



ARTICLE



<https://doi.org/10.1057/s41599-025-06369-4>

OPEN

Exploring the co-evolution and obstacles between tourism development and environmental sustainability: a synergistic perspective

Chaoyue Cai^{1,2}, Xiaorong He^{1✉} & Wenhao Chen^{1,3}

Tourism is widely recognized as a catalyst for achieving Sustainable Development Goals (SDGs); however, the growing environmental pressures from rapid tourism expansion necessitate a critical reassessment of the relationship between tourism development (TD) and environmental sustainability (ES). This study developed an analytical framework to examine the co-evolution between TD and ES from a synergistic perspective. The Haken model was applied to evaluate the synergy score across 284 prefecture-level cities in China, followed by a systematic investigation of co-evolutionary spatiotemporal dynamics and the identification of key obstacles. The results reveal the following: (1) The comprehensive TD value increased gradually before 2019 but declined sharply during the COVID-19 pandemic, coinciding with a more distinct “central collapse” spatial pattern. In contrast, the comprehensive ES value exhibited only minor fluctuations while consistently displaying a “four high-value clusters with a depressed zone” pattern. (2) ES is identified as the order parameter of the TD-ES composite system. The co-evolution proceeded through three phases: the downturn (2012–2014), the recession (2015–2019), and the recovery (2020–2022). Spatially, it displayed a “central collapse” with minimal nationwide variability, and cities across all synergy levels exhibited path-dependent evolution. Notably, high-synergy cities were particularly vulnerable to negative spillovers from adjacent low- and minimal-synergy cities. (3) At the national and regional scales, SDG6 and the tourism development scale were the obstacle factors with the highest average and most significant upward trend in obstacle degree, respectively. At the urban scale, cities were classified into five typologies based on combinations of significant obstacles: balanced, single, dual, triple, and compound obstacle types. This study provides novel insights from a synergistic perspective and quantitative evidence from China, while proposing strategies to address obstacles in the TD-ES co-evolution.

¹Hunan Normal University, Changsha, China. ²Nankai University, Tianjin, China. ³South China University of Technology, Guangzhou, China.
✉email: 202120071332@hunnu.edu.cn

Introduction

Tourism is widely recognized as a key driver for advancing the United Nations Sustainable Development Goals (SDGs) (United Nations World Tourism Organization, 2017; Boluk et al., 2019; Rasoolimanesh et al., 2023). However, its relationship with the three pillars of sustainability—social, economic, and environmental—is not a straightforward, unidirectional promotion, but rather a complex, non-linear interaction (Schianetz and Kavanagh, 2008; Isik et al., 2018). These intricate dynamics are particularly pronounced in the dimension of environmental sustainability (ES) (Simo-Kengne, 2022). On the one hand, tourism development (TD) exerts a “double-edged sword” effect on environmental systems (Tang, 2015). Moderate tourism development can incentivize the transformation of high-pollution industries (Li et al., 2019) and enhance the cultural ecosystem services and environmental governance capacity of destinations (He et al., 2023a; Seidl, 2014; Puhakka and Saarinen, 2013). Conversely, overtourism tends to trigger a range of adverse effects, including water pollution, increased carbon emissions, ecosystem degradation, and biodiversity loss (Gössling, 2002; Pásková et al., 2024; Katircioglu et al., 2014; Seraphin et al., 2018; Steibl et al., 2021). On the other hand, while environmental systems provide the essential resources and carrying capacity that underpin TD, this support is increasingly fragile under pressures such as global climate change and the growing frequency of extreme weather events, which in turn threaten the sustainable operation of the tourism sector (Leal et al., 2024; Rosselló et al., 2020). In the context of rapid tourism growth and profound global environmental changes, the relationship between TD and ES is becoming increasingly complex and elusive (Scott et al., 2019; Ehigiamusoe, 2020). Without timely clarification of this relationship and the construction of adaptive, synergistic management pathways, it will be challenging to harness the mutual reinforcement effects between tourism and the environment, thereby hindering progress toward the 2030 SDGs and the global transition to sustainable tourism. Therefore, it is necessary to adopt a synergistic perspective to scientifically identify and quantify the co-evolutionary dynamics and obstacle factors between TD and ES. Theoretically, this approach can provide new insights into the co-evolutionary processes between TD and ES, contributing to knowledge spillovers at the intersection of tourism geography and environmental science. Practically, it can offer policymakers valuable guidance for designing forward-looking action pathways that balance tourism growth with environmental sustainability.

Although there is limited literature examining the relationship between TD and ES based on the official SDG indicator framework (United Nations Statistics Division, 2017) and the guide *Tourism and the Sustainable Development Goals—Journey to 2030* (United Nations World Tourism Organization, 2017), scholars have conducted extensive research on the interactions between tourism and environmental systems (Tang, 2015; Gössling, 2002; Buckley, 2011; Liu et al., 2022). Previous studies have extensively documented the negative impacts of tourism on various environmental domains, including the water environment (e.g., Gössling et al., 2012; Zhang and Tian, 2022), atmospheric environment (e.g., Sun et al., 2024; Lee and Brahmasrene, 2013), human settlement environment (e.g., Ma and Tang, 2023; Shahab et al., 2020), marine and coastal environments (e.g., Burak et al., 2004; Wilson and Verlis, 2017), soil environment (e.g., Li et al., 2013; Memoli et al., 2019), and forest and grassland environments (e.g., Gaughan et al., 2009). These studies provide rich quantitative evidence on the pressures tourism exerts on environmental systems; however, they predominantly identify problems without deeply exploring the mechanisms driving tourism’s negative effects or proposing solutions within the SDG framework. More

importantly, scholars have largely focused on the negative correlations between tourism and environmental systems, without adequately considering how different TD models (e.g., extensive vs. intensive) may lead to heterogeneous environmental impacts. This oversight often reinforces the fixed perception that the negative environmental impacts of tourism are inevitable. In fact, some scholars argue that tourism can exert positive effects if its scale is managed within the environmental carrying capacity (Tang et al., 2022a; He et al., 2023a). For instance, Cousins et al. (2008) and Baum et al. (2017) found that responsible nature-based tourism in private land conservation areas (PLCAs) in South Africa contributes to both biodiversity conservation and the maintenance of ecological resilience. Similarly, Wang et al. (2025) reported that moderate TD under ecological monitoring can enhance the ecosystem health of Hainan Island, China. These findings indicate that assessments of tourism’s impacts on environmental systems should not be confined to a unidimensional, linear perspective; instead, they should adopt a holistic approach to objectively evaluate environmental effects. Regarding the impact of environment on tourism, although environmental systems are widely recognized as a fundamental support for sustainable tourism, the challenges posed by environmental changes are becoming increasingly severe in the context of global environmental upheaval (Gössling, 2002; Tang, 2015). Studies have shown that frequent natural disasters, such as tsunamis, floods, and volcanic eruptions, present significant obstacles to the sustainable development of global tourism (Rosselló et al., 2020; Çakar, 2021). In small island developing states, coastal tourism that relies on sandy beaches faces existential threats from sea-level rise (Spencer et al., 2022; Dube et al., 2021). Similarly, winter tourism destinations dependent on ice and snow are increasingly vulnerable to declines in tourism demand caused by global warming, putting associated businesses at risk (Damm et al., 2017; Shi-Jin and Lan-Yue, 2019). However, some scholars note that the effects of environmental change on tourism are not exclusively negative; under a +2 °C global warming scenario, enhanced summer climate favorability is projected to create new opportunities for tourism development in high-latitude regions (Grillakis et al., 2016; Koutroulis et al., 2018).

In summary, although the existing literature has extensively examined the relationship between tourism and the environment, several gaps remain. First, most studies are limited to specific environmental dimensions (e.g., water, atmosphere), lacking a systematic assessment of tourism’s interactions with the overall environmental system. Second, few studies integrate environmental assessments within the official SDG indicator framework, which hinders the formulation of actionable strategies closely aligned with the SDGs. Most importantly, the majority of research adopts a linear perspective, leaving the complex interactive relationships between systems relatively underexplored.

Recently, with the optimization of research tools, studies on the tourism–environment relationship have been rapidly shifting from linear to nonlinear approaches (Ehigiamusoe, 2020). Two dominant methodological approaches characterize contemporary research. First, empirical studies examine whether the relationship between tourism and environmental pollution conforms to the inverted U-shaped hypothesis within the Environmental Kuznets Curve (EKC) framework (Ghosh, 2020; Zaman et al., 2016). Second, the coupling coordination degree model (CCDM) has been widely used to evaluate the coordinated relationships between these complex systems (Xiao et al., 2022; Zhang et al., 2021). Although these advances have significantly enhanced our understanding of the tourism–environment nexus, the EKC framework overlooks the feedback of the environment on tourism because it examines tourism’s impact on the environment in a

unidirectional functional form. Similarly, while the CCDM quantifies the intensity of system interactions and the level of coordinated development, and is widely valued for its simplicity and general applicability (Xing et al., 2019), it has several limitations. From the model design perspective, the weights of subsystems in the CCDM are subjectively determined, which may compromise the objectivity of the results (Li et al., 2025). Additionally, the CCDM treats the relationships among subsystems in a relatively coarse manner, failing to identify the dominant subsystems driving system evolution (An et al., 2025). From the perspective of model applicability, although the CCDM enables basic analysis of system interactions, it has limited capacity to decipher complex subsystem synergies or emergent evolutionary patterns (Wu et al., 2024a; Zhong et al., 2019). Therefore, new theoretical perspectives and quantitative tools are urgently required to investigate the relationship between TD and ES.

Synergetics theory, originally developed by Haken (1977), provides a groundbreaking framework for analyzing complex system interactions. This theoretical paradigm explains how an open macroscopic system—comprising nonlinearly interacting subsystems—undergoes self-organization to form coherent structures through continuous exchanges of energy, matter, and information with its environment (Haken, 1983). The Haken model, as a quantitative implementation of synergetics, enables the identification of order parameters in non-equilibrium systems and the measurement of subsystem synergies during evolutionary processes (Yi et al., 2023; Zhong et al., 2019). Although the Haken model was originally applied to study thermodynamic phase transitions, the core principles of synergetics are universal in nature; that is, the synergistic mechanism between subsystems is the key to driving the evolution of a system from a disordered state to an ordered one (Haken, 1977). Consequently, the model has broad interdisciplinary applicability and has been extended from physics to fields such as economics, tourism ecosystems, and environmental research (Wu et al., 2024a; Wang et al. 2023; Zhu et al., 2021). In recent applied research, Zhang et al. (2024) identified limited synergy between tourism-economic resilience and development efficiency in Hainan Province, China. Furthermore, a case study by Zhu et al. (2023) on Daye—a resource-exhausted Chinese city—revealed a strengthening synergy between industrial transformation and urban sustainability indicators. Furthermore, the Haken model possesses several advantages that the CCDM does not. On the one hand, it can identify order parameters (slow variables) and subordinate variables (fast variables) driving the co-evolution of complex systems through the “adiabatic approximation,” thereby clarifying complex inter-subsystem relationships and providing more precise entry points for policy interventions (Frank et al., 2015). On the other hand, the model is capable of explaining nonlinear, abrupt, and self-organized evolutionary processes in complex systems, enabling it to capture dynamic co-evolutionary interactions between systems—unlike the relatively static descriptions provided by the CCDM (An et al., 2025). Moreover, the Haken model overcomes the limitation of subjective weighting of subsystems inherent in the CCDM, enhancing the objectivity of quantitative results (Li et al., 2025). Overall, the Haken model has demonstrated its efficacy in elucidating inter-system synergies, making it a potentially valuable quantitative tool for advancing the understanding of the interdependencies between TD and ES.

In this research, to demonstrate the application of the Haken model to the relationship between TD and ES, we focus on China—the world’s largest tourism spender and a key actor in global environmental governance and sustainability—as a practical case study. The core research questions addressed in this study are: (1) **How can the co-evolutionary state between TD and ES be quantified in the Chinese context?** (2) **What are the tempo-**

spatial patterns of their co-evolution? (3) **What are the obstacle factors constraining their co-evolution, and how can these obstacles be overcome?** To address these questions, this study establishes three primary objectives: (1) Based on synergetics theory, we construct a conceptual framework for the co-evolution between TD and ES, and develop indicator systems for TD and ES that integrate the SDG framework with China’s national context. On this basis, the Haken model is employed to quantify the synergy score at the urban scale in China. (2) The temporal patterns of co-evolution between TD and ES are explored using the Hodrick-Prescott filter, semi-variogram function, and spatial Markov chains. (3) An obstacle-degree model is applied to identify the factors constraining the co-evolution of TD and ES, and strategies are proposed to overcome these barriers, providing policy insights for governments.

Materials and methods

Research design. To investigate the co-evolution and its obstacles in the TD-ES composite system, this study comprises four main components (Fig. 1): (1) Establishment of a conceptual framework and construction of indicator systems for TD and ES. Multi-source data were collected and quantitatively evaluated using the entropy-weighted TOPSIS method. (2) Identification of temporal co-evolution patterns through the Haken model, Hodrick-Prescott Filter, semi-variance function model, and spatial Markov chains. (3) Analysis of obstacles of co-evolution across national, regional, and urban scales using an obstacle degree model. (4) Discussion of research findings coupled with proposed strategies for overcoming obstacles of co-evolution.

Conceptual framework. The environment serves as the foundation for tourism development, while tourism activities, in turn, exert both direct and indirect impacts on environmental systems (Pigram, 1980; Simo-Kengne, 2022). According to synergetics theory, TD and ES—two systems with nonlinear interactions—can form a TD-ES composite system (Fig. 2). This system exhibits self-organization within its subsystems while continuously exchanging matter, energy, and information with the external environment during co-evolution. When TD and ES continuously cooperate to generate synergistic effects, the composite system will spontaneously evolve from disorder to order or from a lower order to a higher order. Typically, in destinations implementing sustainable or regenerative tourism models, natural environments not only serve as the foundational resource and primary attraction for tourism development but also become protected entities. Such dynamics establish a mutually reinforcing synergy between tourism and environmental systems (Li et al., 2006; Dredge, 2022; Suárez-Rojas et al., 2023). Conversely, when TD exerts pressures exceeding environmental carrying capacity, or when drastic environmental changes undermine the ecological foundations of tourism, the synergistic equilibrium of the TD-ES composite system becomes compromised. For instance, Venice’s excessive cruise tourism has degraded the integrity of its lagoon ecosystem, triggering a system-wide imbalance between tourism and environmental systems (Seraphin et al., 2018). In Small Island Developing States (SIDS), global climate change threatens coastal tourism infrastructure and critical resources such as beaches and coral reefs, rendering the tourism-environment synergy increasingly unsustainable (Pathak et al., 2021; Wolf et al., 2024).

Study area and data sources

Study area. The Chinese government attaches great importance to the United Nations’ 2030 Agenda for Sustainable Development and has released the *National Plan of China for Implementing the 2030 Agenda for Sustainable Development*, which establishes an

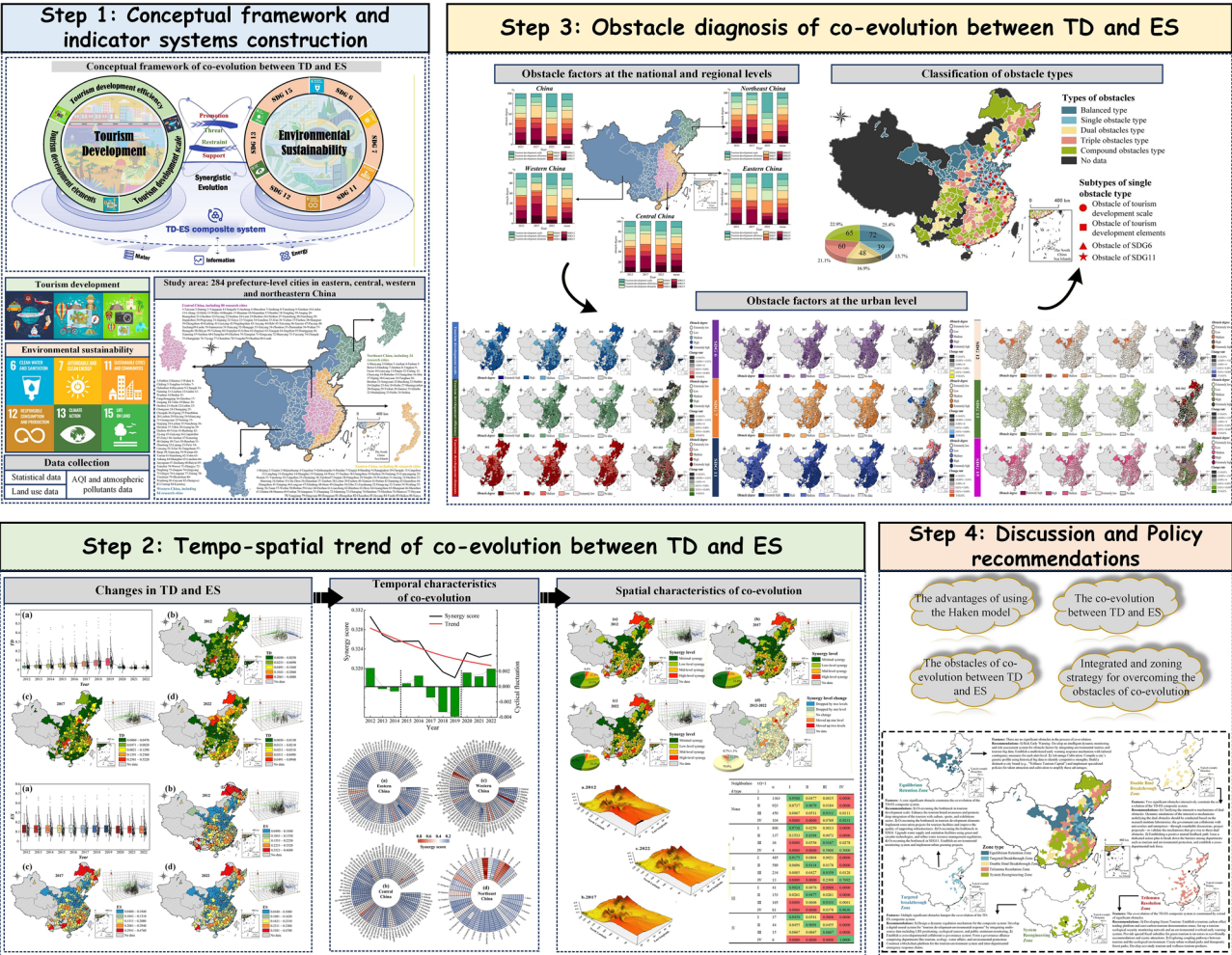


Fig. 1 The workflow of this study.

