

Article

Measuring Tourism Eco-Efficiency and Its Influencing Factors in Anhui Province

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Abstract

Promoting the green development of the tourism industry is a crucial pathway for achieving coordinated progress in ecological civilization development and industrial transformation and upgrading. Based on panel data for 16 prefecture-level cities in Anhui Province from 2011 to 2022, this study constructs an “inputs–desirable outputs–undesirable outputs” indicator system, measures city-level tourism eco-efficiency (TEE) using a super-efficiency SBM model incorporating undesirable outputs, decomposes provincial disparities and their sources using the Theil index and its decomposition, and further identifies city-specific heterogeneity in influencing factors by employing a panel variable-coefficient fixed-effects model. The results show that: (1) Anhui’s TEE exhibited an overall fluctuating upward trend during 2011–2022, with provincial efficiency values ranging from 1.465 (2016) to 1.500 (2022), and a more pronounced rebound after 2017; (2) spatially, TEE displays a pattern of “higher in the south, lower in the north, with a central uplift,” with southern Anhui cities such as Huangshan and Xuancheng performing relatively well, while many northern Anhui cities lag behind; (3) Theil decomposition indicates that overall disparities are driven mainly by within-region differences, whereas between-region differences contribute relatively little; and (4) influencing factors are markedly heterogeneous: scale- and affluence-related variables promote TEE in core cities such as Hefei, but tend to inhibit it in cities such as Bozhou, Anqing, Chuzhou, and Wuhu. The mechanisms associated with technology and structural variables are more complex; in particular, the expansion of energy consumption exerts a significantly negative effect on TEE in most cities and constitutes a common constraint on efficiency improvement, while the effects of R&D investment, digitalization, and the share of the tertiary sector vary across cities. Accordingly, policy efforts should prioritize energy-efficiency improvement and low-carbon substitution at the provincial level while implementing differentiated, city-specific pathways at the municipal level to jointly advance the low-carbon transition and high-quality development of the tourism industry.



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1. Introduction

Against the backdrop of global efforts to address environmental challenges and pursue sustainable development, the concept of green development has become an important direction for policy practice and academic inquiry [1]. Since the United Nations began to establish a theoretical framework for green development in the 1980s, with the notion of sustainable development further consolidated by Our Common Future (1987) [2] and

widely recognized as a global strategic consensus after 1992, a broad range of sectors have actively embraced green transitions. As a resource-dependent industry, tourism faces increasing pressure under accelerating globalization and the growing salience of climate-related risks. The shortcomings of conventional tourism development models—excessive resource consumption, environmental pollution, and ecological degradation—have become increasingly evident, forcing the tourism sector to pursue greener development pathways. In this context, enhancing the green transition of tourism has become a core issue in global tourism governance.

The concept of eco-efficiency was initially proposed by Ayres and is essentially defined as the output benefits obtained per unit of ecological resource input [3]. In 2002, Gössling et al. [4] introduced this concept into tourism studies and developed an evaluation framework using ecological footprint analysis, laying a foundation for subsequent research on tourism-related resource and environmental efficiency. Existing studies indicate that tourism eco-efficiency has become a key indicator for assessing the extent of green transformation and the capacity for sustainable development in tourism, and improvements in this indicator can significantly enhance the overall competitiveness of destinations [5,6]. As tourism systems become more complex, research has continued to deepen in terms of spatial scales and influencing mechanisms. In scope, studies have expanded from micro-level scenic areas to macro-level industrial systems [7]. In dimensions, the focus has evolved from the early economic–environmental dual relationship to more comprehensive assessments incorporating climate change, biodiversity, and other factors [8].

The measurement of tourism eco-efficiency has undergone an evolution from preliminary explorations to more advanced evaluations. Early-stage studies often relied on single-ratio methods [9], indicator system approaches [10], life-cycle theory [11], or carbon footprint comparisons [12], generally emphasizing accounting along a single dimension. As the topic entered mainstream research, Viet-Ngu Hoang et al. introduced data envelopment analysis (DEA) to address efficiency evaluation problems involving multiple inputs and multiple outputs [13]. To overcome estimation bias in traditional radial DEA models, Tone proposed the slacks-based measure (SBM) model, enabling efficiency scores to be adjusted according to input–output slacks [14]. In the frontier stage, SBM, EBM, and super-efficiency variants have been widely adopted, often combined with dynamic time-series analysis, substantially improving measurement precision. More recently, Du et al. developed a hybrid TEA-IS model to assess ecological efficiency across 248 Chinese cities, finding generally low efficiency levels and confirming that low-carbon pilot policies can improve eco-efficiency through green technology innovation [15]. Notably, in 2012, Liu Changsheng and colleagues developed an “input–output” integrated evaluation system suited to China’s context, marking an important milestone in China’s green development assessment for this area [16].

