Soc 1:231–245
Becken S, Patterson M (2006) Measuring national carbon dioxide emissions from tourism as a key step towards achieving sustainable tourism. J Sustain Tour 14:323–338
Ben Aissa S, Goaied M (2016) Determinants of tourism hotel market efficiency. Int J Cult, Tour Hospitality Res 10:173–190
Chaabouni S (2019) China's regional tourism efficiency: A two-stage double bootstrap data envelopment analysis. J Destination Mark Manag 11:183–191
Charnes A, Cooper W, Lewin AY, Seiford LM (1997) Data envelopment analysis theory, methodology and applications. J Operational Res Soc 48:332–333
Corne A, Peypoch N (2020) On the determinants of tourism performance. Ann Tour Res 85:103057
Gabarda-Mallorquí A, Garcia X, Ribas A (2017) Mass tourism and water efficiency in the hotel industry: A case study. Int J Hospitality Manag 61:82–93
Gan C, Wang K, Voda M, Ye J, Chen L (2023) Analysis on the impact of technological innovation on tourism development: The case of Yangtze River Delta Urban Agglomeration in China. Tour Econ 29:1251–1271
Gao Y, Su W, Wang K (2019) Does high-speed rail boost tourism growth? New evidence from China. Tour Manag 72:220–231

Gössling S, Humpe A, Sun Y-Y (2024) On track to net-zero? Large tourism enterprises and climate change. Tour Manag 100:104842

Gössling S, Peeters P, Ceron J-P, Dubois G, Patterson T, Richardson RB (2005) The eco-efficiency of tourism. Ecol Econ 54:417–434

Greenwood R, Raynard M, Kodeih F, Micelotta ER, Lounsbury M (2011) Institutional complexity and organizational responses. Acad Manag Ann 5:317–371

Guo L, Li P, Zhang J, Xiao X, Peng H (2022) Do socio-economic factors matter? A comprehensive evaluation of tourism eco-efficiency determinants in China based on the Geographical Detector Model. J Environ Manag 320:115812

Hadjielias E, Christofi M, Christou P, Hadjielia Drotarova M (2022) Digitalization, agility, and customer value in tourism. Technol Forecast Soc Change 175:121334

Jiang J, Wang C (2024). Pathways to tourism eco-efficiency: fresh insights from a configuration perspective. Current Issues in Tourism, 1-21. https://www.tandfonline.com/doi/abs/10.1080/13683500.2024.2406413

Kytzia S, Walz A, Wegmann M (2011) How can tourism use land more efficiently? A model-based approach to land-use efficiency for tourist destinations. Tour Manag 32:629–640

Lenzen M, Sun Y-Y, Faturay F, Ting Y-P, Geschke A, Malik A (2018) The carbon footprint of global tourism. Nat Clim Change 8:522–528

Li X, Zhao M, Xu W, Cui S, Yang F (2023) The achievement of carbon emission reduction targets for three typical tourism industries: A coordinated analysis based on efficiency and potential. Sustain Energy Technol Assess 60:103549

Li Z, Liu H (2022) How tourism industry agglomeration improves tourism economic efficiency? Tour Econ 28:1724–1748

Mandić A (2020) Structuring challenges of sustainable tourism development in protected natural areas with driving force–pressure–state–impact–response (DPSIR) framework. Environ Syst Decis 40:560–576

Marrocu E, Paci R (2011) They arrive with new information. Tourism flows and production efficiency in the European regions. Tour Manag 32:750–758

Montgomery DC, Peck EA, Vining GG (2021) Introduction to linear regression analysis

Okafor L, Khalid U, Gama LEM (2023) Do the size of the tourism sector and level of digitalization affect COVID-19 economic policy response? Evidence from developed and developing countries. Curr Issues Tour 26:3040–3063

Pascual-Fernández P, Santos-Vijande ML, López-Sánchez JÁ, Molina A (2021) Key drivers of innovation capability in hotels: implications on performance. Int J Hospitality Manag 94:102825

Peng H, Zhang J, Lu L, Tang G, Yan B, Xiao X, Han Y (2017) Eco-efficiency and its determinants at a tourism destination: A case study of Huangshan National Park, China. Tour Manag 60:201–211

Perch-Nielsen S, Sesartic A, Stucki M (2010) The greenhouse gas intensity of the tourism sector: The case of Switzerland. Environ Sci Policy 13:131–140

Pérez-Granja U, Inchausti-Sintes F (2023) On the analysis of efficiency in the hotel sector: Does tourism specialization matter? Tour Econ 29:92–115

Ritchie JB, Crouch GI (2003) The competitive destination: A sustainable tourism perspective. Cabi

Romer PM (1986) Increasing returns and long-run growth. J Political Econ 94:1002–1037

Roodbari H, Olya H (2024) An integrative framework to evaluate impacts of complex tourism change initiatives. Tour Manag 100:104829