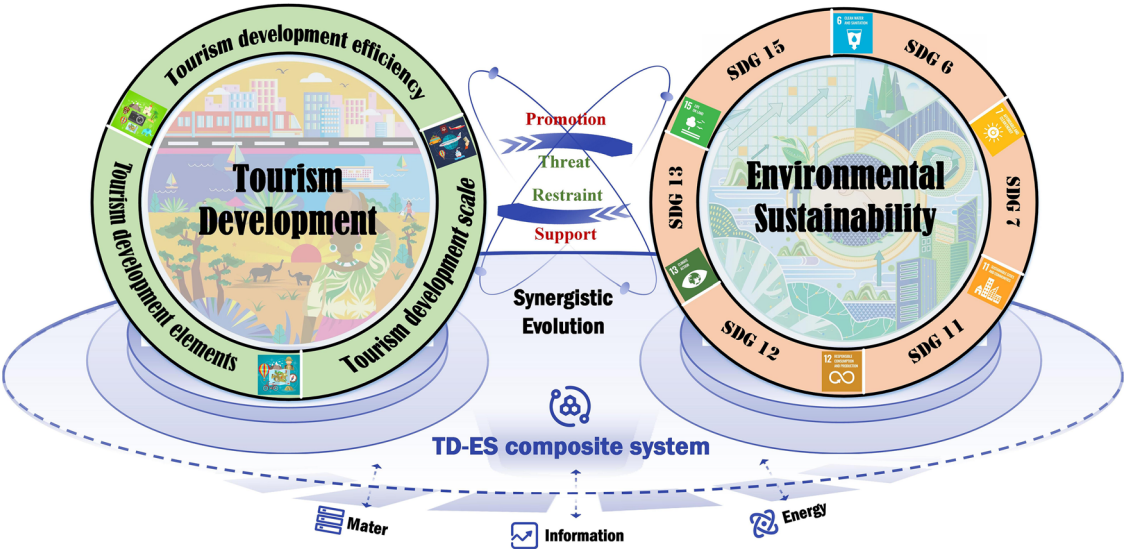


Fig. 2 Conceptual framework of the co-evolution between TD and ES.

action framework for addressing economic, social, and environmental sustainability. Among these initiatives, the “Ecological Civilization Construction Strategy” and the “Beautiful China Initiative” represent nation-level actions implemented by the Chinese government to achieve environmental sustainability.

As a strategic tool for attaining the 2030 SDGs, tourism’s prominence within China’s industrial landscape has been steadily increasing. Beyond its recognized role in stimulating economic growth and enhancing social welfare, it is increasingly acknowledged as holding significant potential to advance environmental

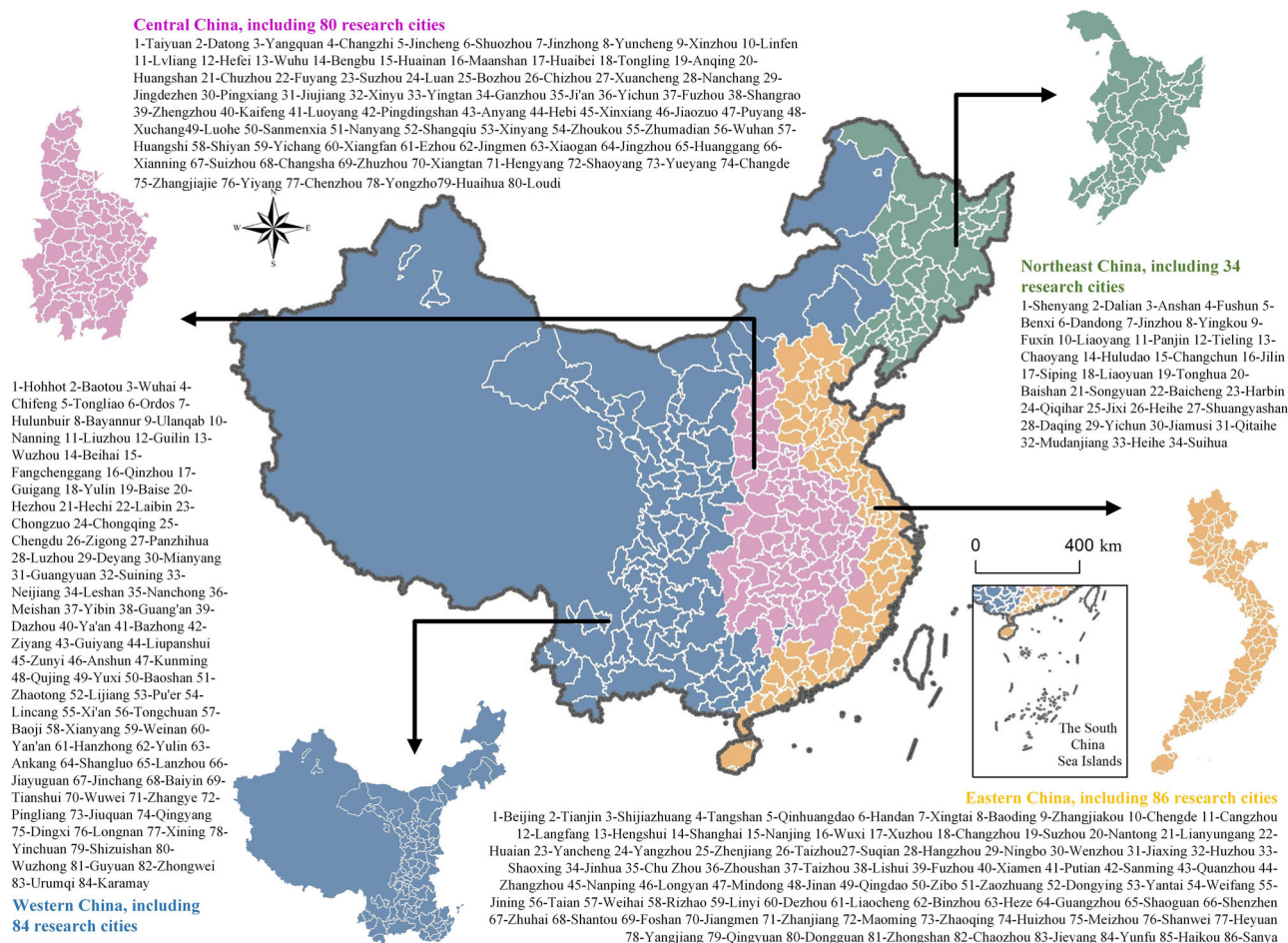


Fig. 3 Study area.

sustainability. However, the relationship between TD and ES in China exhibits complex dynamics, necessitating a national-level analysis to deepen the understanding of their interactions. Consequently, 284 Chinese cities were selected as case studies based on urban datasets that balance research precision with data accessibility. While the sample does not encompass all Chinese cities due to data limitations, it covers most major cities across eastern, central, western, and northeastern China (Fig. 3).

Data source. This study used the following data: (1) Statistical data were obtained from the China Statistical Yearbook (2013–2023), China Urban Statistical Yearbook (2013–2023), China Energy Statistical Yearbook (2013–2023), China Environment Yearbook (2013–2023), China Rural Statistical Yearbook (2013–2023), China Tourism Statistical Yearbook (2013–2018), Statistical Yearbook of Chinese Culture and Tourism (2019), Chinese Cultural Relics and tourism Statistical Yearbook (2020–2023) and the statistical bulletin of each city. (2) The land use data came from the China annual Land Cover Dataset (CLCD), which had a 30 m spatial resolution and was made available by Yang and Huang's team from Wuhan University (<https://zenodo.org/records/>). Land use types are classified into cultivated land, forestland, grassland, water area, unused land, and construction land. (3) AQI and atmospheric pollutants data were gained from “China air quality online monitoring and analysis platform” (<https://www.aqistudy.cn/>), which reports the daily air quality index (AQI) and particulates (PM_{2.5}) for Chinese cities.

To ensure data quality and reliability, missing values in the time series were handled using linear interpolation, which estimates missing observations based on adjacent available data points. In addition, consistency checks were performed for all datasets, including range checks (e.g., verifying that values fall within plausible physical or statistical ranges) and type checks (ensuring correct numerical and categorical formats). These procedures help to minimize errors and ensure that the compiled dataset is suitable for subsequent quantitative analyses.

Construction of the indicator systems

Tourism development (TD). The construction of a comprehensive TD index system constitutes the foundational framework for evaluating urban tourism development levels. Based on development theory (Sharpley, 2022) and related studies, this study established an evaluation system through the integration of three core principles: universal applicability, indicative validity, and statistical reliability (Table 1). The system encompasses three dimensions: tourism development scale (quantifying urban tourism volume), tourism development efficiency (assessing urban tourism quality), and tourism development elements (evaluating tourism reception capacity). A total of ten indicators were systematically selected to comprehensively measure tourism development levels. Following data standardization, the entropy-weighted Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method was applied to quantify the TD index. This hybrid approach, which integrates entropy weighting with TOPSIS algorithms, demonstrates particular efficacy in

Table 1 Evaluation indicator system of tourism development (TD).				
System	Categories	Indicators	Attributes	References
Tourism development	Tourism development scale	Total tourism revenue (10 ⁸ yuan)	+	(Tang, 2015; He et al. 2023a)
		Total number of tourists (10 ⁸ person)	+	(Tang, 2022; He et al. 2023a)
		Percentage of total tourism income in GDP (%)	+	(He et al. 2023a; Liu and Yin 2022)
	Tourism development efficiency	Output rate of tourism fixed assets(%)	+	(Zhang et al. 2022a)
		Labor productivity of tourism industry (yuan/person)	+	(Liu and Yin 2022)
		Per capita tourism income (yuan)	+	(Wang et al. 2020a)
		Percentage of total tourism revenue in the tertiary industry (%)	+	(Tang, 2022; He et al. 2023a)
	Tourism development elements	Number of A-level scenic spots	+	(He et al. 2023a; Zhang et al. 2022a)
		Number of star hotels	+	(Wang et al. 2022a; Wu and Xie 2025)
		Number of tourism employees (10 ⁴ person)	+	(Wang et al. 2020a; Xiao et al. 2022)
<i>Output rate of tourism fixed assets (%)</i> refers to the efficiency of capital utilization in the tourism industry, reflecting the economic output generated by fixed assets investment, such as hotels, scenic spot facilities, transportation infrastructure, and related service platforms. It is calculated by total tourism revenue/tourism fixed asset investment × 100%. <i>Labor productivity of the tourism industry (yuan/person)</i> is commonly used to measure the output efficiency of tourism labor, reflecting the level of economic output generated by tourism employees within a given period of time. It is calculated as the ratio of total tourism income to the number of tourism employees. <i>Per capita tourism income (yuan)</i> refers to the average tourism revenue generated by each tourist during the travel process, which is used to measure the consumption level of the tourism market. It is calculated as total tourism income divided by the total number of tourists.				

evaluating the development levels of complex systems through its dual capacity for objective weighting and multi-criteria decision analysis (He et al. 2023b).

Environmental sustainability (ES). The environmental dimension is increasingly recognized as the foundation for the three pillars of sustainable development (social, economic, and environmental) (Moldan et al., 2012). Therefore, it is necessary to establish a reasonable environmental sustainability evaluation system. Based on the global indicator framework for the Sustainable Development Goals, SDG 6, SDG 7, SDG 11, SDG 12, SDG 13, SDG 14, and SDG 15 are related to environmental sustainability. However, since SDG 14—“Life Below Water” (conserve and sustainably use the oceans, seas, and marine resources)—is not a target that vast inland areas of China need to focus on (Wang et al., 2022b; Zhang et al., 2022b), we do not include it as a subsystem in the indicator system. Furthermore, with reference to *Sustainable Development Goals Report (2024)* (United Nations, 2024), *Tourism and the Sustainable Development Goals—Journey to 2030* (United Nations World Tourism Organization, 2017), *China’s National Plan on Implementation of the 2030 Agenda for Sustainable Development* (Ministry of Foreign Affairs of the People’s Republic of China, 2017), *China’s Progress Report on Implementation of the 2030 Agenda for Sustainable Development (2023)* (Center for International Knowledge on Development of China, 2023) and related studies, we reconstructed the indicator system applicable to China (Table 2). The 23 selected indicators follow the principles of universal applicability, reasonable indicativeness, and statistical reliability. On the basis of standardizing the data, the entropy weight TOPSIS method was used to measure ES level.

Methods. This study employs six methods to ensure rigorous and comprehensive analysis in exploring the co-evolution between TD and ES (Fig. 4). (1) The entropy-weighted TOPSIS method objectively evaluates and ranks the comprehensive levels of TD and ES across cities. Its objective weighting avoids subjective bias, while the proximity-based ranking provides clear relative comparisons, making it particularly suitable for this study. (2) The Haken model quantifies the synergy between TD and ES subsystems and identifies the order parameter governing system evolution. It effectively captures nonlinear interactions and self-

organizing mechanisms in complex systems, making it well-suited for synergy analysis. (3) The Hodrick-Prescott filter decomposes the synergy score series into long-term trends and short-term fluctuations to delineate evolutionary stages. As a standard time-series decomposition tool, it objectively reveals intrinsic trends, making it appropriate for identifying continuous evolutionary phases. (4) The semi-variance function model quantifies and reveals the spatial variation of TD-ES synergy scores. As a core geostatistical tool, it accurately characterizes spatial association structures and provides the basis for Kriging interpolation. (5) Spatial Markov chains analyze the transition probabilities of cities across synergy levels under neighborhood effects. Their applicability stems from overcoming the traditional Markov chain’s neglect of spatial interactions, making them ideal for analyzing spatially dynamic transitions. (6) The obstacle degree model identifies key restrictive indicators hindering TD-ES co-evolution. By integrating indicator weights with deviation degrees, it quantifies obstacle levels, enabling scientifically objective identification of constraints and providing guidance for targeted policymaking. Further details on each method are provided in Sections “Entropy weight TOPSIS Method”–“Obstacle degree model”.

Entropy weight TOPSIS method. The entropy-weighted TOPSIS method not only avoids errors caused by subjective weighting but also considers the temporal variations in variables (Wu and Xie, 2025). It is composed of two parts: the entropy weight method can effectively solve the interference of subjective weighting on the objectivity of the evaluation results, and the TOPSIS method can rank cities by comparing their TD and ES levels with the closeness of the optimal solution (Li et al., 2024; Zhang et al., 2022e). After standardizing the data, we used this method to evaluate TD and ES. The specific calculation process is detailed in the research by Liu and Zhang (2025).

Haken model. The Haken model is employed to evaluate the synergistic scores between TD and ES, as it uniquely quantifies their interaction dynamics by identifying an order parameter—a slow variable that dominates the system’s evolution—and applying the adiabatic approximation to simplify the system’s behavior (Haken, 1977). This approach provides indispensable

Table 2 Evaluation indicator system of environmental sustainability (ES).				
System	Categories	Indicators	Attributes	References
Environmental sustainability	SDG 6-Ensure availability and sustainable management of water and sanitation for all	Proportion of population using safe drinking water (%)	+	(Miao et al., 2023; Wang et al., 2020a)
		Treatment rate of domestic sewage (%)	+	(Cai et al., 2021; Zhang et al., 2022b)
		Water consumption per GDP (m ³ /yuan)	+	(Xu et al., 2020; Zhang et al., 2022b)
		Per capita water resource (m3)	+	(Yi et al., 2021; Li et al., 2023)
		The penetration rate of sanitary toilet in rural area (%)	+	(Wang et al., 2020a; Zhang et al., 2022b)
	SDG 7-Ensure access to affordable, reliable, sustainable and modern energy for all	Penetration rate of natural gas (%)	+	(Yin et al., 2023; Zhang et al., 2022c)
		Renewable energy share in the total final energy consumption (%)	+	(Wang et al., 2020a; Cheng et al., 2023)
		Energy intensity (ton standard coal/10 ⁴ yuan)	-	(Xu et al., 2020; Zhang et al., 2022d)
	SDG 11-Make cities and human settlements inclusive, safe, resilient and sustainable	Greening rate of urban built-up area (%)	+	(Wang et al., 2020a; Yin et al., 2023)
		Park green area per capita (m2)	+	(Yi et al., 2021; Zhang et al., 2022b)
		Harmless treatment rate of household waste (%)	+	(Zhang et al., 2022b; Wang et al., 2020a)
		Air Quality Index	-	(Yi et al., 2021; Fang et al., 2023)
	SDG 12-Ensure sustainable consumption and production patterns	SO ₂ emissions per capita (kg/person)	-	(Zhang et al., 2022c; Wang et al., 2020a)
		Per capita emission of nitrogen oxides (kg/person)	-	(Wang et al., 2020a; Zhou et al., 2024)
		Wastewater treatment rate (%)	-	(Xu et al., 2020; Yin et al., 2023)
		Comprehensive utilization rate of industrial solid waste (%)	+	(Zhang et al., 2022d; Yin et al., 2023)
	SDG 13-Take urgent action to combat climate change and its impacts	Electricity consumption Per GDP (kW/104 yuan)	-	(Zhang and Chen, 2021; Chen and Zhang, 2021)
		CO ₂ emissions per capita (ton/person)	-	(Xu et al., 2020; Wang et al., 2022b)
		CO ₂ emissions intensity per GDP (ton/10 ⁴ yuan)	-	(Xu et al., 2020; Wang et al., 2022b)
		Average annual concentration of PM2.5 (ug/m ³)	-	(Wei et al., 2023; Sun et al., 2022)
	SDG 15-Terrestrial ecosystems and halt biodiversity loss	The proportion of forestland in total land area (%)	+	(Sun et al., 2022; Xu et al., 2020)
		The proportion of wetland and water area in total land area (%)	+	(Zhang et al., 2022b; Xu et al., 2020)
		Biological abundance index	+	(You et al., 2024; Wei et al., 2022)

Energy intensity (ton standard coal/10⁴ yuan) is defined as the energy consumption per unit GDP and is the most widely used measure of energy efficiency. The lower the index value, the higher the energy efficiency. CO₂ emissions intensity per GDP (ton/10⁴ yuan) measures the decoupling between economic growth and carbon emissions, reflecting the “carbon efficiency” of economic activities. A lower value indicates that economic development is less dependent on carbon emissions. Biological abundance index is an indicator used to measure the richness or scarcity of biodiversity in a given region. It indirectly reflects the number of species within the area by assessing the variation among different ecosystem types per unit area.

insights into the TD-ES nexus by revealing which subsystem acts as the dominant driver, thus dictating the system’s long-term trajectory. The adiabatic approximation principle, which assumes the fast variable rapidly relaxes to the state dictated by the slow order parameter, allows us to reduce the complexity of the two interacting subsystems into a single governing equation (Wu et al., 2024a). This simplification is crucial for modeling the co-evolution process, enabling us to identify the system’s stability point and measure synergistic scores by calculating the distance between the order parameter’s state variable and this equilibrium. The specific modeling steps are as follows:

First, suppose there are two subsystems in a self-organized system, one of which is the order parameter q_1 and the other is the variable q_2 . The motion equations of the system are as follows:

$$\dot{q}_1 = -\gamma_1 q_1 - a q_1 q_2 \tag{1}$$
$$\dot{q}_2 = -\gamma_2 q_2 - b q_1^2 \tag{2}$$

where \dot{q}_1 and \dot{q}_2 are the derivations of the state variables to time, γ_1 and γ_2 are the damping coefficients of the two state variables, a and b are the strength coefficients. When $\gamma_2 \gg 0$ and $|\gamma_2| \gg |\gamma_1|$,

which are called to satisfy the ‘adiabatic approximation hypothesis’ of the system, there must be an order of magnitude difference between them (Zhu et al., 2021).