In parallel with methodological advances, a growing body of empirical research has examined tourism eco-efficiency across diverse spatial scales, revealing pronounced heterogeneity in both efficiency levels and driving mechanisms. At the national scale, Fu and Zhang analyzed the spatial association network of TEE across 30 Chinese provinces using a three-stage SE-SBM-DEA model, identifying a persistent dual-core structure centered on the Beijing–Tianjin–Hebei and Yangtze River Delta regions, with eastern coastal provinces occupying core network positions while northeastern and western provinces remain peripheral [17]. Similarly, an empirical study covering Chinese provinces found significant spatial spillover effects in regional tourism eco-efficiency, with development levels in neighboring areas exerting measurable influence on local TEE [18]. At the international level, Bianchi et al. assessed eco-efficiency across European NUTS-2 regions and documented substantial

spatial heterogeneity driven by territorial characteristics such as tourism intensity and economic structure [3].

At the urban agglomeration scale, Ma et al. documented an east-high, west-low spatial pattern in the Yangtze River Delta [19]; Fang et al. extended this by comparing the YRD and Pearl River Delta, demonstrating that core–periphery structures within each city cluster produce distinct efficiency landscapes [20]. At the individual destination and province scales, Peng et al. conducted a seminal SBM-DEA of Huangshan National Park over a 34-year period, finding that scale efficiency, rather than pure technical efficiency, was the decisive factor driving TEE improvement, and that tourism development level, industrial structure, and technology exerted significant positive effects [11]. More recently, a study focusing on typical tourist cities, including Huangshan, further confirmed the spatial heterogeneity of TEE at the city level [21]. At the provincial scale, Wu et al. examined Fujian Province using a super-SBM model and found a northeast–southwest spatial orientation with Xiamen as the dominant high-efficiency core, with tourism industry structure identified as the most influential factor [22]; Zhao et al. documented a central-plain > southern-mountain > northern-plateau gradient in Shaanxi [23]; and Chu et al. reported that within-region differences—rather than between-region disparities—constituted the primary source of overall TEE inequality in Henan [24].

In terms of influencing factors, a comprehensive evaluation using the Geographical Detector Model across Chinese provinces identified economic development level, transportation accessibility, and industrial structure as the principal determinants of TEE, while also revealing significant interactive effects among paired factors [25]. Wang et al. investigated environmental regulation in the YRD and found a significant negative short-run correlation with TEE, though the effect weakened over longer lags, indicating temporal heterogeneity in the regulation–efficiency relationship [26]. Chen et al. found that the digital economy can enhance TEE through technological, structural, and resource allocation channels, but its benefits are contingent on local absorptive capacity [27]. At the international level, Gabarda-Mallorquí et al. demonstrated that even within a single Mediterranean destination, hotel resource efficiency varied substantially depending on facility scale, management models, and infrastructure quality [28].

Despite this progress, a notable gap remains: most existing studies employ pooled-coefficient or average-effect models that implicitly assume the uniform influence of driving factors across all spatial units, thereby masking potentially significant within-region heterogeneity. While the spatial patterns of TEE are increasingly well-documented, the cross-city heterogeneity in the direction and magnitude of influencing factors within a single province has rarely been systematically examined. Moreover, within-province TEE research for Anhui—a province characterized by stark north–south developmental gradients and an economy transitioning from heavy industry to services—remains notably scarce, with existing work limited to single-destination case studies such as Huangshan.

To address these gaps, the present study applies an SBM-based framework grounded in input–output theory and incorporates undesirable outputs to estimate TEE for 16 cities in Anhui Province from 2011 to 2022. We further examine temporal dynamics via time-series analysis and spatial disparities via the Theil index. On this basis, influencing factors are identified with reference to the STIRPAT framework, and a fixed-effects model with variable coefficients is used to quantify cross-city heterogeneity in these effects. The study aims to support targeted policy design, optimize tourism resource allocation, and improve TEE for Anhui Province and similar regions, thereby contributing to regional sustainable development. The study’s main novelty and contributions are threefold: (i) it provides the province-wide, city-level TEE assessment for Anhui using a super-efficiency SBM framework with undesirable outputs; (ii) it decomposes TEE disparity via the Theil

index to identify whether intra-regional or inter-regional differences dominate; and (iii) it employs a variable-coefficient panel model to reveal cross-city heterogeneity in influencing factors—shifting from the conventional “average-effect” paradigm to a “conditional-effect” perspective that better captures context-dependent mechanisms.

2. Research Design

2.1. Study Area

Anhui Province (Figure 1) is located in eastern China in the lower reaches of the Yangtze River ($114^{\circ}54'–119^{\circ}37'$ E, $29^{\circ}41'–34^{\circ}38'$ N) and constitutes an important part of the Yangtze River Delta. The province administers 16 prefecture-level cities and features diverse tourism resources, integrating natural landscapes, historical and cultural attractions, and modern leisure amenities. These characteristics make it well-suited for examining the spatiotemporal differentiation of tourism eco-efficiency. To characterize within-province disparities and facilitate the regional comparisons required for the Theil index decomposition, this study divides the 16 cities into three subregions—Northern Anhui, Central Anhui, and Southern Anhui—based on commonly used geographic zoning and administrative delineations in Anhui Province. Northern Anhui includes Suzhou, Huaibei, Bozhou, Fuyang, Bengbu, and Huainan; Central Anhui includes Hefei, Lu'an, and Chuzhou; and Southern Anhui includes Wuhu, Ma'anshan, Tongling, Anqing, Huangshan, Chizhou, and Xuancheng. This subregional division is relatively coherent in terms of location, resource endowments, and industrial structure: Southern Anhui concentrates ecological and mountainous landscape resources and has a stronger foundation for cultural and tourism development; Central Anhui benefits from the radiating effect of the provincial capital and its role as a transportation hub, exhibiting stronger synergies between culture–tourism and modern services; and Northern Anhui, constrained by its industrial structure and resource–environment conditions, has a comparatively weaker tourism development base but greater potential for efficiency improvement. Considering that Chaohu City was dissolved in 2011 and its jurisdictions were incorporated into Hefei, Wuhu, and Ma'anshan, this study selects 2011–2022 as the study period to ensure consistent statistical definitions and data comparability in analyzing tourism eco-efficiency and its determinants in Anhui Province.