Saienko V, Mezentseva I, Tolchieva H, Salkova I (2021) Efficiency of tourism operators' and tourism agents' activities in the market of tourist services of Ukraine. J Environ Manag Tour 11:1960–1966

Song Y, Wang J, Ge Y, Xu C (2020) An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: Cases with different types of spatial data. GIScience Remote Sens 57:593–610

Sun R, Ye X, Li Q, Scott N (2024) Assessing the eco-efficiency of cruise tourism at the national Level: Determinants, challenges, and opportunities for sustainable development. Ecol Indic 160:111768

Sun Y-Y, Pratt S (2014) The economic, carbon emission, and water impacts of Chinese visitors to Taiwan: Eco-efficiency and impact evaluation. J Travel Res 53:733–746

Tandon A, Dhir A, Madan P, Srivastava S, Nicolau JL (2023) Green and non-green outcomes of green human resource management (GHRM) in the tourism context. Tour Manag 98:104765

Tang R (2021) Trade facilitation promoted the inbound tourism efficiency in Japan. Tour Manag Perspect 38:100805

Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. Eur J Operational Res 130:498–509

Van der Zee E, Bertocchi D, Vanneste D (2020) Distribution of tourists within urban heritage destinations: a hot spot/cold spot analysis of TripAdvisor data as support for destination management. Curr Issues Tour 23:175–196

Wang C, Xu L, Huang M, Su X, Lai R, Xu A (2022a) Research on the evolution of spatial network structure of tourism eco-efficiency and its influencing factors in China's provinces based on carbon emission accounting. PLoS One 17:e0272667

Wang C, Zheng Q, Zeng H, Wu Y, Wei C (2022b) What configurational conditions promote tourism eco-transformation? a fuzzy-set qualitative comparative analysis based on the TOE framework. Front Environ Sci 10:1012856

Wang JinFeng WJ, Li XinHu LX, Christakos G, Liao YiLan LY, Zhang Tin ZT, Gu Xue GX, Zheng XiaoYing ZX (2010) Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China

Wang M, Liu J, Zhang S, Zhu H, Zhang X (2022c) Spatial pattern and micro-location rules of tourism businesses in historic towns: A case study of Pingyao, China. J Destination Mark Manag 25:100721

Wang R, Xia B, Dong S, Li Y, Li Z, Ba D, Zhang W (2020) Research on the spatial differentiation and driving forces of eco-efficiency of regional tourism in China. Sustainability 13:280

Wang S, Li Z, Long Y, Yang L, Ding X, Sun X, Chen T (2024) Impacts of urbanization on the spatiotemporal evolution of ecological resilience in the Plateau Lake Area in Central Yunnan, China. Ecol Indic 160:111836

Wu X, Liang X (2023) Tourism development level and tourism eco-efficiency: Exploring the role of environmental regulations in sustainable development. Sustain Dev 31:2863–2873

Xiaobin M, Biao S, Guolin H, Xing Z, Li L (2021) Evaluation and spatial effects of tourism ecological security in the Yangtze River Delta. Ecol Indic 131:108190

Xu A, Wang C, Tang D, Ye W (2022) Tourism circular economy: Identification and measurement of tourism industry ecologization. Ecol Indic 144:109476

Yang S, Duan Z, Jiang X (2023) Spatial dynamics and influencing factors of carbon rebound effect in tourism transport: evidence from the Yangtze-river delta urban agglomeration. J Environ Manag 344:118431

Yunita S, Mahrinasari M, Ahadiat A, Marselina M (2019) Model of improving tourism industry performance through innovation capability. J Environ Manag Tour 10:853–864

Zeng H, Wang C, Chen J, Tang D, Xu A (2023) Pathways to tourism industry ecologization: A technology-organization-environment configuration framework. Ecol Indic 156:111119

Zha J, Yuan W, Dai J, Tan T, He L (2020) Eco-efficiency, eco-productivity and tourism growth in China: A non-convex metafrontier DEA-based decomposition model. J Sustain Tour 28:663–685

Zhang D, Tu J, Zhou L, Yu Z (2020) Higher tourism specialization, better hotel industry efficiency? Int J hospitality Manag 87:102509

Zhang J (2024) The effects of ecosystem of business environment on tourism: a configurational perspective. Curr Issues Tourism 27:4676–4692

Zhang J (2025) Patterns of innovation-driven tourism competitiveness: Insights from 270 Chinese cities. Tour Manag 107:105063

Zhang W, Zhan Y, Yin R, Yuan X (2022) The tourism eco-efficiency measurement and its influencing factors in the Yellow River Basin. Sustainability 14:15654

Zhang Z, Zhang H, Lin MS, Jia W(2025) Is more rural digitization always better for tourism? An innovativemultiscale spatial perspective. Tourism Econ 31:285–308

Zhao X, Tan S, Li Y, Wu H, Wu R (2024) Quantitative analysis of fractional vegetation cover in southern Sichuan urban agglomeration using optimal parameter geographic detector model, China. Ecol Indic 158:111529

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The authors declare no competing interests.

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Additional information