When q_2 is quickly deleted, order parameter q_1 has no time to change. Setting $\dot{q}_2=0$, we obtain the following:

$$q_2 = \frac{b}{\gamma_2} q_1^2 \tag{3}$$

By substituting it into the order parameter evolution equation, the system evolution equation can be obtained:

$$\dot{q}_1 = -\gamma_1 q_1 - \frac{ab}{\gamma_2} q_1^3 \tag{4}$$

The system’s potential function is obtained after solving the inverse integral, which reflects the system’s state:

$$v = \frac{1}{2} \gamma_1 q_1^2 + \frac{ab}{4\gamma_2} q_1^4 \tag{5}$$

It is important to note that the Haken model was originally developed for physical research, and its application in other fields has certain limitations (Zhang et al., 2024). Therefore, to better

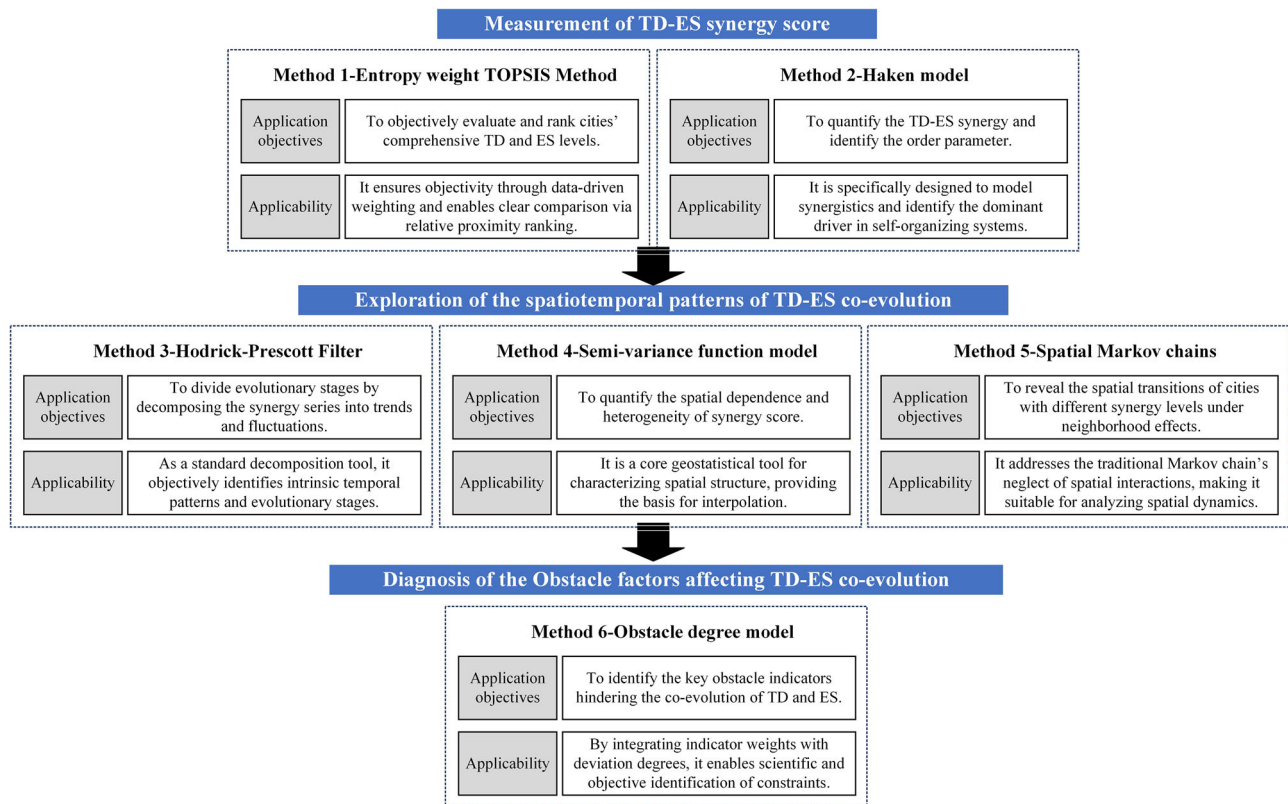


Fig. 4 Methodological framework.

describe the synergistic effect between TD and ES, it is necessary to discretize the model (Zhong et al., 2019). The adjusted synergistic evolution equations are as follows:

$$q_{1(t)} = (1 - \gamma_1)q_{1(t-1)} - aq_{1(t-1)}q_{2(t-1)} \quad (6)$$

$$q_{2(t)} = (1 - \gamma_2)q_{2(t-1)} - bq_{1(t-1)}^2 \quad (7)$$

Hodrick-prescott filter. The Hodrick-Prescott (HP) Filter can be used to reveal the temporal co-evolution. It is a popular trend-filtering method applied to univariate time series (Wu et al., 2024b). According to the principle of symmetric data moving average, the observed time series X_t could be viewed as the sum of low-frequency trend component X_t^T and high-frequency cyclic component X_t^C , that is $X_t = X_t^T + X_t^C, t = 1, 2, 3, \dots, T$. HP Filter is a useful tool to separate the two components from each other (Qian and Wang, 2020). The trend component X_t^T is defined as the solution to minimize the problem, which is calculated according to Eq. (8):

$$\min(X_t^T) = \min \left\{ \sum_{t=1}^T (X_t - X_t^T)^2 + \lambda \sum_{t=2}^{T-1} [(X_{t+1}^T - X_t^T) - (X_t - X_{t-1}^T)^2] \right\} \quad (8)$$

Where λ is a smoothing parameter used to adjust the weight of the two terms. Hodrick and Prescott (1997) recommend a smoothing parameter of $\lambda = 100$ for annual data, $\lambda = 1600$ for quarterly, and $\lambda = 14400$ for monthly data. Currently, scholars have reached a consensus on the yearly time series, which is normally 100 (Ball et al., 2017; Phillips and Shi, 2021; Dritsaki and Dritsaki, 2022). After substituting the smooth parameter into the formula, the trend component and the cyclic component could be obtained. Then, using the division method of “trough-to-trough” (Nan et al., 2022), the stages of temporal co-evolution can be divided.

Semi-variance function model. The semi-variance function model, also known as the spatial variogram model, can be used to reveal the spatial co-evolution patterns in different cities. It is a function of data point variances and distances in geostatistics (Ai et al., 2022). The calculation formula is as follows:

$$N(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad (9)$$

where $N(h)$ is the number of samples of the segmentation distance h , $Z(x_i)$ and $Z(x_i + h)$ are the observed values of the geographical variable $Z(x)$ at points x_i and $x_i + h$, respectively. Nugget value, still value, bullion coefficient, variation range, and fractal dimension are the main characterization parameters of a semi-variance function.

Then, based on the results of the semi-variance function, Kriging interpolation can be applied to simulate the unbiased optimal estimation of variables (He et al., 2023a). The formula is as follows:

$$Z(X_0) = \sum_{i=1}^n \lambda_i Z(x_i) \quad (10)$$

where $Z(X_0)$ is the unknown point; $Z(x_i)$ is a known sample point; λ_i is the weight of the i th sample point to the unknown point; and n is the number of known points.

Spatial Markov chains. The spatial Markov chain incorporates the concept of “spatial lag,” addressing the limitation of the traditional Markov chain in overlooking spatial interactions (Flores-Segovia and Castellanos-Sosa, 2021). First, we discretize the measured data of the synergy score to determine the state space and parameter set of the Markov prediction model. Then, the synergy score is classified into k types, and the probability distribution and changes of each type are calculated to construct the state shift probability matrix M (He et al., 2023b). Assuming the

probability of a city that is type i in year t changing to type j in year $t + 1$ is P_{ij} , the calculation formula is:

$$P_{ij} = \frac{n_{ij}}{n_i} \quad (11)$$

where n_{ij} denotes the number of cities that are type i in year t and changed to type j in year $t + 1$ during the study period, and n_i denotes the number of cities of type i .

Based on the traditional $k \times k$ Markov chain transfer probability matrix, a spatial weight matrix is introduced to construct a $k \times k \times k$ conditional transition probability matrices (Li et al., 2023). The specific formula is as follows:

$$Lag_i = \sum_{j=1}^n W_{ij} Y_j \quad (12)$$

where Lag_i is the spatial lag value of city i , Y_j is the observed value of city j , n is the total number of cities, the spatial weight matrix W_{ij} indicates the spatial relationship between city a and b . The neighboring principle is used to define the spatial relationship.

Obstacle degree model. The obstacle degree model is used to reveal the obstacles that affect the improvement of the co-evolution between TD and ES, so as to provide more practical solutions for different cities. The formulas are as follows:

$$I_{ij} = 1 - Y_{ij} \quad (13)$$

$$y_{ij} = \frac{F_{ij} I_{ij}}{\sum_{ij=1}^m F_{ij} I_{ij}} \quad (14)$$

Y_{ij} is the index weight value. I_{ij} is the index deviation, which refers to the gap between the single index and the synergy score. F_{ij} is the factor contribution, which refers to the weight of a single indicator to the synergy score. y_{ij} is the obstacle degree of each index to the synergy score.

Results

Analysis of TD and ES

Changes in TD. As shown in Fig. 5a, on the time scale, China's comprehensive TD value (the points in the boxes) exhibited an upward trend prior to 2019, rising from 0.037 in 2012 to 0.095 in 2019, with an average annual growth rate of 22.56%. However, due to the impact of COVID-19, the average TD value plummeted to 0.027 in 2020 and remained around 0.020 during the pandemic period. Furthermore, the height of the box plots gradually increased before 2019, and the scatter points on the right side became more dispersed, indicating a widening disparity in tourism development among cities. However, during 2020–2022, the box height significantly decreased, and the scatter matrix was compressed into the $[0, 0.1]$ interval, suggesting that tourism development in nearly all cities entered a dormant state during this period.

Spatially, during the initial phase of the study period (Fig. 5b), the spatial distribution of TD exhibited a pattern of scattered, relatively high-value zones and expansive low-value areas. Shanghai, Beijing, and Chongqing emerged as growth poles for China's tourism development, with values reaching 0.408, 0.371, and 0.287, respectively. The spatial trend revealed a central-eastern uplift in TD value. By the mid-phase of the study period (Fig. 5c), the TD value had shifted to a configuration of small clustered concentrations of relatively high-value zones and contiguously distributed low-value areas. Leading regions included the Yangtze River Delta metropolitan cluster, the Beijing-Tianjin urban agglomeration, the Chengdu-Chongqing metropolitan cluster, as well as Wuhan and Changsha. During

this period, the spatial polarization—characterized by central-eastern uplift—became more pronounced. By the end of the study period (Fig. 5d), despite all cities' TD indices falling below 0.1 due to the impact of COVID-19, significant spatial heterogeneity in TD persisted across cities, driven by variations in pandemic containment policies. Relatively high-value zones were observed in sparsely populated northern border regions and the Pearl River Delta, where flexible containment measures were implemented. In contrast, low-value areas clustered in densely populated Yellow River Basin regions, where prolonged population mobility containment policies were enforced.

Changes in ES. As illustrated in Fig. 6a, temporally, China's comprehensive ES value (the points in the boxes) exhibited minor fluctuations within the range $[0.133, 0.140]$, with 2019 and 2022 marking the peaks and troughs, respectively. The stable height of the box plots indicates that inter-city disparities in ES value did not widen over the study period. Although the scatter matrix on the right consistently maintained a pyramid-shaped distribution, a notable shift occurred after 2019—numerous data points near the mean value dropped below the median line—suggesting that more cities with mid-level ES faced heightened risks of falling into a “low-level equilibrium trap.”

Spatially, at the beginning of the study period (Fig. 6b), four major high-ES clusters emerged: (1) the Northeastern Cluster, comprising cities such as Hulunbuir, Heihe, and Yichun; (2) the Qinling Mountains Cluster, including Hanzhong, Ankang, and Shiyan; (3) the Southwestern Cluster, centered on cities like Pu'er and Lijiang; and (4) the Southern China Cluster, characterized by Ganzhou, Sanming, and neighboring cities. Conversely, low-ES areas were widely distributed among cities within the Yellow River Basin (YRB). The spatial trend revealed a pronounced “central collapse” pattern in ES values. By the mid-study period (Fig. 6c), the four high-ES clusters showed modest expansion, while low-ES zones in the YRB remained stable in extent. Additionally, the central collapse pattern persisted without significant variation. By the end of the study period (Fig. 6d), both the Southwestern and Southern China high-ES clusters underwent slight contraction, whereas low-ES areas in the YRB expanded contiguously. The central collapse pattern became spatially entrenched, reflecting a locked-in spatial configuration of ES disparities.

Co-evolution between TD and ES

Model construction and order parameter identification. The multicollinearity test between TD and ES yielded a variance inflation factor (VIF) of 1 (< 5), indicating no collinearity. Subsequently, the model hypotheses were formulated with TD and ES as order parameters, respectively. The motion equations were obtained using EViews 11, and the validity of the hypotheses was assessed via the adiabatic elimination method. As shown in Table 3, when the order parameter (q_1) was defined as ES, the motion equations held true under the adiabatic approximation assumption, identifying ES plays a leading role in the co-evolution of the TD-ES composite system. The system evolution equation is:

$$\dot{q}_1 = -0.0096q_1 + 0.0129q_1^3 \quad (15)$$

The potential function is:

$$v = 0.0048q_1^2 - 0.0032q_1^4 \quad (16)$$

Let $\dot{q}_1 = 0$, three solutions of the potential function can obtain, namely, $q_1^* = 0$, $q_1^{**} = 0.8627$, $q_1^{***} = -0.8627$. Since TD and ES do not have negative values or zero, the stable point is determined to be $(0.8627, 0.0018)$. In the system, the distance between any

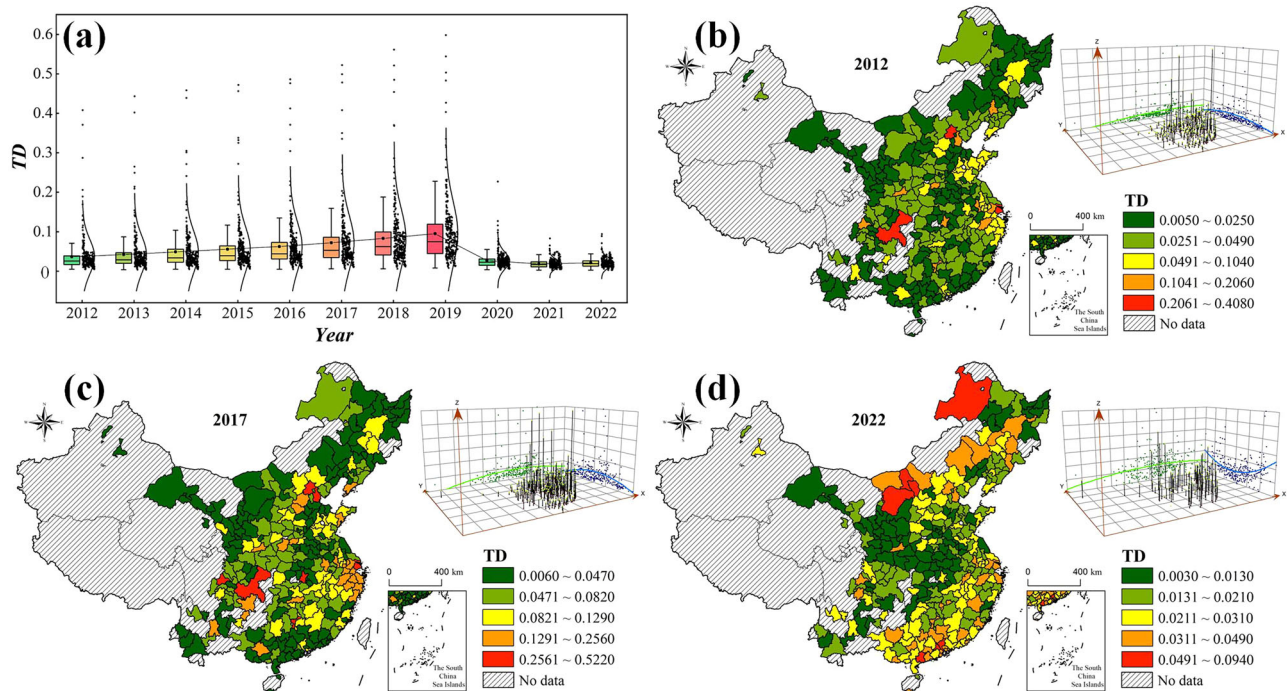


Fig. 5 The temporal and spatial characteristics of tourism development (TD). **a** Box plot of the temporal evolution of tourism development (TD) value. **b–d** Spatial distribution of tourism development (TD) value in 2012, 2017 and 2022, respectively.

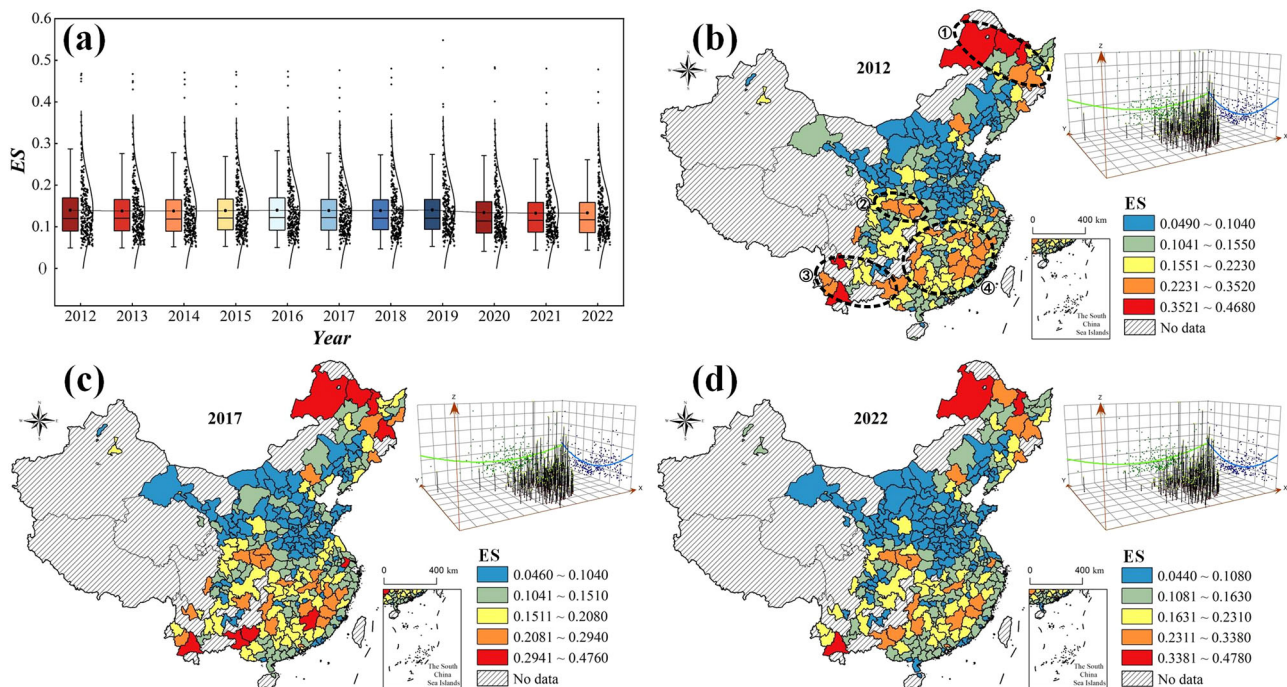


Fig. 6 The temporal and spatial characteristics of environmental sustainability (ES). **a** Box plot of the temporal evolution of environmental sustainability (ES) value. **b–d** Spatial distribution of environmental sustainability (ES) value in 2012, 2017 and 2022, respectively.

point and the stable point represents its state trend. Therefore, the evaluation function of the system status is:

$$s = \sqrt{(q - 0.8627)^2 + (v(q) - 0.0018)^2} \quad (17)$$

In the equation, a larger s -value indicates a greater deviation from the equilibrium state, implying a lower degree of synergy,

whereas a smaller s -value corresponds to higher synergy. To facilitate comparative analysis of synergy levels across cities, the s -values were normalized using range standardization, yielding the synergy score between TD and ES (Wang et al., 2023).

Temporal characteristics of co-evolution. As shown in Fig. 7, China's comprehensive synergy score exhibited a “V-shaped”

Table 3 Sequence parameters of the co=evolution of the TD-ES composite system.