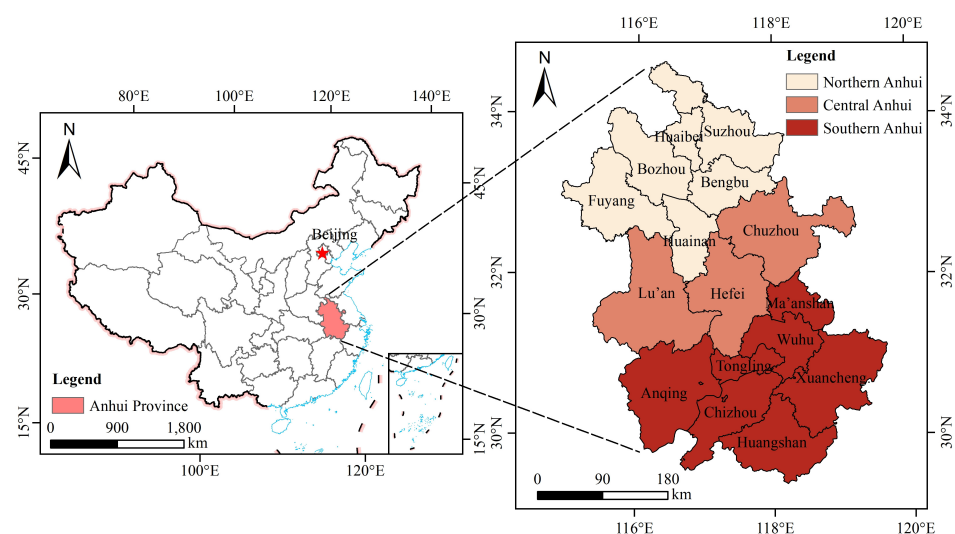


Figure 1. Research area overview.

2.2. Research Questions

Guided by the above context, this study addresses three research questions: (1) What are the temporal trends and spatial distribution characteristics of tourism eco-efficiency across 16 prefecture-level cities in Anhui Province from 2011 to 2022? (2) To what extent do within-region versus between-region differences contribute to overall TEE disparity, and which cities or sub-regions are the primary sources of inequality? (3) How do scale, affluence, technology, and structural factors—drawn from the STIRPAT framework—influence TEE, and do the direction and magnitude of these effects vary systematically across cities with different development stages and industrial structures? Rather than testing directional hypotheses, which would presuppose uniform effects across heterogeneous cities, this study adopts a variable-coefficient panel model to let the data reveal city-specific effect patterns. This approach is consistent with the exploratory nature of the third research question and with the study's broader aim of uncovering conditional, context-dependent relationships rather than universal linear associations.

2.3. Methods

2.3.1. Super-Efficiency Model

The super-efficiency SBM model extends the conventional non-radial, non-angular SBM model to address the limitation that decision-making units (DMUs) with efficiency scores equal to 1 cannot be effectively compared horizontally [29]. By incorporating the principle of super-efficiency DEA, the model retains SBM's advantages in handling multiple inputs and outputs—especially in the presence of undesirable outputs—while enhancing its ability to discriminate and compare efficiency levels across DMUs [30]. Specifically, by constructing a super-efficiency frontier, DMUs that are “efficient” under the standard SBM model can be further differentiated according to their distances from the super-efficiency frontier, enabling more effective cross-sectional comparisons.

Mathematically, the super-efficiency SBM model modifies the objective function of the original SBM formulation to incorporate undesirable outputs while introducing a super-efficiency evaluation mechanism [31]. In essence, the model solves a linear programming problem to identify an input combination that maximizes desirable outputs subject to constraints on inputs and undesirable outputs. The model expression is shown as follows:

$$\begin{aligned} \text{Min } \rho &= \frac{\frac{1}{m} \sum_{i=1}^m \left(\frac{\bar{x}}{x_{ik}} \right)}{\frac{1}{r_1 + r_2} \left(\sum_{s=1}^{r_1} \frac{\bar{y}^d}{y_{sk}^d} + \sum_{q=1}^{r_2} \frac{\bar{y}^u}{y_{qk}^u} \right)} \\ \bar{x} &\geq \sum_{j=1, \neq k}^n x_{ij} \lambda_j; \quad \bar{y}^d \leq \sum_{j=1, \neq k}^n y_{sj}^d \lambda_j; \quad \bar{y}^d \geq \sum_{j=1, \neq k}^n y_{qj}^d \lambda_j \\ \bar{x} &\geq x_k; \quad \bar{y}^d \leq y_k^d; \quad \bar{y}^u \geq y_k^u; \quad \lambda_j \geq 0, i = 1, 2, \dots, m \\ &\quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n, q = 1, 2, \dots, r_2 \end{aligned} \quad (1)$$