Model hypotheses	Equation of motion	Parameter information	Model conclusions
$q_1 = \text{TD}$ $q_2 = \text{ES}$	$q_{1(t)} = 0.9122^{**} q_{1(t-1)} - 0.0505 q_{1(t-1)} q_{2(t-1)}$ $q_{2(t)} = 0.9909^{***} q_{2(t-1)} + 0.0106^{***} q_1^2(t-1)$	$\gamma_1 = 0.0878, \gamma_2 = 0.0091 \alpha = 0.0505, b = 0.0106$	1. The equation of motion are not holds ; 2. The adiabatic approximation assumption is not satisfied; 3. The model assumptions do not hold.
$q_1 = \text{ES}$ $q_2 = \text{TD}$	$q_{1(t)} = 0.9904^{***} q_{1(t-1)} + 0.0183^{**} q_{1(t-1)} q_{2(t-1)}$ $q_{2(t)} = 0.8885^{***} q_{2(t-1)} + 0.0784^{**} q_1^2(t-1)$	$\gamma_1 = 0.0096, \gamma_2 = 0.1115 \alpha = -0.0183, b = 0.0784$	1. The equation of motion are holds ; 2. The adiabatic approximation assumption is satisfied; 3. The model assumptions hold. ES is the order parameter.

Regression results of the Haken model. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. No *** indicates insignificance.

trend with a trough in 2019 (0.318) and a peak in 2012 (0.331). Additionally, due to the nonlinear and nonstationary characteristics of the co-evolution in composite self-organizing systems (Zhong et al., 2019), the co-evolution process between TD and ES may exhibit cyclical variations. Using the HP Filter, we calculated the cyclical fluctuations of the synergy score and divided the process into three stages according to the cycle division method of “trough-to-trough”: the downturn stage (2012–2014), the recession stage (2015–2019), and the recovery stage (2020–2022). In the downturn stage, the expansion-oriented tourism development model adopted by most Chinese cities was a key driver of the decline in the synergy score, which decreased from 0.331 to 0.325. During the recession stage, rapid tourism urbanization and overtourism imposed significant pressure on the ES system, causing the synergy score to drop from 0.326 to 0.318. In the recovery stage, the tourism development model transitioned from an expansion-oriented to a sustainability-oriented under the impact of COVID-19, leading to an increase in the synergy score from 0.318 in 2019 to 0.323 in 2022.

Figure 8a–d illustrate the evolving trends of the synergy score across 284 prefecture-level cities in China. Among the cities in Eastern China, 52.33% demonstrated an increasing synergy score. Notably, Shanghai and Beijing exhibited significantly higher growth rates of synergy score than other cities, reaching 109.39% and 84.35%, respectively, while Nanjing recorded the steepest decline in synergy score at 25.04%. In Central China, 57.5% of cities experienced varying degrees of synergy reduction. Xiangtan and Nanchang suffered the most substantial decreases, at 31.06% and 30.99%, respectively. Wuhan and Zhengzhou showed the most favorable evolutionary trajectories in this region, with growth rates of the synergy score reaching 16.12% and 15.85%, respectively. In Western China, 58.33% of cities displayed a declining synergistic state. Longnan emerged as the worst performer, with a 48.22% decrease, in contrast to Chongqing’s 33.70% growth. Notably, the areas representing Hulunbuir and Pu’er maintained a deep red coloration in the synergy heatmaps throughout, indicating persistently high synergistic inertia between TD and ES. In Northeastern China, 88.24% of cities achieved synergy growth. Tieling led the trend with a remarkable 43.30% increase, while Heihe experienced a 21.63% decline. Overall, 50.35% of Chinese cities demonstrated the growth in the synergy score, primarily concentrated in northeastern China, the Bohai Bay, and the Qinling Mountain areas. Conversely, declining synergy expanded contiguously across southern China and the central-northern Loess Plateau (Fig. 8e). The Bohai Bay and the southern part of northeastern China formed distinct growth hotspots of the synergy score,

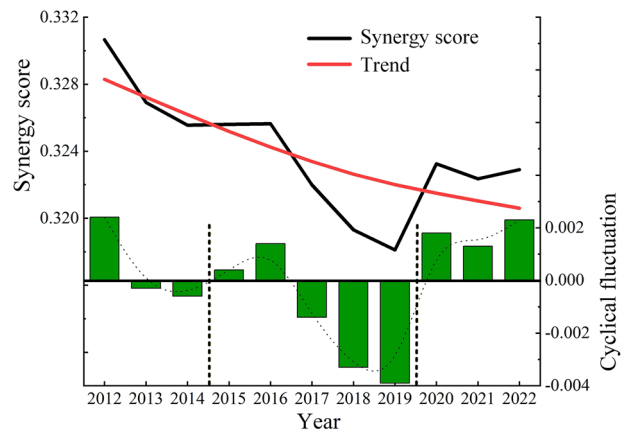


Fig. 7 The temporal evolution of the comprehensive synergistic score.

while coldspots predominantly clustered in the Hohhot-Baotou-Ordos-Yulin Urban Agglomeration and southwestern China (Fig. 8f).

Spatial characteristics of co-evolution

Spatial distribution pattern of co-evolution: Based on the methodology of Wang et al. (2023), we employed the natural breakpoint method to categorize the synergy score into four tiers: minimal synergy (0, 0.2876], low-level synergy (0.2876, 0.3966], mid-level synergy (0.3966, 0.5798], and high-level synergy (0.5798, 1). The synergistic levels were visualized using ArcGIS 10.8.

Figure 9a–c reveals a stable spatial distribution pattern characterized by a persistent central depression. Minimal synergy zones predominantly cluster in the North China Plain and the Loess Plateau, exhibiting slight spatial expansion. Low-level synergy cities are extensively distributed across southeastern coastal regions and northeastern China, typically occupying the peripheral areas of mid- and high-level synergy clusters. Mid-level synergy regions concentrate in South China, the Qinling Mountain areas, and the peripheries of northeastern high-synergy zones. High-level synergy cities primarily aggregate along the northeastern border regions while also sporadically scattering across South China. Notably, Hulunbuir, Yichun, Mudanjiang, Heihe, Ganzhou, Baise, Hechi, and Pu’er consistently maintained a state of high-level synergy throughout the study period. The comprehensive analysis (Fig. 9d) indicates that 79.9% of cities preserved their original synergy level. Cities experiencing downgraded synergy levels are sporadically distributed along the

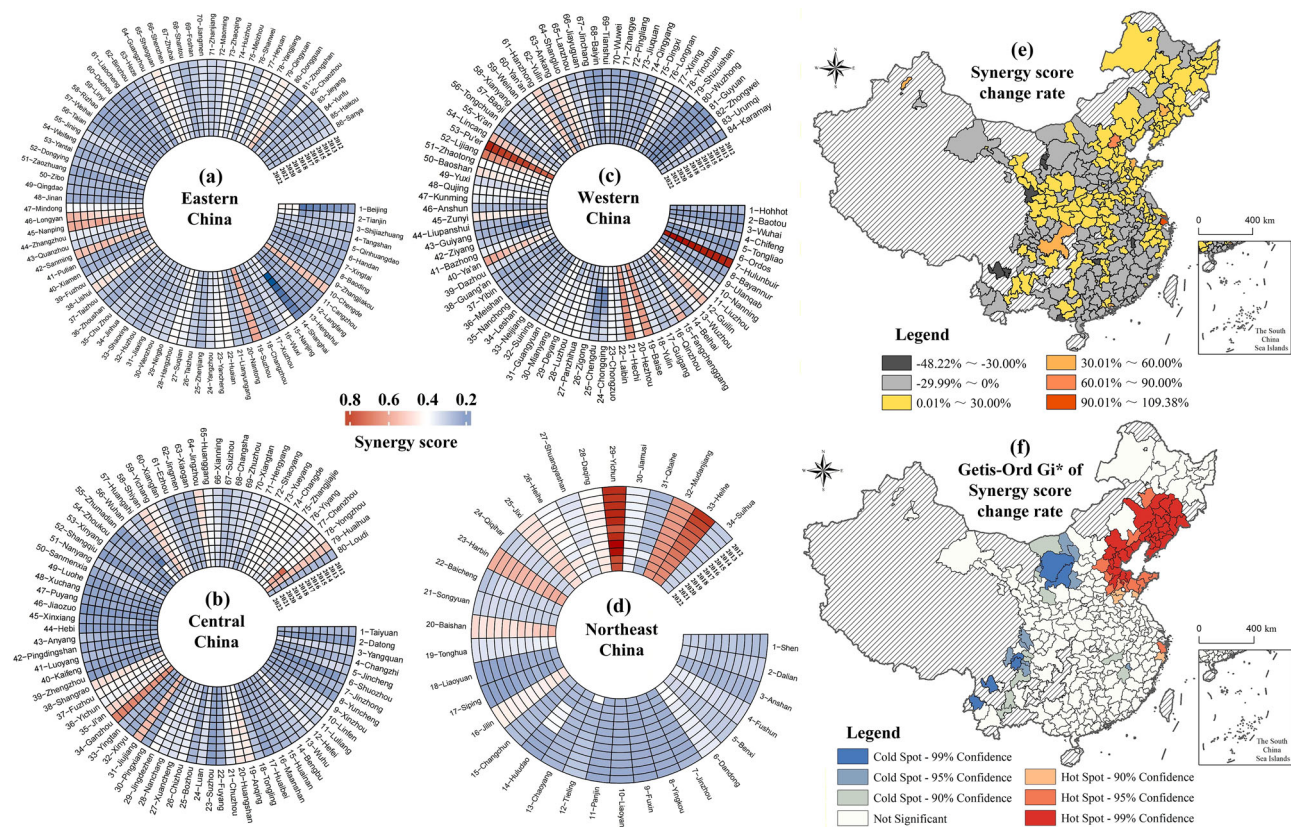


Fig. 8 The temporal evolution of synergistic scores in 284 prefecture-level cities in China. **a–d** Heatmaps of synergistic scores for cities in Eastern, Central, Western, and Northeastern China, respectively. **e** Spatial distribution of the change rate of synergistic scores in Chinese cities. **f** Getis-Ord G_i^* of the change rate of synergistic scores in Chinese cities.

margins of major urban agglomerations. Jingdezhen, Dingxi, and Shizuishan exhibited two-tier declines in synergy levels, all undergoing transitional phases from resource-intensive industries to modern service sectors. Cities with upgraded synergy levels predominantly clustered in the core zones of major urban clusters, particularly the Beijing-Tianjin-Hebei and Shandong Peninsula agglomerations. Among them, Beijing and Tieling achieved two-tier improvements in their synergy levels.

Spatial variation of co-evolution: The semi-variance function model was used to reveal the spatial variation characteristics of the synergy score. First, synergy scores were assigned as geographical attributes (projected coordinates from latitude and longitude), and the semi-variance function value for each year was calculated using GS+ Version 9. Subsequently, the Gaussian model with the optimal goodness-of-fit was selected to determine critical parameters and directional fractal indices across orientations. Finally, the spatial heterogeneity characteristics of the synergy score were visualized through Kriging interpolation. The fitting parameters are shown in Table 4. The fitting coefficients consistently exceeded 0.9 across all years, indicating robust model performance, primarily due to the strong spatial continuity of the TD-ES synergy score and the large sample size of 284 cities, which together enhance the stability and accuracy of semivariogram fitting. The nugget fluctuated only slightly within the range of [0.0059, 0.0069], indicating limited nationwide variability in the synergy score. The consistently low nugget values suggest that spatial variation is predominantly driven by structural factors rather than random noise. This implies a high degree of spatial continuity and self-organized stability in the synergy score across the study area, which also indirectly reflects the effectiveness of

our sampling design and the high precision of the measurement data. A general downward trend in the sill reveals that the contribution of random components to data variation decreased. Notably, the bullion coefficient remained predominantly above 0.8 prior to 2020, reflecting weak spatial autocorrelation in co-evolution. However, reductions in this coefficient after 2021 signify intensifying structural differentiation driven by spatial dependence. This change can be attributed to the differentiated impacts of the COVID-19 pandemic and the uneven implementation of control measures across regions. In metropolitan clusters such as Beijing-Tianjin-Hebei and the Yangtze River Delta, strict lockdowns sharply reduced tourism activity, alleviating environmental pressures and enabling short-term ecological recovery, thereby enhancing the TD-ES synergy scores. In contrast, in regions that were already ecologically sound and sparsely populated, relatively lenient pandemic control policies led to limited ecological improvement; meanwhile, the pandemic's negative impact on the tourism economy caused a shortage of funding for environmental management, resulting in little progress in the co-evolution between TD and ES. Consequently, these region-specific pandemic control policies intensified spatial disparities in TD-ES synergy scores, transforming the system from a predominantly random spatial pattern into a more structured configuration, in which co-evolutionary dynamics became increasingly dependent on heterogeneous regional policy responses. Furthermore, the variation range exhibited an inverted U-shaped trajectory, demonstrating that the spatial association scope induced by structural heterogeneity expanded during 2012–2019 but contracted from 2019 to 2022.

The fractal dimensions in various directions are shown in Table 5. The directional fractal indices for all orientations, South-

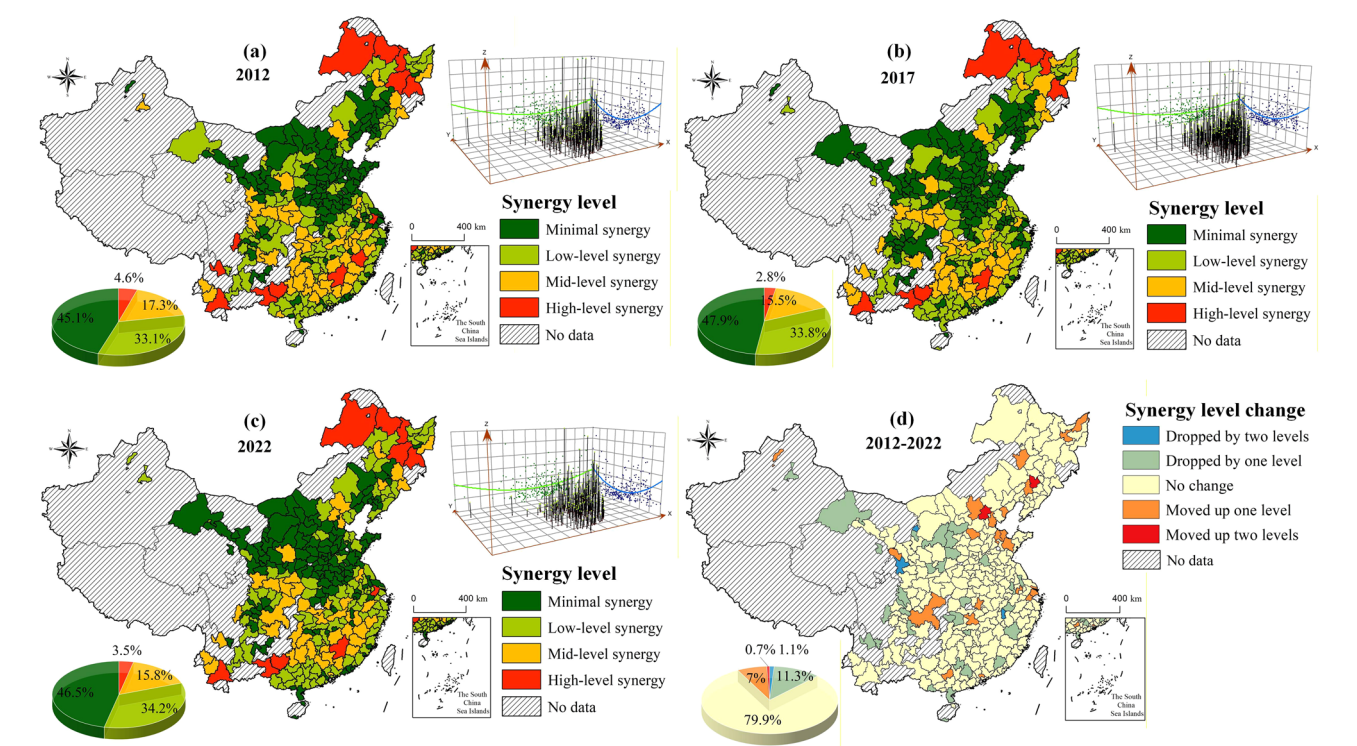


Fig. 9 The spatial distribution pattern of co-evolution. **a–c** Spatial distribution of synergy levels in 2012, 2017, and 2022, respectively. **d** Spatial distribution of synergy level changes from 2012 to 2022.

Table 4 Fitting parameters of spatial semi-variance function of the synergy score.						
Year	Nugget C_0	Sill $C_0 + C$	Bullion coefficient $C/C_0 + C$	Range/km	Fitting model	Decision coefficient R^2
2012	0.0068	0.0378	0.8200	40.4087	Gaussian	0.9370
2013	0.0063	0.0358	0.8240	40.3914	Gaussian	0.9410
2014	0.0062	0.0353	0.8240	40.7725	Gaussian	0.9410
2015	0.0059	0.0345	0.8260	41.7597	Gaussian	0.9350
2016	0.0064	0.0328	0.8060	40.3914	Gaussian	0.9280
2017	0.0063	0.0296	0.7890	39.7852	Gaussian	0.9290
2018	0.0062	0.0355	0.8250	44.4617	Gaussian	0.9330
2019	0.0069	0.0359	0.8070	45.4837	Gaussian	0.9250
2020	0.0063	0.0329	0.8080	41.8463	Gaussian	0.9230
2021	0.0063	0.0286	0.7800	40.8244	Gaussian	0.9180
2022	0.0061	0.0279	0.7810	39.7159	Gaussian	0.9250

North, and Northeast-Southwest, exhibit consistent evolutionary trajectories: a pronounced increasing trend during 2012–2019 followed by post-2019 fluctuations. This pattern suggests progressive homogenization of spatial differentiation in the synergy score along these orientations prior to 2019, with no discernible regularity emerging during the COVID-19 pandemic. The East-West orientation demonstrates minimal variation in fractal dimensions, indicating stable spatial differentiation of the synergy score along this axis. The fractal indices in Southeast-Northwest approximate the ideal value of 2 for homogeneous distributions, coupled with lower fitting coefficients, confirming weak spatial heterogeneity in this orientation.

The observed directional anisotropy can be explained as follows. First, the Northeast region, serving as both a key ecological protection area and a traditional industrial base, accelerated industrial transformation and actively developed ice-snow tourism and ecological tourism following the ecological civilization strategy after 2012, significantly enhancing TD-ES synergy and leading to more pronounced changes along the South-North and Northeast-Southwest axes. In contrast, although

ecological civilization policies were also implemented in western China, the weak ecological baseline and continued dependence on resource-intensive industries limited improvements in TD-ES synergy, resulting in minimal variation in fractal dimensions along the East-West axis. Moreover, the lower fitting coefficients for the Southeast-Northwest orientation primarily reflect incomplete statistical coverage of cities in northwest China, which reduces spatial continuity in the data.

Figure 10 visualizes the spatial heterogeneity of the synergy score at initial, intermediate, and terminal study phases. The synergy score consistently exhibits a “valley-shaped” spatial pattern. Two “elevated plateaus” emerge in northeastern and southwestern China, contrasting with predominantly low synergy levels in central regions. Although minor “hillocks” occur along latitudes 25°N–35°N (primarily within the Yangtze River Basin), they fail to alter the overarching spatial pattern.