In this formula, among the n DMUs, each DMU consists of m inputs, r_1 desirable outputs, and r_2 undesirable outputs. x , y_d , and y_u denote the elements in the input matrix, the desirable output matrix, and the undesirable output matrix, respectively; ρ represents the tourism eco-efficiency score. When $\rho < 1$, the tourism eco-efficiency level is relatively low, and the DMU is considered inefficient. When $\rho \geq 1$, the tourism eco-efficiency level is relatively high, and the DMU is considered efficient; the larger the value, the higher the level. Based on these principles and the calculation method, the Super-SBM model shows strong application potential in regional eco-efficiency evaluation. Therefore, this study adopts the Super-SBM model to measure tourism eco-efficiency, so as to conduct a more detailed analysis and comparison of the tourism eco-efficiency of Anhui Province and its 16 prefecture-level cities.

Regarding indicator construction, this study draws on prior research (e.g., Sun et al., Liao et al., Li et al., Jiang, among others) [18,32–34] and considers data availability and representativeness to build a TEE evaluation indicator system (Table 1). Following the “inputs–desirable outputs–undesirable outputs” structure, input indicators reflect resource inputs and ecological support conditions for tourism development across four dimensions: labor, physical capital, financial inputs, and environmental inputs. Desirable outputs and undesirable outputs represent economic gains and environmental pollution pressures associated with tourism development, respectively.

Table 1. Input–output indicator system for tourism eco-efficiency.

Primary Indicator	Secondary Indicator	Third-Level Indicator
Output Indicator	Expected Output	Total Tourism Revenue (Ten Thousand Yuan)
		Total number of tourist visits (in thousands)
	Unexpected Output	Total volume of wastewater discharged from tourism activities (in ten thousand tons)
		Tourism-related sulfur dioxide emissions (tons)
		Emission amount of travel smoke (or dust particles) (in tons)
Input Indicator	Human input	Number of employees in the accommodation and catering industry (in persons)
		Number of employees in the culture, sports, and entertainment industries (in persons)
		Accommodation facilities for star-rated tourist hotels (hotels): Number of hotels (hotels)
		Tourism—Star-rated hotels (guesthouses); Accommodation facilities—Number of rooms
		Number of scenic areas rated A or above (number)
	Financial Investment	Greening and landscaping investment (in ten thousand yuan)
		The proportion of tourism education expenditure in total fiscal expenditure (%)
	Environmental Input	Green space ratio in the developed area (%)
		Harmless treatment rate of domestic waste (%)

For desirable outputs, total tourism revenue and total tourist visits are used. Total tourism revenue is a key indicator of tourism’s economic benefits and directly reflects tourism’s contribution to regional economic growth. Total tourist visits indicate the market scale and activity level of tourism development and serve as an important proxy for overall tourism development [35,36]. For undesirable outputs, tourism wastewater discharge, tourism SO₂ emissions, and tourism smoke (dust) emissions are adopted to represent pollution pressures on water and atmospheric environments generated by tourism-related activities [37]. Together, these indicators capture the coordination between economic output and the ecological impacts of tourism.

For inputs, a relatively comprehensive indicator system is constructed from major production factors and environmental conditions supporting tourism development. Labor inputs are measured by employment in accommodation and catering and employment in culture, sports, and entertainment, reflecting human resource support for tourism service supply. Physical inputs include the number of star-rated hotels, the number of rooms in star-rated hotels, and the number of A-level and above scenic attractions, reflecting reception capacity and resource-carrying foundations. Financial inputs include tourism education

expenditure as a share of fiscal expenditure and investment in landscaping/green space, reflecting local government support for tourism development and ecological construction. Environmental inputs are represented by the green coverage ratio in built-up areas and the harmless treatment rate of domestic waste, reflecting ecological baseline conditions and environmental governance capacity. These indicators correspond to key links in tourism production, reception, and ecology, and support robust measurement of TEE.

It should be noted that tourism wastewater discharge, tourism SO₂ emissions, tourism smoke (dust) emissions, and tourism education expenditure are derived variables rather than direct statistical entries in yearbooks. They are estimated based on a unified allocation principle. Specifically, tourism wastewater, tourism SO₂, and tourism smoke (dust) are calculated via a proportional allocation method: the share of tourism revenue in GDP is used as an allocation coefficient to apportion city-level total pollutant emissions. The formula is: $E_{it} = \frac{TR_{it}}{GDP_{it}} \times P_{it}$, where E_{it} denotes tourism-related pollutant emissions in city i in year t ; TR_{it} denotes total tourism revenue; GDP_{it} denotes GDP; and P_{it} denotes total wastewater discharge, total SO₂ emissions, and total smoke (dust) emissions, respectively. Tourism education expenditure is estimated similarly using the tourism revenue share and local fiscal education expenditure: $TE_{it} = \frac{TR_{it}}{GDP_{it}} \times FEdu_{it}$, where TE_{it} denotes tourism education expenditure in city i in year t , and $FEdu_{it}$ denotes local fiscal education expenditure. To improve completeness and comparability, missing values and outliers are treated as appropriate. Overall, the indicator system balances theoretical logic, data availability, and empirical analysis needs. It should be acknowledged that the proportional allocation method implicitly assumes the emission intensity and fiscal expenditure intensity of the tourism sector equal the city-wide average. This simplifying assumption, while necessitated by the absence of sector-disaggregated environmental statistics at the prefecture level, introduces potential measurement bias. Specifically, tourism-related emissions may be overestimated in industrial cities such as Ma'an Shan and Tongling—where industrial emission intensities substantially exceed those of service sectors—and underestimated in tourism-dominant cities such as Huangshan. Nevertheless, the tourism revenue-to-GDP ratio remains the most consistently available allocation base across all 16 cities and the full 12-year period, given that China's provincial and municipal statistical yearbooks do not report pollutant emissions or fiscal expenditure by individual economic sectors. The use of this allocation method is consistent with prior tourism environmental accounting studies that have faced similar data constraints [38,39]. Future research may refine these estimates when city-level, sector-specific environmental statistics become available.