Spatial transition characteristics of different synergy levels: The spatial Markov chain method was applied to elucidate the dynamic transition patterns of cities across varying synergy levels

Table 5 Fractal dimension of spatial semi-variance function of the synergy score.										
Year	All direction		South-North (0°)		Northeast-Southwest (45°)		East-West (90°)		Northwest-Southeast (135°)	
	D	R ²	D	R ²	D	R ²	D	R ²	D	R ²
2012	1.739	0.881	1.801	0.796	1.681	0.895	1.713	0.848	1.946	0.195
2013	1.735	0.884	1.805	0.792	1.681	0.896	1.697	0.859	1.926	0.330
2014	1.735	0.888	1.806	0.794	1.677	0.902	1.702	0.855	1.932	0.318
2015	1.736	0.884	1.812	0.801	1.681	0.894	1.697	0.846	1.961	0.079
2016	1.747	0.883	1.809	0.801	1.689	0.888	1.718	0.838	1.966	0.062
2017	1.753	0.894	1.823	0.817	1.693	0.902	1.710	0.812	1.984	0.012
2018	1.751	0.868	1.821	0.802	1.694	0.891	1.712	0.787	1.996	0.007
2019	1.769	0.867	1.854	0.722	1.720	0.878	1.726	0.801	1.989	0.010
2020	1.747	0.885	1.823	0.739	1.697	0.886	1.707	0.829	1.961	0.058
2021	1.765	0.882	1.840	0.757	1.724	0.867	1.710	0.803	1.963	0.058
2022	1.761	0.886	1.828	0.735	1.719	0.881	1.708	0.811	1.954	0.083

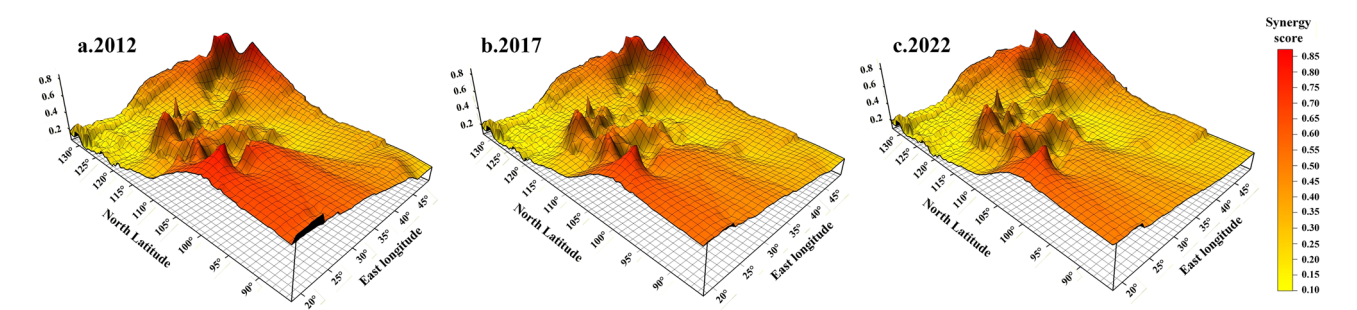


Fig. 10 Evolution of the spatial variogram of co-evolution. **a–c** The spatial heterogeneity of the synergy score in 2012, 2017, and 2022, respectively.

under different neighborhood types. Levels I, II, III, and IV correspond to minimal synergy, low-level synergy, mid-level synergy, and high-level synergy, respectively.

Table 6 reveals several key findings: (1) Under neighborhood type I conditions, level I cities demonstrated a 2.3% reduction in upward transition probability compared to non-adjacent scenarios, while level II, III, and IV cities exhibited increased downward transition probabilities of 7.96%, 0.45%, and 42.31%, respectively. (2) Under neighborhood type II conditions, level I cities exhibited an elevated upward transition probability of 8.25%, while level II cities showed an 8.37% decrease in downward transition probability compared to adjacency type I scenarios. Level III cities maintained stability with a 93.59% probability, contrasting with level IV cities that persisted with a significant downward transition probability of 23.08%. (3) Under neighborhood type III conditions, level I cities demonstrated a 9.76% upward transition probability, while level II and III cities maintained stability probabilities of 94.77% and 93.33%, respectively. Concurrently, level IV cities achieved a reduction in downward transition probability to 3.7%. (4) Under neighborhood type IV scenarios, level I cities exhibited stabilization at 94.59%, while level II cities displayed symmetric transition probabilities of 4.55% for both upward and downward movements. Level III cities exhibited a 7.28% increase in downward transitions compared to adjacency type III conditions, while level IV cities fully eliminated downgrading risks. Overall, the diagonal elements of the spatial Markov transition probability matrices under different neighborhood types are all greater than 0.5, demonstrating the spatial transition activity of synergy types is relatively low and that the co-evolution process exhibits path dependence. Specifically, level I cities are trapped in an evolutionary inertia characterized by low-tier synergy lock-in; level II and III cities show marginal susceptibility to coordination pattern transitions influenced by adjacent urban units; and level

IV cities are subject to significant negative spatial spillover effects from level I and II cities.

Obstacle diagnosis of co-evolution

Obstacle factors at the national and regional levels. Figure 11 illustrates the changes in obstacle degrees of the nine subsystems at both national and regional levels. (1) In China, SDG7 (increasing from 0.0440 to 0.2434) and the tourism development scale (rising from 0.0952 to 0.2624) exhibited the most pronounced upward trends in obstacle degrees. In contrast, SDG11 (declining from 0.1468 to 0.0100) and SDG13 (dropping from 0.1461 to 0.0170) showed significant reductions in obstacle levels. Overall, SDG6 recorded the highest average obstacle degree (0.1640), followed by tourism development efficiency (0.1311) and tourism development scale (0.1265). (2) In Northeast China, the obstacle degree of the tourism development scale increased more markedly than that of other subsystems, rising from 0.0648 in 2012 to 0.3887 in 2022. Meanwhile, SDG11 (declining from 0.1270 to 0) and SDG13 (decreasing from 0.1247 to 0) exhibited the most substantial reductions in obstacle degrees. Overall, SDG6 recorded the highest average obstacle degree (0.1336), followed closely by SDG15 (0.1335). (3) In Eastern China, both SDG7 (increasing from 0.0410 to 0.2483) and the tourism development scale (rising from 0.0816 to 0.2824) demonstrated significant growth in obstacle degrees. In contrast, SDG6 (declining from 0.1314 to 0) and SDG11 (dropping from 0.1408 to 0) showed pronounced downward trends. SDG6 exhibited the highest average obstacle degree (0.1584), followed by tourism development efficiency (0.1279) and SDG13 (0.1262). (4) In Central China, SDG7 (increasing from 0.0419 to 0.1883) and tourism development scale (rising from 0.0990 to 0.1903) mirrored the upward trends observed in Eastern China. SDG11 displayed a notable decline in obstacle degree, decreasing from

Table 6 Spatial Markov probability transition matrix of the synergy levels.

Neighborhood type	$t/(t + 1)$	n	I	II	III	IV
None	I	1363	0.9508	0.0477	0.0015	0.0000
	II	923	0.0737	0.9079	0.0184	0.0000
	III	450	0.0067	0.0511	0.9311	0.0111
	IV	104	0.0000	0.0000	0.0769	0.9231
I	I	800	0.9738	0.0250	0.0013	0.0000
	II	137	0.1533	0.8394	0.0073	0.0000
	III	36	0.0000	0.0556	0.9167	0.0278
	IV	4	0.0000	0.0000	0.5000	0.5000
II	I	485	0.9175	0.0804	0.0021	0.0000
	II	589	0.0696	0.9134	0.0170	0.0000
	III	234	0.0085	0.0427	0.9359	0.0128
	IV	13	0.0000	0.0000	0.2308	0.7692
III	I	41	0.9024	0.0976	0.0000	0.0000
	II	153	0.0261	0.9477	0.0261	0.0000
	III	165	0.0000	0.0606	0.9333	0.0061
	IV	81	0.0000	0.0000	0.0370	0.9630
IV	I	37	0.9459	0.0541	0.0000	0.0000
	II	44	0.0455	0.9091	0.0455	0.0000
	III	15	0.0667	0.0667	0.8667	0.0000
	IV	6	0.0000	0.0000	0.0000	1.0000

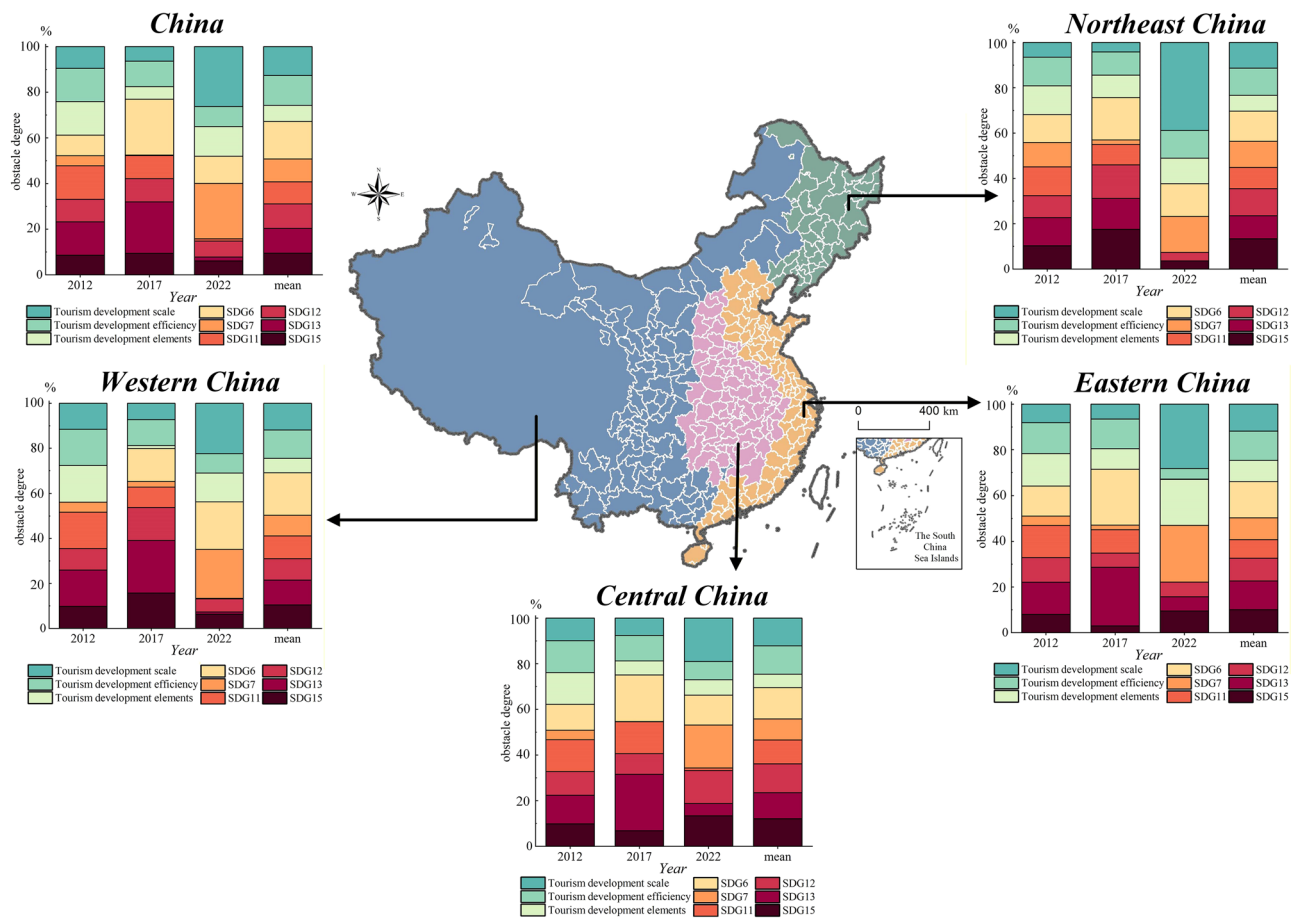


Fig. 11 The results of obstacles of the co-evolution at the national and regional levels.

0.1395 in 2012 to 0.0110 in 2022. The average obstacle degrees across subsystems exhibited little gap, with SDG6 (0.1368) being the highest and SDG7 (0.0923) the lowest. (5) In Western China, SDG6 (rising from 0.0000 to 0.2116), SDG7 (increasing from 0.0446 to 0.2183), and tourism development scale (growing from 0.1156 to

0.2238) all exhibited substantial upward trends in obstacle degrees. Conversely, SDG11 (declining from 0.1618 to 0.0022) and SDG13 (falling from 0.1618 to 0.0100) demonstrated significant downward trajectories. SDG6 (0.1880) recorded a notably higher average obstacle degree compared to the other subsystems.

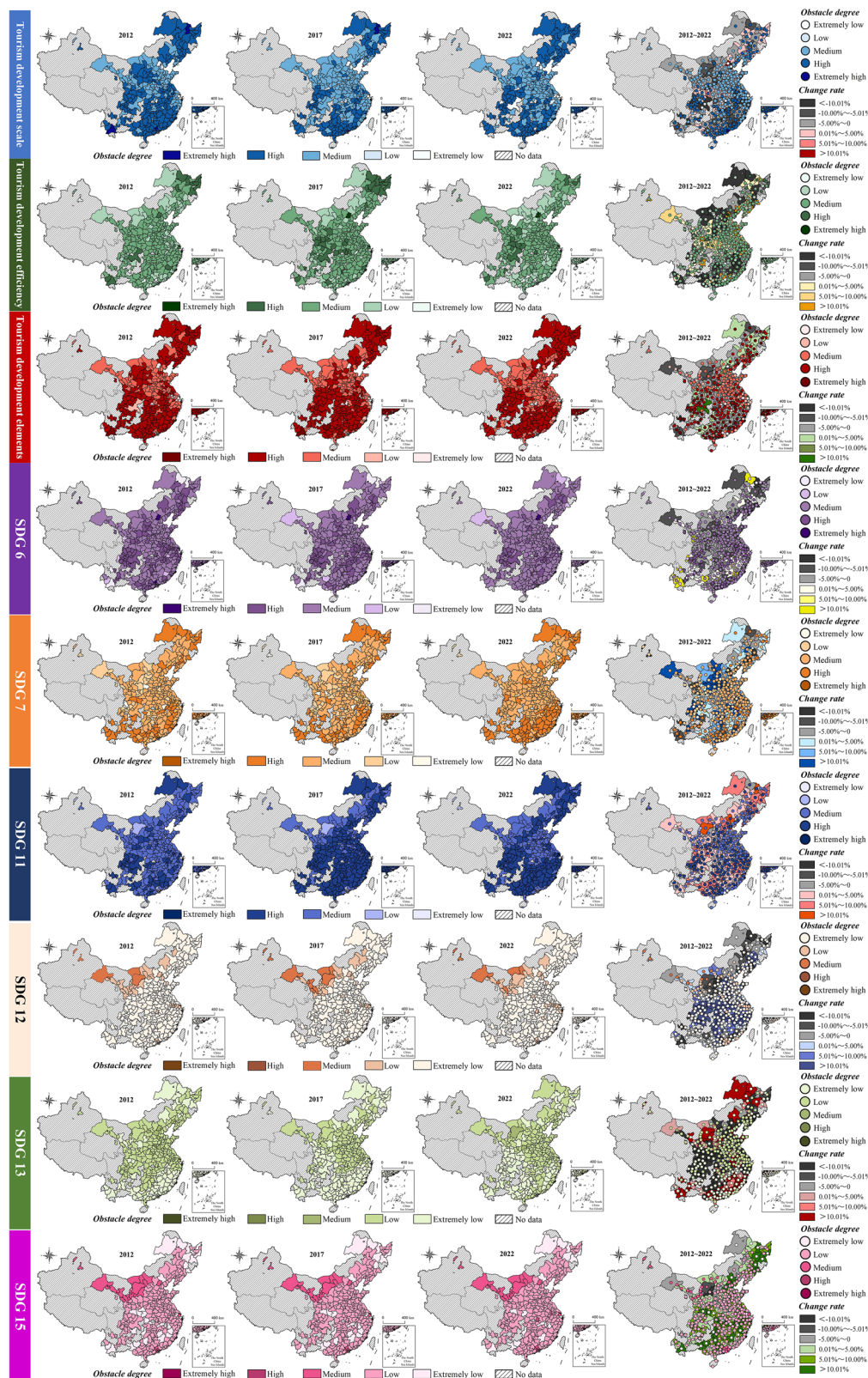


Fig. 12 The results of obstacles of the co-evolution at the urban level.

Obstacle factors at the urban level. To reveal the obstacles for each element at the urban scale, the obstacle degrees were classified into five grades using the equal interval method (He et al., 2023a): extremely low (<0.050), low ($0.051-0.100$), medium ($0.100-0.1500$), high ($0.1501-0.2000$), and extremely high (>0.2000). Figure 12

illustrates the obstacle degrees and their rates of change for nine subsystems (obstacle factors) for the years 2012, 2017, and 2022.

(1) Regarding tourism development scale, the spatial distribution of cities with high or extremely high obstacle levels gradually contracted to northeastern and southwestern China, with the

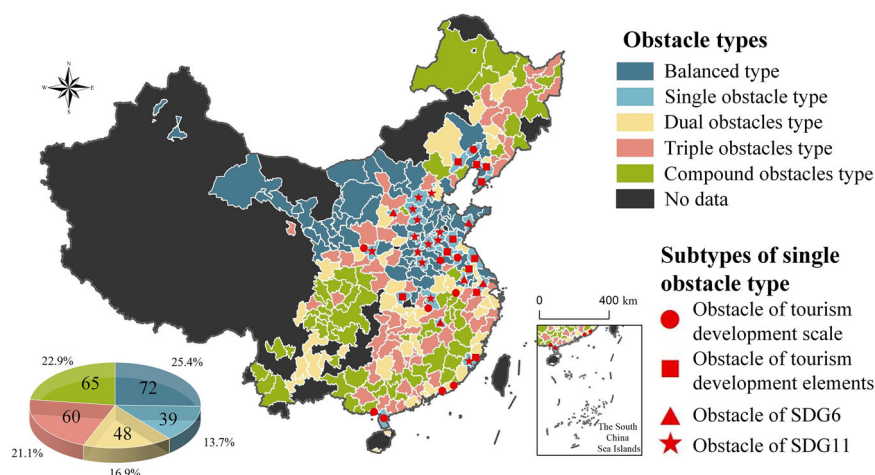


Fig. 13 Classification of obstacle types.

proportion decreasing from 64.43% in 2012 to 51.41% in 2022. Chengdu and Beijing exhibited the most significant changes, with reduction and growth rates of -76.96% and $+52.75\%$ respectively. (2) For tourism development efficiency, cities classified as high or extremely high obstacle levels consistently accounted for less than 15%, while over 70% remained in the medium obstacle level. Notably, 51.41% of cities experienced increased obstacle degrees, with Guigang, Guang'an, and Urumqi exhibiting more than threefold growth. (3) In terms of tourism development elements, the proportion of cities with high or extremely high obstacle levels declined from 61.62% in 2012 to 47.53% in 2022. Moreover, 70.77% of cities demonstrated decreasing obstacle degrees, particularly Wuhan and Shenzhen, showing the most dramatic reductions of 87.23% and 88.49%, respectively. (4) Regarding SDG6, the proportion of cities with obstacle degrees exceeding 0.15 decreased from 37.68% in 2012 to 16.19% in 2022. However, over 50% of cities consistently remained in the medium obstacle level. Furthermore, 76.06% of cities demonstrated declining barrier degrees, with Baishan showing the most significant reduction of 55.30%. (5) For SDG7, cities classified as high or extremely high obstacle levels were primarily distributed across northeastern and southern China, with the proportion of cities increased from 21.13% in 2012 to 26.76% in 2022. Notably, over 60% of cities persistently remained in the medium-obstacle zone, while 76.06% exhibited increasing obstacle degrees. (6) For SDG11, the spatial distribution of high or extremely high obstacle levels demonstrated contiguous expansion patterns, with the proportion increased from 25% in 2012 to 67.25% in 2017, subsequently stabilizing above 50%. Additionally, 85.56% of cities experienced the improvement of obstacles, with Ordos recording the most substantial growth of 96.11%. (7) For SDG12, consistently over 95% of cities maintained obstacle degrees below 0.1. Medium-barrier cities clustered in northwestern China. Significantly, 85.56% of cities showed upward trends in obstacle degrees. (8) Regarding SDG13, over 95% of cities consistently exhibited obstacle degrees below 0.1. The maximum obstacle degree occurred in Beijing (0.1429) in 2012. Moreover, 62.67% of cities displayed declining obstacle degrees. (9) For SDG15, 90% of cities maintained low or extremely low obstacle levels, with the peak obstacle degree recorded in Shenzhen (0.1516) in 2022. Notably, 84.51% of cities demonstrated measurable increases in obstacle degrees.