A further clarification regarding the input indicators concerns the absence of tourism-dedicated energy consumption and tourist transport fuel use. These variables are conceptually central to eco-efficiency measurement, as fossil fuel consumption in tourism transport constitutes a major component of the sector's environmental footprint [9]. However, China's prefecture-level statistical yearbooks do not report energy consumption or fuel use disaggregated by economic sector, and city-level tourism satellite accounts—which could provide such estimates—remain unavailable for Anhui's 16 cities across the full sample period. While total city electricity consumption is examined as an influencing factor in the second-stage regression (see Section 2.3.4), incorporating it as a DEA input would conflate tourism-related energy use with non-tourism industrial and residential consumption, introducing potentially greater measurement error than omission. This data constraint is common in city-level tourism eco-efficiency research in China, where studies typically rely on proportional allocation of aggregate environmental indicators rather than direct energy measurement [38,39]. The implications are further discussed in Section 5.4.

2.3.2. Theil Index

As a measure of income inequality, the Theil index exhibits strong decomposability: when the sample is divided into multiple groups, it can separately quantify the contributions of intra-group disparities and inter-group disparities to the overall disparity [40]. Suppose a sample comprising n individuals is divided into K groups, each denoted as g_k ($k = 1, 2, \dots, K$), with the number of individuals in group k being n_k . Let y_i and y_k represent the income share of individual i and the total income share of group k , respectively. Denoting T_b and T_w as the intergroup disparity and intragroup disparity, the Theil index can be decomposed as follows:

$$T = T_b + T_w = \sum_{k=1}^K y_k \log \frac{y_k}{\frac{n_k}{n}} + \sum_{k=1}^K y_k \left(\sum_{i \in g_k} \frac{y_i}{y_k} \log \frac{\frac{y_i}{y_k}}{\frac{1}{n_k}} \right) \quad (2)$$

In Equation (2), the inter-group disparity T_b and intra-group disparity T_w are expressed as follows:

$$T_b = \sum_{k=1}^K y_k \log \frac{y_k}{\frac{n_k}{n}} \quad (3)$$

$$T_w = \sum_{k=1}^K y_k \sum_{i \in g_k} \frac{y_i}{y_k} \log \frac{\frac{y_i}{y_k}}{\frac{1}{n_k}} \quad (4)$$

2.3.3. Panel Variable-Coefficient Fixed-Effects Model

A panel variable-coefficient fixed-effects model combines fixed effects with heterogeneous slopes and is suitable for analyzing differentiated responses across individuals (here, prefecture-level cities) to explanatory variables. This model has notable advantages for examining TEE in Anhui. On the one hand, Anhui's cities differ in time-invariant characteristics such as geographical location, resource endowments, industrial structure, and policy support intensity. Introducing city fixed effects helps control such unobserved heterogeneity, allowing more accurate identification of relationships between core explanatory variables and TEE. On the other hand, allowing slope coefficients to vary by city (and potentially over time) helps capture heterogeneous effects across cities, thereby revealing the dynamics and underlying mechanisms of TEE development.

To illustrate the varying responses of different cities to influencing factors, this study employs an individualized variable-coefficient fixed-effects model. Let $i = 1, \dots, N$ denote the cities ($N = 16$ in this study), and $t = 1, \dots, T$ represent the years (2011–2022; $T = 12$ in this study). The dependent variable is tourism ecological efficiency TEE_{it} . Considering that common macroeconomic shocks (such as policy cycles, economic fluctuations, and public events) may influence temporal trends at the provincial level, the model simultaneously controls for both individual fixed effects and time fixed effects, with the basic setup as follows:

$$TEE_{it} = \alpha_i + \lambda_t + \sum_{k=1}^K \beta_{ik} X_{kit} + \varepsilon_{it} \quad (5)$$

where α_i denotes city fixed effects; λ_t denotes year fixed effects; X_{kit} denotes explanatory variables ($K = 8$); β_{ik} denotes city-specific slope coefficients capturing heterogeneity; and ε_{it} is the error term.