Classification of obstacle types. Based on the analysis results of obstacles at the urban scale, the obstacle types in the co-evolution between TD and ES are classified to guide local governments in adopting appropriate improvement strategies. An obstacle factor is

identified as a significant obstacle when its obstacle level is classified as high or extremely high. Following these criteria, the obstacle types can be categorized into balanced type (no significant obstacle factors), single obstacle type (one significant obstacle factor), dual obstacle type (two significant obstacle factors), triple obstacle type (three significant obstacle factors), and compound obstacle type (more than three significant obstacle factors).

As illustrated in Fig. 13, cities categorized as balanced type accounted for 25.4%, primarily concentrated in northwestern China and the North China Plain. The single-obstacle type constituted 13.7% of cities, predominantly distributed across the North China Plain, Liaodong Peninsula, and southeastern coastal areas. Among these, 10, 11, 5, and 13 cities were identified with critical obstacle factors in tourism development scale, tourism development elements, SDG6, and SDG11, respectively. The dual obstacle type constituted 16.9% of cities, sparsely distributed across most regions except northwestern China. Among dual obstacle combinations, the SDG11–tourism development elements pairing emerged as the predominant configuration, accounting for 35.42% of cases. Triple-obstacle type cities comprised 21.1% of the total, widely distributed throughout China. The most frequent triple combination involved tourism development scale, tourism development elements, and SDG11, representing 36.67% of such cases. The compound obstacle type represented 22.9%, mainly clustered in northeastern, southwestern, and southern China. Within this category, tourism development elements, SDG11, and tourism development scale emerged as the most frequently occurring critical obstacle factors.

Discussion

The advantages of using the Haken model. From a synergistic perspective, this study quantitatively analyzes the co-evolutionary process of the TD–ES composite system using the Haken model. Compared with the widely applied Coupling Coordination Degree Model (CCDM), the Haken model offers several distinct methodological advantages.

First, existing studies applying the CCDM often oversimplify inter-subsystem relationships—commonly by assigning equal weights to the tourism and environmental subsystems (Tang, 2015; Zhang et al., 2024). Such a subjective approach lacks a solid theoretical basis and may compromise the robustness of the findings. In contrast, the Haken model, grounded in the principles of adiabatic approximation and the separation of fast and slow variables, objectively identifies the order parameter

(slow variable) and the slaved variable (fast variable) that govern system evolution. Based on this mechanism, this study determines that ES functions as the system's order parameter, while TD serves as the slave variable, thereby clarifying the intrinsic interrelationship between the two subsystems.

Second, the CCDM is limited in its ability to depict the full dynamic trajectory of system co-evolution. Researchers typically infer evolutionary trends through cross-sectional comparisons of multi-year data, which restricts the model's capacity to capture the nonlinear and non-stationary characteristics of composite system dynamics. By contrast, the Haken model produces results that directly reveal the nonlinear, dynamic, and non-stationary features of the TD-ES system's co-evolution, providing a more accurate depiction of the system's synergistic evolutionary trajectory (An et al., 2025).

Moreover, the CCDM evaluation framework incorporates both "coupling degree" and "coordination degree" indicators, which are often conflated in empirical research. Some studies fail to clearly distinguish between these concepts or even use them interchangeably, resulting in model misuse and biased conclusions (Ji et al., 2022). In contrast, the Haken model directly computes synergy scores based on the internal relationships among variables to quantify the state of co-evolution between subsystems, effectively avoiding conceptual ambiguity and indicator misinterpretation.

The co-evolution between TD and ES. The results of the Haken model identify ES as the order parameter (slow variable) governing the co-evolution of the TD-ES composite system. This finding, from a synergetic perspective, empirically supports the view that environmental sustainability constitutes an important foundation for tourism development (Pulido-Fernández et al., 2019). Although extensive tourism development that disregards the environmental baseline may yield significant economic benefits in the short term, over the long term, whenever tourism development attempts to exceed or ignore the constraints imposed by this ES order parameter, the system exhibits a trend towards disorder and even decline (Russo, 2002). Illustrative real-world examples corroborate this dynamic. In Venice, overtourism has led to severe degradation of its ecosystem and environmental landscape, subsequently undermining the destination's appeal and competitiveness and trapping its tourism industry in a vicious cycle of long-term decline (Seraphin et al., 2018). Similarly, in Dubrovnik, a persistent exceedance of the environmental carrying capacity by tourism growth has triggered a cascade of issues, including resident dissatisfaction, the proliferation of a negative tourism image, and a decline in service quality, ultimately pushing the local tourism sector towards the risk of recession (Camatti et al., 2020). Therefore, achieving sustainable tourism necessitates strictly situating tourism development within the supporting framework of environmental sustainability. Any development strategy that diverges from the environmental baseline is unsustainable at the systemic level.

From the perspective of the temporal changes, the synergy score index exhibited a declining trend from 2012 to 2019, demonstrating that expanding tourism development exerted pressure on environmental sustainability, consistent with findings by Pulido-Fernández et al. (2019) and Lee et al. (2022). Although the China National Tourism Administration introduced tourism quality evaluation standards in 2013, local governments prioritized economic gains through large-scale tourism urbanization projects, resulting in aquatic ecosystem degradation and biodiversity loss (Ma and Tang, 2022; Ong and Liu, 2022). Additionally, the expansion of self-drive tourism and air travel increased tourism-related carbon emissions and exacerbated

atmospheric pollution (Tang et al., 2018; Liu and Pan, 2016). However, the comprehensive synergy score has gradually improved since 2019, which may be attributed to the following reasons. For one thing, the pandemic-induced tourism recession has driven China's tourism sector to explore a transformation in its industry structure (Lee et al., 2024). For another, reduced tourism intensity during COVID-19 has enabled ecological restoration in areas affected by overtourism (Wang et al., 2020b). However, the pandemic-era recovery should be interpreted with caution. The observed improvement may reflect a temporary convergence toward equilibrium driven by reduced tourist flows and eased environmental pressures, rather than a fundamental shift toward long-term sustainable co-evolution. In the post-pandemic context, the lifting of strict mobility controls may prompt revenge tourism (Fang et al., 2024; Wang et al., 2024), potentially overloading the environmental carrying capacity of destinations. Without structural reforms in tourism models and robust environmental governance, the recovery gains may be transient, potentially leading to a renewed decline in TD-ES synergy scores. This study further identifies three evolutionary phases—contraction, recession, and recovery—in the co-evolution of the TD-ES composite system, thereby validating synergistics' principles regarding the non-equilibrium and non-linear characteristics of self-organizing systems (Zhong et al., 2019; Haken, 1977). At the urban scale, cities in Northeast China, the Bohai Bay, and the Qinling Mountains demonstrated widespread growth in the synergy score, attributable to their implementation of eco-friendly tourism models—including wellness tourism, industrial heritage tourism, and ecotourism (He et al., 2023a; Jin et al., 2020). Conversely, urban clusters in South China and the Hohhot-Baotou-Ordos-Yulin region exhibited declining synergy scores, primarily due to disorderly tourism development and overtourism, which exacerbated the degradation of fragile ecosystems.

Spatially, the co-evolution exhibited a "central collapse" spatial pattern, similar to the findings of Zheng and Yang (2023). Moreover, our city-scale analysis surpasses their provincial-level studies by precisely delineating high/low synergy zones. The synergy score collapse clusters are mainly located in the Central Plains and the Loess Plateau, where decades of disorderly tourism development have chronically exceeded local environmental carrying capacities (Hao et al., 2022). In addition, compounded by inherent water scarcity and ecological fragility in these regions, tourism expansion has intensified secondary environmental degradation (Ma and Tang, 2023). In contrast, a distinct "uplift zone" is found along the northeast border, attributable to ecocentric tourism strategies implemented by local governments that prioritize winter sports and forest tourism (Li et al., 2021; Yang et al., 2023). From the perspective of spatial variation, the co-evolution exhibits a stable spatial pattern, indicating a path dependence in the co-evolution of the TD-ES composite system. This phenomenon is likely rooted in the strong institutional constraints imposed by the government-dominated model of tourism development and environmental governance in the Chinese context (Li et al., 2020). Under the influence of institutional inertia, cities that have long implemented green development strategies and prioritized eco-tourism tend to maintain consistently high TD-ES synergy scores. In contrast, cities that have long relied on resource-based industries while neglecting environmental foundations remain persistently trapped at lower levels of synergy. Consequently, the developmental trajectories of these two types of cities have become spatially entrenched. Spatial transition analysis further reveals that cities with low synergy levels remain caught in "low-level equilibrium traps," failing to benefit from the positive spillover effects generated by clusters of highly synergized cities. This

pattern may stem from the “promotion tournament” mechanism of China’s administrative system (Wang and Lei, 2021), under which local governments—driven by performance-based competition—are often reluctant to share experiences related to environmental governance and the green transformation of tourism. Such competitive behavior reinforces intercity disparities and perpetuates uneven spatial development. It’s worth noting that cities with high-level synergy prove vulnerable to negative spillover effects from their low-tier counterparts, likely due to implicit pollution transfer and the emulation of low-cost, disorderly tourism development practices.

The obstacles of co-evolution between TD and ES. At both national and regional levels, SDG6 was the most critical obstacle to the co-evolution of the TD-ES composite system, which may be due to two interrelated factors: First, tourism development oriented toward scale expansion had intensified the degradation of urban aquatic ecosystems and exacerbated water resource scarcity (Pang et al., 2022). Second, insufficient sanitation infrastructure (e.g., tourism toilets) and inequitable water allocation mechanisms had significantly constrained tourism growth (Gössling et al., 2012). Chinese authorities should integrate SDG6 into tourism planning frameworks while implementing nationwide initiatives for tourism toilet modernization and the construction of water-efficient recreational facilities.

Notably, the obstacle degrees of tourism development scale and SDG7 demonstrated significant upward trajectories. The former’s increasing barrier effect stemmed primarily from COVID-19’s catastrophic impact on tourism ecosystems (Wang et al., 2022c), while the latter’s increasing obstacles resulted from global energy supply chain disruptions that compelled China to prioritize domestic coal utilization for industrial stability (Su et al., 2024). The obstacle degrees of SDG11 and SDG13 exhibited the most pronounced downward trends at both national and regional levels, with neither being identified as significant obstacle factors by the study’s terminal period. Evidence supporting for SDG11’s declining barrier effect was derived from the studies of Liu et al. (2017) and Tang et al. (2022b). The former demonstrated urban livability’s catalytic role in tourism development, while the latter established that tourism development significantly enhances urban livability. The study of Wang et al. (2020b) provided evidence for the low obstacle of SDG13 in 2022, namely that the plunge in tourist arrivals during COVID-19 had led to a reduction in carbon emissions. However, the research concurrently cautioned about potential emission escalations resulting from post-pandemic economic stimulus policies.

At the urban scale, the proportion of cities with high or extremely high obstacle levels in tourism development scale gradually decreased, benefiting from increased tourist volume and enhanced tourism consumption capacity. However, the proportion of cities experiencing moderate obstacle levels in tourism development efficiency showed no decline, suggesting that the quality of tourism development remained relatively low in most Chinese cities, which was consistent with the findings of He et al. (2024). Notably, the majority of cities in Northeast and South China exhibited high-level obstacles in tourism development elements, indicating that local tourism infrastructure was inadequate to meet tourist demands. Among ES-related obstacles, SDG6, SDG7, and SDG11 have been identified as predominant obstacles in most cities, typically exhibiting moderate-to-extremely high obstacle levels. In contrast, over 90% of cities consistently demonstrated low or minimal obstacle levels for SDG12, SDG13, and SDG15. This pattern underscored the necessity for municipal governments to urgently integrate performance metrics related to water and sanitation

infrastructure, clean energy systems, and sustainable urban habitats into the specific provisions of tourism development plans and urban planning frameworks.

Integrated and zoning strategies for overcoming the obstacles of co-evolution

Integrated strategies. Based on the key findings of SDG 6 (Ensure availability and sustainable management of water and sanitation for all) consistently constitute the primary obstacle of the co-evolution, and that ES is identified as the order parameter of the TD-ES composite system, the following integrated policy implications are proposed. First, an institutional reform of tourism planning and project admission should be implemented under the principle of “environmental primacy.” The “ecological conservation redlines,” “environmental quality baseline,” and “resource utilization upper limits” should be established as pre-conditions for the approval and development of tourism projects, thereby systematically improving the tourism ecological efficiency. Meanwhile, the strategy for high-quality transformation of the tourism industry should be comprehensively advanced, facilitating a shift from extensive to intensive growth models. Moreover, improving the efficiency of all tourism-related factors can further strengthen the synergy between TD and ES. At the specific operational level, two key measures should be prioritized. First, water security must be placed at the core of tourism planning and development. A negative list system for tourism development should be established based on the carrying capacity of watershed water resources, and both water consumption intensity and total pollutant emissions should be incorporated into the mandatory performance evaluation system for local tourism authorities. Second, it is recommended that the Ministry of Culture and Tourism and the Ministry of Housing and Urban-Rural Development jointly lead interdepartmental collaboration to advance tourism sanitary facilities construction into a new phase characterized by low-carbon, smart, and resource-efficient development, moving beyond the previous emphasis on coverage and hygiene.

Zoning strategies. Integrated strategies merely provide an overarching direction at the macro level. Based on the identified obstacle types (Fig. 13), five governance zones were delineated—the Equilibrium Retention Zone, Targeted Breakthrough Zone, Double Bind Mitigation Zone, Trilemma Resolution Zone, and System Reengineering Zone. For each zone, specific policy recommendations were proposed to alleviate the corresponding co-evolutionary bottlenecks (Fig. 14). To enhance the empirical and practical relevance of these strategies, the most demographically representative city within each zone was selected as a prototypical case study for in-depth policy illustration and validation.

- (1) Balanced type cities are classified under the Equilibrium Retention Zone, where municipal governments should cultivate development advantages on the basis of strengthening risk warning mechanisms concerning the co-evolution of the TD-ES composite system. As a representative case, Zhengzhou’s authorities should implement a dual-track strategy. First, establishing an early intelligent monitoring—such as the Songshan Mountain UNESCO Global Geopark and the Yellow River Ecological Corridor—to track real-time data on negative oxygen ion density, soil erosion coefficients, and biodiversity indices. Second, policymakers should leverage urban water networks and peri-urban green spaces to create an interconnected Blue-Green Circular Corridor, strategically positioning Zhengzhou as the “Eco-Hub” in the Central Plains.

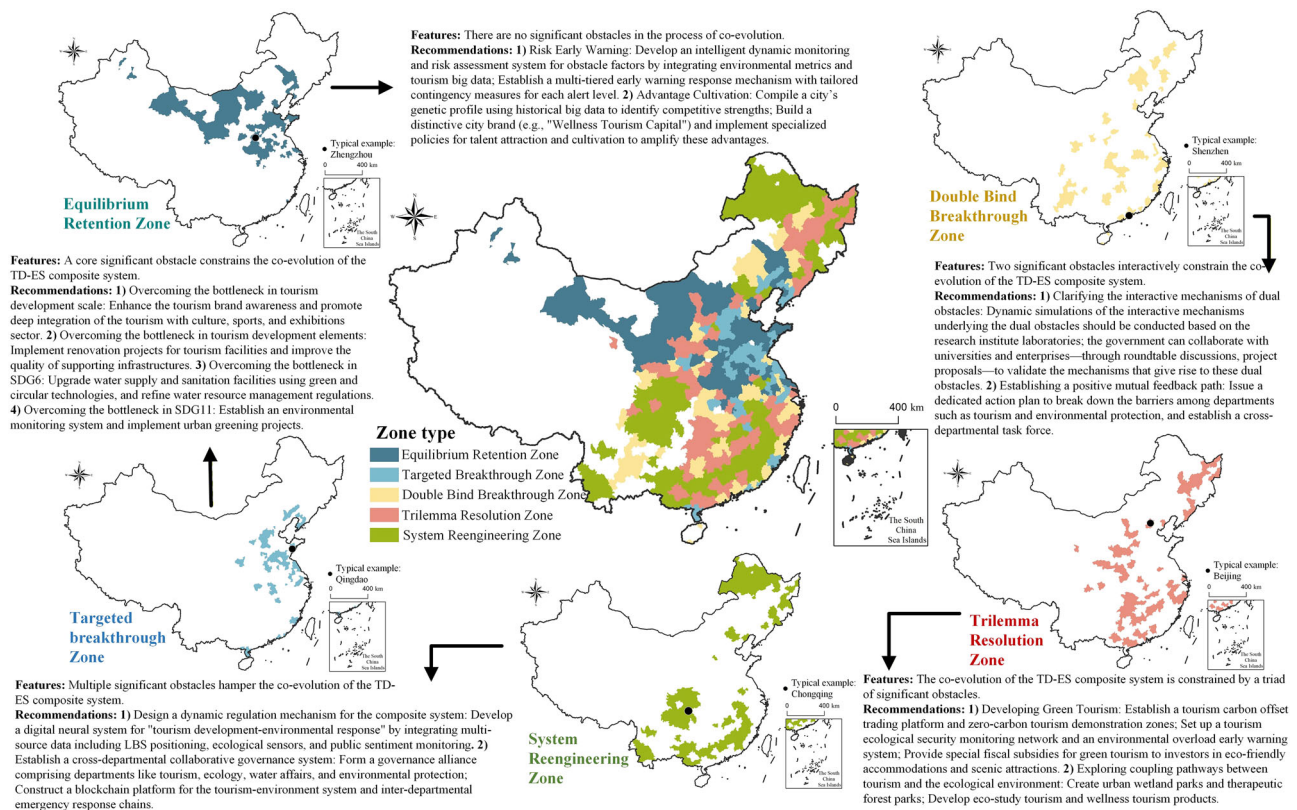


Fig. 14 Zoning strategy for overcoming the obstacles of co-evolution in different obstacle types.

- (2) Cities with single obstacle type are classified under the Targeted Breakthrough Zone, where municipal governments should prioritize resource allocation to address issues. Exemplified by Qingdao's case—where SDG6 impedes the co-evolution of the TD-ES composite system—three tactical interventions should implement: first, strategic deployment of multi-parameter water quality sensors and intelligent flow monitoring arrays in high-density tourism zones, such as Laoshan and Huangdao, enables real-time surveillance of groundwater tables, sea-water intrusion patterns, and fluctuations in potable water sources. Second, a "Hydro-Ecological Digital Twin System" can be developed by integrating water, environmental protection, and tourism departments to dynamically match tourist flow with water demand. Third, smart rainwater harvesting infrastructure and circular water management paradigms should be constructed at city scenic spots.
- (3) Cities exhibiting dual-obstacle characteristics are designated to the Double Bind Mitigation Zone, where governments should establish a positive mutual feedback mechanism between coexisting constraints through systematic interaction analysis. Exemplified by Shenzhen's case—where SDG6 and tourism development scale jointly disrupt the co-evolution of the TD-ES composite system—two implementation strategies emerge: First, collaborative modeling with the Complex System Dynamics Laboratory simulates the interdependencies between SDG6 and tourism development scales, projecting water stress under various spatiotemporal tourism scenarios to inform adaptive regulatory frameworks. Second, municipal authorities should leverage ecological assets such as the Shenzhen Mangrove Wetlands to design water-centric ecotourism curricula. Meanwhile, authorities should pilot water ecotourism projects in coastal recreation areas (e.g., Dapeng Peninsula) and urban cultural hubs (e.g., OCT Harbor Complex) to establish water-tourism symbiosis paradigms.
- (4) Cities exhibiting triple-obstacle characteristics are categorized within the Trilemma Resolution Zone, where governments should promote the green transformation of tourism to break the "impossible triangle" in the TD-ES system. For example, in Beijing—where tourism development efficiency, SDG6, and SDG11 collectively constrain the co-evolution—policymakers should implement two tactical interventions: First, they should prioritize the development of green tourism products, such as forest hiking and wetland birdwatching, while transforming ecological conservation areas like Mentougou and Yanqing into hubs for nature education and low-carbon experiences. Second, they could promote the integration of rural ecotourism with modern agriculture by creating eco-agricultural tourism products such as the "Miyun Reservoir Fish Feast" and "Pinggu Peach Orchard Picking," thereby establishing closed-loop value chains encompassing cultivation, processing, and experiential tourism.
- (5) Cities with the compound obstacle type are classified as System Reengineering Zones. Local governments should adopt a holistic approach to overcome the multiple obstacles hindering co-evolution. For example, in Chongqing—where tourism development efficiency, tourism development elements, SDG6, and SDG11 collectively constrain co-evolution—the following measures could be implemented: First, local authorities could establish a tourism AI platform to issue ecological carrying capacity warnings and dynamically adjust visitor flow regulation strategies. Second, they could pilot a "carbon sink-tourism" model in the Jinyun Mountain National Nature Reserve, while building an energy consumption monitoring platform to monitor real-time carbon emissions data in scenic areas

such as Gele Mountain. Furthermore, policymakers could leverage natural resources to develop an industrial chain focused on ecological experiences, wellness-driven consumption, and environmental education.

Innovations and contributions. The primary innovations and contributions of this study are as follows: First, based on the official SDGs framework, this study constructs a city-level evaluation system for tourism development (TD) and environmental sustainability (ES), providing a standardized foundation for assessing the tourism-environment nexus within the context of sustainable development. Second, from the perspective of synergetics, the Haken model is employed to quantitatively measure the synergy score between TD and ES across 284 Chinese cities, thereby revealing its spatiotemporal evolutionary patterns and dynamic co-evolutionary characteristics. Finally, obstacle factors hindering TD-ES co-evolution are diagnosed at the national, regional, and urban scales, upon which integrated strategies and zoning strategies are formulated to overcome these co-evolutionary barriers and promote high-quality, sustainable development of urban tourism-environment systems.

Limitations and future research directions. This study has several limitations that should be addressed in future research. First, although the urban-level evaluation index system for TD and ES was constructed based on the official SDGs framework, the comprehensiveness of the indicator system remains constrained due to limited data availability in certain cities. Second, while this research provides insights into the co-evolution characteristics of TD and ES within the Chinese context, its generalizability could be enhanced by extending the proposed analytical paradigm to cross-country comparative analyses across diverse global regions. Third, the “pattern–process–obstacle diagnosis” analytical paradigm adopted in this study primarily focuses on identifying the obstacles to the co-evolution of the TD–ES composite system and may not fully address all academic concerns. Future research could adopt alternative paradigms (such as “pattern–process–driving mechanism” or “pattern–process–trend prediction”) to contribute new theoretical insights to this field from different perspectives.

Conclusions

Based on synergistic theory, this study employed the Haken model to evaluate the synergy score between TD and ES across 284 prefecture-level cities in China. Subsequently, HP filter analysis, the semi-variance function model, and spatial Markov chains were applied to investigate the tempo-spatial evolution characteristics of the co-evolution. Finally, the obstacle degree model was utilized to identify obstacles of co-evolution and categorize cities by obstacle types. The conclusions are as follows:

- (1) The comprehensive TD value gradually increased before 2019, with a modest expansion of relatively high-value zones; however, it plummeted sharply during COVID-19 pandemic, revealing a distinct “central collapse” spatial pattern. From 2012 to 2022, the comprehensive TD value exhibited minor fluctuations while consistently maintaining four relatively high-value clusters—the northeastern cluster, Qinling Mountains cluster, southwestern cluster, and southern China cluster—alongside a stable low-value zone in the Yellow River Basin.
- (2) ES is identified as the order parameter of the co-evolution between TD and ES. The co-evolution progressed through three phases: the downturn stage (2012–2014), the recession stage (2015–2019), and the recovery stage (2020–2022). 50.35% of cities exhibited synergy score growth, primarily

concentrated in Northeast China, the Bohai Bay region, and the Qinling Mountain areas. Spatially, the co-evolution demonstrated limited nationwide variability while persistently maintaining a “central collapse” pattern. Cities with different synergy levels displayed path dependence in their evolutionary trajectories. Notably, spatial transitions of high-level synergy cities were significantly constrained by negative spatial spillover effects originating from minimal- and low-level synergy cities.

- (3) At national and regional scales, SDG6 exhibited the highest average obstacle degree, while the tourism development scale demonstrated the most pronounced increasing trend in constraint intensity. At the urban scale, cities exhibited different combinations of obstacles in their co-evolution processes, which can be categorized into five obstacle typologies: balanced type, single obstacle type, dual obstacle type, triple obstacle type, and compound obstacle type.

Data availability

The dataset used in the study is indicated within the text. The data generated during and analysed during the current study are available from the corresponding author on reasonable request.

Received: 18 April 2025; Accepted: 24 November 2025;

Published online: 16 December 2025

References

- Ai J, Yu K, Zeng Z et al. (2022) Assessing the dynamic landscape ecological risk and its driving forces in an island city based on optimal spatial scales: Haitan Island, China. *Ecol Indic* 137: 108771. <https://doi.org/10.1016/j.ecolind.2022.108771>
- An M, Xu W, Wang X et al. (2025) Synergetic evolution of energy-economy-environment-society system: a case study of Chengdu-Chongqing urban agglomeration, China. *Energy Strateg Rev* 59: 101755. <https://doi.org/10.1016/j.esr.2025.101755>
- Ball L, Leigh D, Loungani P (2017) Okun's law: fit at 50?. *J Money Credit Bank* 49(7):1413–1441. <https://doi.org/10.1111/jmcb.12420>
- Baum J, Cumming GS, De Vos A (2017) Understanding spatial variation in the drivers of nature-based tourism and their influence on the sustainability of private land conservation. *Ecol Econ* 140:225–234. <https://doi.org/10.1016/j.ecolecon.2017.05.005>
- Boluk KA, Cavaliere CT, Higgins-Desbiolles F (2019) A critical framework for interrogating the United Nations Sustainable Development Goals 2030 Agenda in tourism. *J Sustain Tour* 27(7):847–864. <https://doi.org/10.1080/09669582.2019.1619748>
- Buckley R (2011) Tourism and environment. *Annu Rev Environ Resour* 36(1):397–416. <https://doi.org/10.1146/annurev-enviro-041210-132637>
- Burak S, Dogan E, Gazioglu C (2004) Impact of urbanization and tourism on coastal environment. *Ocean Coast Manag* 47(9–10):515–527. <https://doi.org/10.1016/j.ocecoaman.2004.07.007>
- Cai J, Zhao D, Varis O (2021) Match words with deeds: curbing water risk with the Sustainable Development Goal 6 index. *J Clean Prod* 318: 128509. <https://doi.org/10.1016/j.jclepro.2021.128509>
- Çakar K (2021) Tourophobia: fear of travel resulting from man-made or natural disasters. *Tour Rev* 76(1):103–124. <https://doi.org/10.1108/TR-06-2019-0231>
- Camatti N, Bertocchi D, Carić H et al. (2020) A digital response system to mitigate overtourism. The case of Dubrovnik. *J Travel Tour Mark* 37(8–9):887–901. <https://doi.org/10.1080/10548408.2020.1828230>
- Center for International Knowledge on Development of China (2023) China's Progress Report on Implementation of the 2030 Agenda for Sustainable Development (2023). https://www.mfa.gov.cn/web/ziliao_674904/zt_674979/dnzt_674981/qtzt/2030kcxzyc_686343/zw/202310/P020231018366004072326.pdf. Accessed 30 March 2025
- Chen Y, Zhang D (2021) Evaluation and driving factors of city sustainability in Northeast China: an analysis based on interaction among multiple indicators. *Sustain Cities Soc* 67: 102721. <https://doi.org/10.1016/j.scs.2021.102721>
- Cheng Y, Wang J, Shu K (2023) The coupling and coordination assessment of food–water–energy systems in China based on sustainable development goals. *Sustain Prod Consum* 35:338–348. <https://doi.org/10.1016/j.spc.2022.11.011>

- Cousins JA, Sadler JP, Evans J (2008) Exploring the role of private wildlife ranching as a conservation tool in South Africa: stakeholder perspectives *Ecol Soc* 13(2):43. <https://www.jstor.org/stable/26267980>
- Damm A, Greuell W, Landgren O et al. (2017) Impacts of +2 °C global warming on winter tourism demand in Europe. *Clim Serv* 7:31–46. <https://doi.org/10.1016/j.cliser.2016.07.003>
- Dredge D (2022) Regenerative tourism: transforming mindsets, systems and practices. *J Tour futures* 8(3):269–281. <https://doi.org/10.1108/JTF-01-2022-0015>
- Dritsaki M, Dritsaki C (2022) Comparison of HP filter and the Hamilton's regression. *Mathematics* 10(8):1237. <https://doi.org/10.3390/math10081237>
- Dube K, Nhamo G, Chikodzi D (2021) Rising sea level and its implications on coastal tourism development in Cape Town, South Africa. *J Outdoor Rec Tour* 33: 100346. <https://doi.org/10.1016/j.jort.2020.100346>
- Ehigiamusoe KU (2020) Tourism, growth and environment: analysis of non-linear and moderating effects. *J Sustain Tour* 28(8):1174–1192. <https://doi.org/10.1080/09669582.2020.1729164>
- Fang C, Fan Y, Bao C et al. (2023) China's improving total environmental quality and environment-economy coordination since 2000: progress towards sustainable development goals. *J Clean Prod* 387: 135915. <https://doi.org/10.1016/j.jclepro.2023.135915>
- Fang M, Lu CS, Wang X et al. (2024) When a revenge evolves into a loyal follower: the causes and consequences of revenge travel. *Curr Issues Tour* 27(24):4659–4675. <https://doi.org/10.1080/13683500.2024.2269573>
- Flores-Segovia MA, Castellanos-Sosa FA (2021) Proximity effects and labour specialization transitions in Mexico: a spatial Markov chain analysis. *Reg Stud* 55(4):575–589. <https://doi.org/10.1080/00343404.2020.1836342>
- Frank TD, Profeta VLS, Harrison HS (2015) Interplay between order-parameter and system parameter dynamics: considerations on perceptual-cognitive-behavioral mode-mode transitions exhibiting positive and negative hysteresis and on response times. *J Biol Phys* 41(3):257–292. <https://doi.org/10.1007/s10867-015-9378-z>
- Gaughan AE, Binford MW, Southworth J (2009) Tourism, forest conversion, and land transformations in the Angkor basin, Cambodia. *Appl Geogr* 29(2):212–223. <https://doi.org/10.1016/j.apgeog.2008.09.007>
- Ghosh S (2020) Tourism and the environmental Kuznets Curve: a panel estimation. *Int J Tour Res* 22(6):839–852. <https://doi.org/10.1002/jtr.2387>
- Gössling S (2002) Global environmental consequences of tourism. *Glob Environ change* 12(4):283–302. [https://doi.org/10.1016/S0959-3780\(02\)00044-4](https://doi.org/10.1016/S0959-3780(02)00044-4)
- Gössling S, Peeters P, Hall CM et al. (2012) Tourism and water use: Supply, demand, and security. An international review. *Tour Manag* 33(1):1–15. <https://doi.org/10.1016/j.tourman.2011.03.015>
- Grillakis MG, Koutroulis AG, Seiradakis KD et al. (2016) Implications of 2 °C global warming in European summer tourism. *Clim Serv* 1:30–38. <https://doi.org/10.1016/j.cliser.2016.01.002>
- Haken H (1977) Synergetics. *Phys Bull* 28(9):412. <https://doi.org/10.1088/0031-9112/28/9/027>
- Haken H (1983) Advanced synergetics: Instability Hierarchies of Self-Organizing Systems and Devices (Springer Series in synergetics). Springer-Verlag, Berlin Heidelberg
- Hao Z, Ye D, Hui W et al. (2022) An empirical analysis of tourism eco-efficiency in ecological protection priority areas based on the DPSIR-SBM model: a case study of the Yellow River Basin, China. *Ecol Inf* 70: 101720. <https://doi.org/10.1016/j.ecoinf.2022.101720>
- He H, Tuo S, Lei K et al. (2024) Assessing quality tourism development in China: an analysis based on the degree of mismatch and its influencing factors. *Environ Dev Sustain* 26(4):9525–9552. <https://doi.org/10.1007/s10668-023-03107-1>
- He X, Cai C, Shi J (2023b) Evaluation of tourism ecological security and its driving mechanism in the Yellow River Basin, China: based on open systems theory and DPSIR model. *Systems* 11(7):336. <https://doi.org/10.3390/systems11070336>
- He X, Cai C, Tang J et al. (2023a) Analysis of coupling coordination and obstacle factors between tourism development and ecosystem services value: a case study of the Yellow River Basin, China. *Ecol Indic* 157: 111234. <https://doi.org/10.1016/j.ecolind.2023.111234>
- Hodrick RJ, Prescott EC (1997) Postwar US business cycles: an empirical investigation. *J Money Credit Bank* 19:1–16. <https://www.jstor.org/stable/2953682>
- Isik C, Dogru T, Turk ES (2018) A nexus of linear and non-linear relationships between tourism demand, renewable energy consumption, and economic growth: Theory and evidence. *Int J Tour Res* 20(1):38–49. <https://doi.org/10.1002/jtr.2151>
- Ji J, Tang Z, Zhang W et al. (2022) Spatiotemporal and multiscale analysis of the coupling coordination degree between economic development equality and eco-environmental quality in China from 2001 to 2020. *Remote Sens* 14(3):737. <https://doi.org/10.3390/rs14030737>
- Jin S, Yang J, Wang E et al. (2020) The influence of high-speed rail on ice-snow tourism in northeastern China. *Tour Manag* 78: 104070. <https://doi.org/10.1016/j.tourman.2019.104070>
- Katircioglu ST, Feridun M, Kilinc C (2014) Estimating tourism-induced energy consumption and CO₂ emissions: the case of Cyprus. *Renew Sustain Energy Rev* 29:634–640. <https://doi.org/10.1016/j.rser.2013.09.004>
- Koutroulis AG, Grillakis MG, Tsanis IK et al. (2018) Mapping the vulnerability of European summer tourism under 2 °C global warming. *Clim Change* 151:157–171. <https://doi.org/10.1007/s10584-018-2298-8>
- Leal Filho W, Dinis MAP, Nagy GJ et al. (2024) A ticket to where? Dwindling snow cover impacts the winter tourism sector as a consequence of climate change. *J Environ Manag* 356: 120554. <https://doi.org/10.1016/j.jenvman.2024.120554>
- Lee CC, Olasehinde-Williams GO, Ibikunle JA (2022) An asymmetric examination of the environmental effect of tourism in China. *Tour Eco* 28(7):1872–1887. <https://doi.org/10.1177/13548166211021173>
- Lee JW, Brahmasrene T (2013) Investigating the influence of tourism on economic growth and carbon emissions: evidence from panel analysis of the European Union. *Tour Manag* 38:69–76. <https://doi.org/10.1016/j.tourman.2013.02.016>
- Lee LC, Wang Y, Zhang L et al. (2024) Impact of COVID-19 on the economic loss and resource conservation of China's tourism industry from the supply chain perspective. *Cities* 144: 104633. <https://doi.org/10.1016/j.cities.2023.104633>
- Li J, Qu B, Jiang E et al. (2025) Coevolution and its influencing factors of the water resources–economy–society–environment composite system in the Yellow River basin. *Ecol Indic* 172: 113304. <https://doi.org/10.1016/j.ecolind.2025.113304>
- Li J, Yang N, Shen Z (2024) Evaluation of the water quality monitoring network layout based on driving-pressure-state-response framework and entropy weight TOPSIS model: a case study of Liao River, China. *J Environ Manag* 361: 121267. <https://doi.org/10.1016/j.jenvman.2024.121267>
- Li L, Liu T, Xu S et al. (2021) Evaluation on sustainable development of forest tourism in Heilongjiang Province, China. *Environ Dev Sustain* 23:13382–13402. <https://doi.org/10.1007/s10668-020-01217-8>
- Li M, Liu T, Qiu S (2020) Governance of sustainable tourism development in China. *J China Tour Res* 16(2):261–278. <https://doi.org/10.1080/19388160.2019.1637317>
- Li S, Liu A, Song H (2019) Does tourism support supply-side structural reform in China? *Tour Manag* 71:305–314. <https://doi.org/10.1016/j.tourman.2018.10.022>
- Li W, Yi P, Yu H et al. (2023) Assessment on sustainable development of three major urban agglomerations in China based on sustainability-differentiation-combined weighting method. *Sustain Dev* 31(4):2678–2693. <https://doi.org/10.1002/sd.2538>
- Li W, Zhang Q, Liu C et al. (2006) Tourism's impacts on natural resources: a positive case from China. *Environ Manag* 38:572–579. <https://doi.org/10.1007/s00267-004-0299-z>
- Li WJ, Wu TH, Li XJ (2013) The effects of tourism interference on the soil of grassland tourist spots—a study of gold saddle tourist spots of Xilamuren grassland in Inner Mongolia. *Adv Mater Res* 610:3034–3041. <https://www.scientific.net/AMR.610-613.3034>
- Liu D, Yin Z (2022) Spatial-temporal pattern evolution and mechanism model of tourism ecological security in China. *Eco Indic* 139: 108933. <https://doi.org/10.1016/j.ecolind.2022.108933>
- Liu J, Nijkamp P, Huang X et al. (2017) Urban livability and tourism development in China: analysis of sustainable development by means of spatial panel data. *Habitat Int* 68:99–107. <https://doi.org/10.1016/j.habitatint.2017.02.005>
- Liu X, Pan Y (2016) A study of carbon emissions during a tour: a case study of a four-day guided tour in Guilin, China. *J Hosp Tour Manag* 29:80–87. <https://doi.org/10.1016/j.jhtm.2016.01.006>
- Liu Z, Lan J, Chien F et al. (2022) Role of tourism development in environmental degradation: a step towards emission reduction. *J Environ Manag* 303: 114078. <https://doi.org/10.1016/j.jenvman.2021.114078>
- Liu Z, Zhang S (2025) Exploring the relationship between urban green development and heat island effect within the Yangtze River Delta Urban Agglomeration. *Sustain Cities Soc* 121: 106204. <https://doi.org/10.1016/j.scs.2025.106204>
- Ma M, Tang J (2022) Interactive coercive relationship and spatio-temporal coupling coordination degree between tourism urbanization and eco-environment: a case study in Western China. *Eco Indic* 142: 109149. <https://doi.org/10.1016/j.ecolind.2022.109149>
- Ma M, Tang J (2023) Nonlinear impact and spatial effect of tourism urbanization on human settlement environment: evidence from the Yellow River Basin, China. *J Clean Prod* 428: 139432. <https://doi.org/10.1016/j.jclepro.2023.139432>
- Memoli V, Esposito F, Panico SC et al. (2019) Evaluation of tourism impact on soil metal accumulation through single and integrated indices. *Sci Total Environ* 682:685–691. <https://doi.org/10.1016/j.scitotenv.2019.05.211>
- Miao J, Song X, Zhong F et al. (2023) Sustainable development goal 6 assessment and attribution analysis of underdeveloped small regions using integrated multisource data. *Remote Sens* 15(15):3885. <https://doi.org/10.3390/rs15153885>
- Ministry of Foreign Affairs of the People's Republic of China (2017) China's National Plan on Implementation of the 2030 Agenda for Sustainable