In estimation, the variable-coefficient structure is explicitly parameterized via interaction expansion: city dummy variables D_i are interacted with each explanatory variable X_k to form $D_i \times X_k$, allowing each city to have its own slope for each explanatory variable. To avoid perfect multicollinearity, a base category is set (or equivalent constraints are

imposed). Estimation is conducted within a two-way fixed-effects framework using least squares/within transformation.

Regarding parameter scale and sample size: the balanced panel includes $NT = 16 \times 12 = 192$ observations. Under the variable-coefficient specification, the number of slope parameters is on the order of $N \times K$, in addition to $(N - 1)$ city effects and $(T - 1)$ year effects. In implementation, base-category handling and fixed-effects absorption are applied to address collinearity, and robustness checks further examine result reliability using alternative estimation approaches and robust standard errors.

2.3.4. Selection of Influencing Factors

The analysis of factors influencing tourism eco-efficiency is grounded in the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, which evolved from the IPAT identity originally proposed by Ehrlich and Holdren (1971) [41] to formalize the relationship between human activities and environmental impacts. Dietz and Rosa (1994) [42] reformulated this identity into a stochastic, statistically estimable form—STIRPAT—allowing the relative contributions of population scale, affluence, and technology to be empirically assessed rather than assumed proportional. This framework has been widely applied in environmental social science research, including studies of carbon emissions, ecological footprints, and energy efficiency across various spatial scales [43]. The STIRPAT framework is particularly well-suited to the present study for three reasons. First, tourism eco-efficiency—defined as the economic output obtained per unit of environmental pressure—maps directly onto the STIRPAT logic: population scale and affluence condition the demand for tourism services and the associated resource throughput, while technology mediates the efficiency with which inputs are converted into outputs and the intensity of undesirable byproducts. Second, the framework's multiplicative structure aligns with the variable-coefficient specification adopted in this study, wherein the marginal effects of each STIRPAT dimension are allowed to vary across cities, reflecting the reality that population growth, income increases, and technological change do not exert uniform environmental pressures across heterogeneous urban systems. Third, the framework's flexibility in incorporating additional structural variables—here, digitalization and industrial composition—enables a theoretically grounded extension beyond the core P–A–T dimensions to capture city-specific contextual factors relevant to tourism's green transition. In operational terms, the P dimension is represented by resident population (scale) and population density (agglomeration); the A dimension by GDP per capita and per capita disposable income; and the T dimension by R&D intensity, electricity consumption, tertiary industry share, and digitalization. Each variable thus carries a theoretically interpretable role within the overarching STIRPAT logic, while the variable-coefficient estimation strategy ensures that the parameter estimates reflect city-specific conditional effects rather than imposing uniform average relationships.

To investigate the influencing factors of TEE and their mechanisms across cities, this study draws on the STIRPAT framework $I = f(P, A, T)$ [44]. The dependent variable is TEE. Core explanatory dimensions include population scale (P), affluence (A), and technology level (T). Since the efficiency measurement already incorporates variables such as total tourism revenue, total tourist visits, and related input–output indicators, to avoid indicator duplication and same-source bias, the influencing factor analysis does not reuse tourism input–output indicators; instead, it uses representative macro-level city indicators.

Specifically, the P dimension is represented by the resident population and population density to capture population scale and agglomeration pressure. The A dimension is represented by GDP per capita and per capita disposable income to measure economic development and consumption capacity. The T dimension is represented by R&D in-

tensity (R&D expenditure as a share of GDP), annual electricity consumption, the share of tertiary industry value added in GDP, and internet penetration/digitalization indicators (e.g., broadband users), reflecting innovation inputs, energy consumption intensity, industrial upgrading, and digital development. Definitions and mappings are shown in Table 2.

Table 2. Indicators of Factors Affecting Tourism Ecological Efficiency.

STIRPAT Core Factors	Expand the Explanation and Make It More Concrete	Quantifiable Indicators
P (Population) Scale Factor	Urban population concentration and the infrastructure necessary to support tourism activities	Permanent population (in ten thousand)
	Urban agglomeration and spatial capacity constraints	Population Density (people/kilometer ²)
A (Affluence) Economic Factor	Level of regional economic development	Per capita GDP (yuan per person)
	Residential consumption capacity	Per capita disposable income of residents (yuan/person)
T (Technology) Technology Factor	Investment in scientific and technological innovation	Proportion of R&D expenditure to GDP (%)
	Energy Consumption Intensity	Annual electricity consumption (in billion kilowatt-hours)
	Upgrading of an industrial structure	Proportion of the tertiary sector's added value in GDP (%)
	Level of digitalization and informatization	Number of internet users per 10,000 people (households)

2.4. Data Sources

Data are obtained from the China City Statistical Yearbook (2012–2023), the Anhui Statistical Yearbook, and the Statistical Bulletins on National Economic and Social Development for cities in Anhui Province (2011–2022). For indicators requiring further calculation—such as tourism education expenditure share, proportion of tourism employment, carbon emissions per unit of tourism revenue, and tourism science and technology expenditure share—secondary computations are conducted. For a small number of missing observations in total tourist visits, nonlinear fitting is used to estimate and impute values to ensure the feasibility of the analysis.

Regarding missing data, most variables are fully reported across the 16 cities and 12-year sample period. Missing values appear in only two variables. First, total industrial smoke (dust) emissions—the intermediate input used to derive tourism-related smoke and dust emissions via proportional allocation—are missing for 26 city-year observations (13.5% of 192 city-year cells). The missing entries are concentrated in the post-2020 period: 2020–2022 for seven cities (Chizhou, Fuyang, Bozhou, Lu'an, Bengbu, Wuhu, and Huaibei), 2021–2022 for Huangshan and Huainan, and 2022 for Xuancheng. This pattern primarily reflects delays in environmental statistics compilation and reporting adjustments during the COVID-19 pandemic, rather than being driven by the unobserved emission levels themselves. Conditional on city and year fixed effects, the missingness is therefore plausibly random (MAR). Second, greening and landscaping investment is missing for two interior observations (Tongling 2021 and Anqing 2015, 1.04%).

For the interior gap (Anqing 2015), linear interpolation based on the two neighboring years is applied. For the terminal-year gaps in 2021–2022, values are projected using the city-

specific linear trend estimated from the two immediately preceding years (e.g., 2019–2020 for 2021). Although the pandemic introduced economic volatility, industrial smoke emissions exhibit strong short-term persistence at the city level; the imputed values fall within each city's historical range and do not produce structural outliers.

To assess whether these imputed values materially influence the final results, we re-estimate the full analysis after excluding the 26 observations with imputed industrial-emission values. The panel fixed-effects model with city-specific slopes is re-run on the resulting complete-case sample ($n = 166$ city-years). All coefficient signs remain identical to the baseline estimation, and no predictor changes its significance status at the 5% level. The provincial TEE trajectory derived from the complete-case subsample correlates at Pearson $r = 0.998$ with the baseline series. As a further check, we compute an alternative TEE series using last-value-forward imputation for the 26 observations; the correlation with the baseline TEE exceeds 0.995, and no city-year observation shifts its relative efficiency quartile. The negligible impact is attributable to the fact that the imputed observations, although accounting for 13.5% of the industrial-emission variable, are distributed across eight cities and multiple years, preventing any single unit from dominating the city-specific slope estimates. All other variables are complete.

3. Results

3.1. Temporal Evolution

Using Equation (1) and MaxDEA (Version 8.0, Beijing, China), TEE for Anhui Province and its 16 cities is estimated; results are presented in Figure 2.

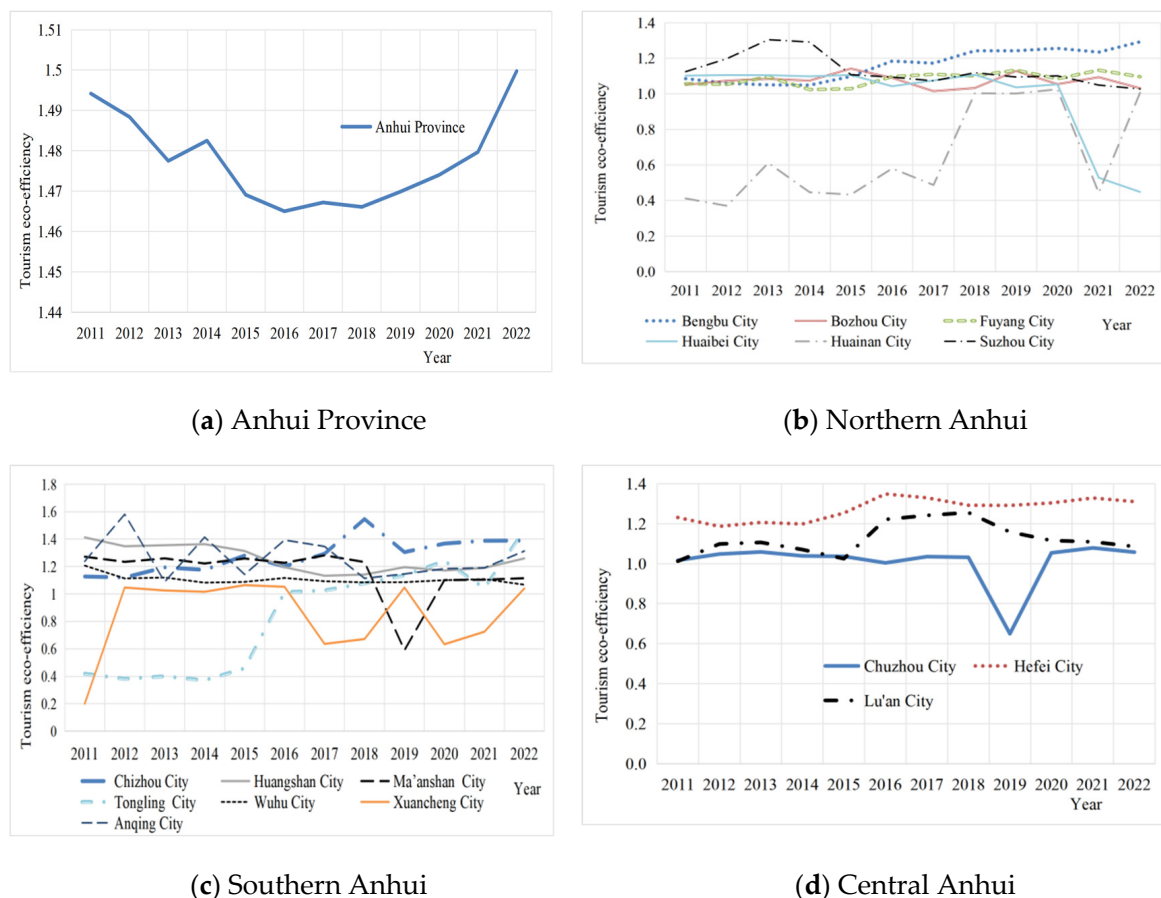


Figure 2. Temporal Evolution of Tourism Eco-efficiency.