- Development. https://www.mfa.gov.cn/web/ziliao_674904/zt_674979/dnzt_674981/qtzt/2030kcxzyzc_686343/zw/201704/P020210929391207917361.pdf. Accessed 30 March 2025
- Moldan B, Janoušková S, Hák T (2012) How to understand and measure environmental sustainability: Indicators and targets. *Eco Indic* 17:4–13. <https://doi.org/10.1016/j.ecolind.2011.04.033>
- Nan Y, Sun R, Zhen Z et al. (2022) Measurement of international crude oil price cyclical fluctuations and correlation with the world economic cyclical changes. *Energy* 260: 124946. <https://doi.org/10.1016/j.energy.2022.124946>
- Ong CE, Liu Y (2022) State-directed tourism urbanisation in China's Hengqin. *Ann Tour Res* 94: 103379. <https://doi.org/10.1016/j.annals.2022.103379>
- Pang W, Pan Y, You Q et al. (2022) Causes of aquatic ecosystem degradation related to tourism and the feasibility of restoration for karst nature reserves. *Aquat Ecol* 56(4):1231–1243. <https://doi.org/10.1007/s10452-022-09983-5>
- Pásková M, Štekerová K, Zanker M et al. (2024) Water pollution generated by tourism: review of system dynamics models. *Heliyon* 10(1):e23824. <https://doi.org/10.1016/j.heliyon.2023.e23824>
- Pathak A, van Beynen PE, Akiwumi FA et al. (2021) Impacts of climate change on the tourism sector of a Small Island Developing State: a case study for the Bahamas. *Environ Dev* 37: 100556. <https://doi.org/10.1016/j.envdev.2020.100556>
- Phillips PC, Shi Z (2021) Boosting: Why you can use the HP filter. *Int Econ Rev* 62(2):521–570. <https://doi.org/10.1111/iere.12495>
- Pigram JJ (1980) Environmental implications of tourism development. *Ann Tour Res* 7(4):554–583. [https://doi.org/10.1016/0160-7383\(80\)90049-3](https://doi.org/10.1016/0160-7383(80)90049-3)
- Puhakka R, Saarinen J (2013) New role of tourism in national park planning in Finland. *J Environ Dev* 22(4):411–434. <https://doi.org/10.1177/1070496513502966>
- Pulido-Fernández JJ, Cárdenas-García PJ, Espinosa-Pulido JA (2019) Does environmental sustainability contribute to tourism growth? An analysis at the country level. *J Clean Prod* 213:309–319. <https://doi.org/10.1016/j.jclepro.2018.12.151>
- Qian W, Wang J (2020) An improved seasonal GM (1, 1) model based on the HP filter for forecasting wind power generation in China. *Energy* 209: 118499. <https://doi.org/10.1016/j.energy.2020.118499>
- Rasoolimanesh SM, Ramakrishna S, Hall CM et al. (2023) A systematic scoping review of sustainable tourism indicators in relation to the sustainable development goals. *J Sustain Tour* 31(7):1497–1517. <https://doi.org/10.1080/09669582.2020.1775621>
- Rosselló J, Becken S, Santana-Gallego M (2020) The effects of natural disasters on international tourism: a global analysis. *Tour Manag* 79: 104080. <https://doi.org/10.1016/j.tourman.2020.104080>
- Russo AP (2002) The “vicious circle” of tourism development in heritage cities. *Ann Tour Res* 29(1):165–182. [https://doi.org/10.1016/S0160-7383\(01\)00029-9](https://doi.org/10.1016/S0160-7383(01)00029-9)
- Schianetz K, Kavanagh L (2008) Sustainability indicators for tourism destinations: a complex adaptive systems approach using systemic indicator systems. *J Sustain Tour* 16(6):601–628. <https://doi.org/10.1080/09669580802159651>
- Scott D, Hall CM, Gössling S (2019) Global tourism vulnerability to climate change. *Ann Tour Res* 77:49–61. <https://doi.org/10.1016/j.annals.2019.05.007>
- Seidl A (2014) Cultural ecosystem services and economic development: World Heritage and early efforts at tourism in Albania. *Ecosys Serv* 10:164–171. <https://doi.org/10.1016/j.ecoser.2014.08.006>
- Seraphin H, Sheeran P, Pilato M (2018) Over-tourism and the fall of Venice as a destination. *J Destin Mark Manag* 9:374–376. <https://doi.org/10.1016/j.jdm.2018.01.011>
- Shahab A, Zhang H, Ullah H et al. (2020) Pollution characteristics and toxicity of potentially toxic elements in road dust of a tourist city, Guilin, China: ecological and health risk assessment. *Environ Pollut* 266: 115419. <https://doi.org/10.1016/j.envpol.2020.115419>
- Sharpley R (2022) Tourism and development theory: Which way now?. *Tour Plan Dev* 19(1):1–12. <https://doi.org/10.1080/21568316.2021.2021475>
- Shi-Jin W, Lan-Yue Z (2019) Integrated impacts of climate change on glacier tourism. *Adv Clim Change Res* 10(2):71–79. <https://doi.org/10.1016/j.accre.2019.06.006>
- Simo-Kengne BD (2022) Tourism growth and environmental sustainability: trade-off or convergence?. *Environ Dev Sustain* 24(6):8115–8144. <https://doi.org/10.1007/s10668-021-01775-5>
- Spencer N, Strobl E, Campbell A (2022) Sea level rise under climate change: Implications for beach tourism in the Caribbean. *Ocean Coast Manag* 225: 106207. <https://doi.org/10.1016/j.ocecoaman.2022.106207>
- Steibl S, Franke J, Laforsch C (2021) Tourism and urban development as drivers for invertebrate diversity loss on tropical islands. *R Soc Open Sci* 8(10):210411. <https://doi.org/10.1098/rsos.210411>
- Su CW, Yang S, Peculea AD et al. (2024) Energy imports in turbulent eras: evidence from China. *Energy* 306: 132586. <https://doi.org/10.1016/j.energy.2024.132586>
- Suárez-Rojas C, Hernández MMG, León CJ (2023) Sustainability in whale-watching: a literature review and future research directions based on regenerative tourism. *Tour Manag Perspect* 47: 101120. <https://doi.org/10.1016/j.tmp.2023.101120>
- Sun J, Jin H, Tsai FS et al. (2022) A global assessment of sustainable development: Integrating socioeconomic, resource and environmental dimensions. *Front Energy Res* 10: 816714. <https://doi.org/10.3389/fenrg.2022.816714>
- Sun YY, Faturay F, Lenzen M et al. (2024) Drivers of global tourism carbon emissions. *Nat Commun* 15(1):1–10. <https://doi.org/10.1038/s41467-024-54582-7>
- Tang C, Zheng Q, Zhong Q (2022b) Evaluation of the green development level of tourism in ecological conservation areas: a case study of Beijing. *Sustain Dev* 30(6):1634–1654. <https://doi.org/10.1002/sd.2332>
- Tang J, Cai C, Liu Y et al. (2022a) Can tourism development help improve urban liveability? An examination of the Chinese case. *Sustainability* 14(18):11427. <https://doi.org/10.3390/su141811427>
- Tang R (2022) A study of the effects and mechanisms of the digital economy on high-quality tourism development: evidence from the Yangtze River Delta in China. *Asia Pac J Tour Res* 27(11):1217–1232. <https://doi.org/10.1080/10941665.2023.2174033>
- Tang Z (2015) An integrated approach to evaluating the coupling coordination between tourism and the environment. *Tour Manag* 46:11–19. <https://doi.org/10.1016/j.tourman.2014.06.001>
- Tang Z, Bai S, Shi C et al. (2018) Tourism-related CO2 emission and its decoupling effects in China: a spatiotemporal perspective. *Adv Meteorol* 2018(1):1473184. <https://doi.org/10.1155/2018/1473184>
- United Nations (2024) The Sustainable Development Goals report 2024. <https://unstats.un.org/sdgs/report/2024/>. Accessed 30 March 2025
- United Nations Statistics Division (2017) SDG indicators. <https://unstats.un.org/sdgs/indicators/indicators-list/>. Accessed 30 March 2025
- United Nations World Tourism Organization (2017) Tourism and the Sustainable Development Goals—Journey to 2030. UNWTO, Madrid
- Wang C, Meng X, Siriwardana M et al. (2022c) The impact of COVID-19 on the Chinese tourism industry. *Tour Eco* 28(1):131–152. <https://doi.org/10.1177/13548166211041209>
- Wang J, Lei P (2021) The tournament of Chinese environmental protection: strong or weak competition?. *Ecol Econ* 181: 106888. <https://doi.org/10.1016/j.ecolecon.2020.106888>
- Wang L, Hu H, Wang X et al. (2023) The synergistic evolution of resilience and efficiency in the digital economy and its path identification: evidence from China. *Systems* 11(8):433. <https://doi.org/10.3390/systems11080433>
- Wang P, Zhang J, Xu D et al. (2025) Study on driving factors of island ecosystem health and multi-scenario ecology simulation using ecological conservation and eco-friendly tourism for achieving sustainability. *J Environ Manag* 373: 123480. <https://doi.org/10.1016/j.jenvman.2024.123480>
- Wang Q, Liu C, Hou Y et al. (2022b) Study of the spatio-temporal variation of environmental sustainability at national and provincial levels in China. *Sci Total Environ* 807: 150830. <https://doi.org/10.1016/j.scitotenv.2021.150830>
- Wang Q, Lu M, Bai Z et al. (2020b) Coronavirus pandemic reduced China's CO2 emissions in short-term, while stimulus packages may lead to emissions growth in medium-and long-term. *Appl Energy* 278: 115735. <https://doi.org/10.1016/j.apenergy.2020.115735>
- Wang X, Fang M, Yang CC et al. (2024) Revenge outbound travel in the post-pandemic era: evidence from an extended TPB model. *Asia Pac J Tour Res* 29(1):79–95. <https://doi.org/10.1080/10941665.2024.2308866>
- Wang X, Wang M, Lu X et al. (2022a) Spatio-temporal evolution and driving factors of the high-quality development of provincial tourism in China. *Chin Geogr Sci* 32(5):896–914. <https://doi.org/10.1007/s11769-022-1307-z>
- Wang Y, Lu Y, He G et al. (2020a) Spatial variability of sustainable development goals in China: a provincial level evaluation. *Environ Dev* 35: 100483. <https://doi.org/10.1016/j.envdev.2019.100483>
- Wei D, Li W, Yang W et al. (2023) Assessing the progress and spatial patterns of sustainable eco-environmental development based on the 2030 Agenda for SDGs in China. *Int J Sus Dev World Ecol* 30(4):387–401. <https://doi.org/10.1080/13504509.2022.2155265>
- Wei M, Huang S, Li L et al. (2022) Evolution of water quality and biota in the Panjiakou Reservoir, China as a consequence of social and economic development: implications for synergies and trade-offs between Sustainable Development Goals. *Sus Sci* 17:1385–1404. <https://doi.org/10.1007/s11625-021-01046-2>
- Wilson SP, Verlis KM (2017) The ugly face of tourism: marine debris pollution linked to visitation in the southern Great Barrier Reef, Australia. *Mar Pollut Bull* 117(1–2):239–246. <https://doi.org/10.1016/j.marpolbul.2017.01.036>
- Wolf F, Moncada S, Surroop D et al. (2024) Small island developing states, tourism and climate change. *J Sustain Tour* 32(9):1965–1983. <https://doi.org/10.1080/09669582.2022.2112203>
- Wu W, Huang Y, Zhang Y et al. (2024a) Research on the synergistic effects of urbanization and ecological environment in the Chengdu–Chongqing urban agglomeration based on the Haken mode. *Sci Rep* 14(1):117. <https://doi.org/10.1038/s41598-023-50607-1>

- Wu Y, Peng C, Peng Z (2024b) Key indicators for Pre-Warning risks associated with urbanization in China. *Eco Indic* 162:112032. <https://doi.org/10.1016/j.ecolind.2024.112032>
- Wu Z, Xie J (2025) The gospel of sustainable development? Spatiotemporal evolution and configuration pathways of the coupling coordination of the digital economy, tourism development and eco-efficiency. *J Environ Manag* 380: 124903. <https://doi.org/10.1016/j.jenvman.2025.124903>
- Xiao Y, Tang X, Wang J et al. (2022) Assessment of coordinated development between tourism development and resource environment carrying capacity: a case study of Yangtze River Economic Belt in China. *Eco Indic* 141: 109125. <https://doi.org/10.1016/j.ecolind.2022.109125>
- Xing L, Xie J (2021) Dynamic simulation and assessment of the coupling coordination degree of the economy–resource–environment system: case of Wuhan City in China. *J Environ Manag* 230:474–487. <https://doi.org/10.1016/j.jenvman.2018.09.065>
- Xu Z, Chau SN, Chen X et al. (2020) Assessing progress towards sustainable development over space and time. *Nature* 577(7788):74–78. <https://doi.org/10.1038/s41586-019-1846-3>
- Yang J, Wang Y, Tang F et al. (2023) Ice-and-snow tourism in China: trends and influencing factors. *Hum Soc Sci Commun* 10(1):1–12. <https://doi.org/10.1057/s41599-023-02288-4>
- Yi P, Dong Q, Li W et al. (2021) Measurement of city sustainability based on the grey relational analysis: the case of 15 sub-provincial cities in China. *Sustain Cities Soc* 73: 103143. <https://doi.org/10.1016/j.scs.2021.103143>
- Yi P, Dong Q, Li W et al. (2023) Assessment of city sustainability with the consideration of synergy among economy–society–environment criteria. *Environ Dev Sustain* 25(8):7645–7668. <https://doi.org/10.1007/s10668-022-02364-w>
- Yin H, Xiao R, Fei X et al. (2023) Analyzing “economy-society-environment” sustainability from the perspective of urban spatial structure: a case study of the Yangtze River delta urban agglomeration. *Sustain Cities Soc* 96: 104691. <https://doi.org/10.1016/j.scs.2023.104691>
- You C, Zhang S, Liu W et al. (2024) Localized sustainable development goals changes and their response to ecosystem services—a case of typical southern hilly regions in China. *Land* 13(7):919. <https://doi.org/10.3390/land13070919>
- Zaman K, Shahbaz M, Loganathan N et al. (2016) Tourism development, energy consumption and Environmental Kuznets Curve: trivariate analysis in the panel of developed and developing countries. *Tour Manag* 54:275–283. <https://doi.org/10.1016/j.tourman.2015.12.001>
- Zhang D, Chen Y (2021) Evaluation on urban environmental sustainability and coupling coordination among its dimensions: a case study of Shandong Province, China. *Sustain Cities Soc* 75: 103351. <https://doi.org/10.1016/j.scs.2021.103351>
- Zhang F, Sun C, An Y et al. (2021) Coupling coordination and obstacle factors between tourism and the ecological environment in Chongqing, China: a multi-model comparison. *Asia Pac J Tour Res* 26(7):811–828. <https://doi.org/10.1080/10941665.2021.1925715>
- Zhang J, Wang S, Pradhan P et al. (2022a) Untangling the interactions among the Sustainable Development Goals in China. *Sci Bull* 67(9):977–984. <https://doi.org/10.1016/j.scib.2022.01.006>
- Zhang J, Wang S, Pradhan P et al. (2022c) Mapping the complexity of the food-energy-water nexus from the lens of Sustainable Development Goals in China. *Resour Conserv Recycl* 183: 106357. <https://doi.org/10.1016/j.resconrec.2022.106357>
- Zhang J, Wang S, Zhao W et al. (2022b) Finding pathways to synergistic development of Sustainable Development Goals in China. *Hum Soc Sci Commun* 9(1):21. <https://doi.org/10.1057/s41599-022-01036-4>
- Zhang P, Yu H, Xu L et al. (2024) Synergistic relationship or not? Understanding the resilience and efficiency of the tourism economy: evidence from Hainan Province, China. *Environ Dev Sustain* 26(2):3793–3817. <https://doi.org/10.1007/s10668-022-02858-7>
- Zhang X, Guo W, Bashir MB (2022d) Inclusive green growth and development of the high-quality tourism industry in China: the dependence on imports. *Sustain Prod Consum* 29:57–78. <https://doi.org/10.1016/j.spc.2021.09.023>
- Zhang Y, Tian Q (2022) Water-tourism nexus: impact of the water footprint of inbound tourists to China. *Water Supply* 22(3):2546–2559. <https://doi.org/10.2166/ws.2021.455>
- Zhang Y, Zhang Y, Zhang H et al. (2022e) Evaluation on new first-tier smart cities in China based on entropy method and TOPSIS. *Eco Indic* 145: 109616. <https://doi.org/10.1016/j.ecolind.2022.109616>
- Zheng X, Yang Z (2023) Coordination or contradiction? The spatiotemporal relationship between ecological environment and tourism development within the tourism ecological security framework in China. *Eco Indic* 157: 111247. <https://doi.org/10.1016/j.ecolind.2023.111247>
- Zhong W, Song J, Ren J et al. (2019) Revealing the nexus among energy-economy system with Haken model: evidence from China's Beijing-Tianjin-Hebei region. *J Clean Prod* 228:319–330. <https://doi.org/10.1016/j.jclepro.2019.04.241>
- Zhou Y, Zhang X, Zhang C et al. (2024) Mitigating air pollution benefits multiple sustainable development goals in China. *Environ Pollut* 349: 123992
- Zhu W, Li B, Han Z (2021) Synergistic analysis of the resilience and efficiency of China's marine economy and the role of resilience policy. *Mar Policy* 132: 104703. <https://doi.org/10.1016/j.marpol.2021.104703>
- Zhu Y, Luo Y, Chen J (2023) Industrial transformation efficiency and sustainable development of resource-exhausted cities: a case study of Daye City, Hubei province, China. *Environ Dev Sustain* SI:1–25. <https://doi.org/10.1007/s10668-023-03269-y>

Acknowledgements

This work was supported by the National Social Science Fund of China (Grant No. 21FGLB070) and National Social Science Fund of China (Grant No. 24VWB026).

Author contributions

CYC: Writing—original draft, formal analysis, conceptualization, validation; XRH: Project administration, investigation; WHC: Methodology, data collection, data analysis. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

The submission of this study and the data used in this study were obtained through the official website with the informed consent of all participants. The basic data and research content of this study have no scientific and technological ethical problems.

Additional information

Correspondence and requests for materials should be addressed to Xiaorong He.

Reprints and permission information is available at <http://www.nature.com/reprints>

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



Open Access This article is licensed under a Creative Commons

Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025