Figure 2a shows that TEE in Anhui Province exhibited a fluctuating pattern during 2011–2022. In 2011, the efficiency score was 1.494, indicating a relatively high level and suggesting an initial foundation for coordination between tourism development and ecological protection. From 2012 to 2016, TEE declined overall; a slight rebound occurred in 2014, followed by another decline in 2015, reaching a low point of 1.465 in 2016. This sustained downturn may reflect increasing pressure on tourism-related ecological management during that period. After 2017, TEE began to rise; the rebound in 2017–2018 was more evident, followed by a decline in 2019. TEE continued to increase in 2020–2021 and reached the highest observed value of 1.500 in 2022. Overall, TEE showed a fluctuating upward trend over the sample period, indicating an overall improvement in tourism-related ecological management in the province. It is worth noting that the provincial-level TEE scores (1.465–1.500) are consistently above unity and higher than typical values reported in many SBM-based tourism eco-efficiency studies. Two methodological features account for this. First, the provincial TEE is not a simple average of city scores; rather, it is computed by aggregating all 16 cities' inputs and outputs into a single provincial decision-making unit (DMU) and then applying the super-efficiency SBM model to this aggregate. Aggregation across heterogeneous cities tends to reduce input and output slacks relative to the best-practice frontier, pushing the aggregate DMU closer to or beyond the efficiency threshold—a well-established property of DEA whereby aggregate efficiency can exceed the mean of individual DMU efficiencies. Second, within a single-province sample, the 16 cities share comparable statistical reporting standards and economic structures; the resulting homogeneity of the reference set narrows the efficiency frontier and makes it comparatively easier for the aggregate DMU to attain super-efficiency scores. By contrast, studies using national multi-province samples typically include structurally diverse DMUs, which produce a more demanding frontier and yield lower average efficiency scores.

For a more representative picture of municipal performance, city-level statistics should be examined. Across the 192 city-year observations (16 cities $\times$ 12 years), the overall mean city-level TEE is 1.078, and the median is 1.101. City-specific 12-year means range from 0.652 (Huainan) to 1.282 (Chizhou), with 12 of 16 cities recording mean scores above 1.0 and four cities (Huainan, Tongling, Xuancheng, and Huaibei) falling below this threshold. These values align more closely with the range typically reported in provincial-scale super-efficiency SBM studies, confirming that the provincial-level figures, while methodologically valid, reflect aggregation effects rather than uniformly high performance across all cities.

Figure 2b shows heterogeneous fluctuations in TEE across cities in Northern Anhui. Bengbu exhibited an overall upward trend; Bozhou showed large volatility; Fuyang generally increased but with fluctuations; Huaibei fluctuated noticeably; Huainan's TEE was relatively low with large swings; Suzhou generally increased but with limited stability. These differences suggest divergence across Northern Anhui in tourism resource allocation, industrial structure, and environmental management capacity: some cities achieved sustained improvements, while others faced persistent coordination challenges between tourism development and ecological protection.

Figure 2c shows that Southern Anhui cities also displayed differentiated dynamics. Chizhou generally increased; Huangshan had large volatility; Ma'anshan generally increased but showed a marked decline in 2019; Tongling had relatively low TEE with pronounced fluctuations; Wuhu was relatively stable but fluctuated in certain years; Xuancheng had relatively low TEE with large fluctuations; Anqing generally increased with stage-specific swings. These features indicate that differences in resource endowments, industrial bases, and environmental constraints lead to differentiated TEE trajectories across Southern Anhui.

Figure 2d shows distinct trends for Chuzhou, Hefei, and Lu'an in Central Anhui. Chuzhou showed a fluctuating upward trend; Hefei remained at a relatively high level with fluctuations, but a downward fluctuation in recent years may be associated with environmental pressures accompanying tourism scale expansion; Lu'an increased initially and then tended to stabilize, with late-stage declines possibly indicating that tourism development approached a stage-specific equilibrium and that further improvements require industrial upgrading and governance optimization to break through bottlenecks. Overall, differentiated trends in Central Anhui reflect differences in development strategies and constraints across cities.

3.2. Spatial Characteristics Analysis

Anhui Province is divided into Northern, Central, and Southern sub-regions based on geographical, economic, and cultural differences, providing a basis for analyzing spatial differentiation in TEE. According to Theil index results (Figure 3a), overall disparity in TEE is mainly driven by within-region differences, whereas between-region differences contribute less. This pattern may be related to unevenness across cities within the same region in resource endowments, economic development, infrastructure, and policy implementation capacity. For example, although Southern Anhui is resource-rich overall, some locations, such as Huangshan and Xuancheng, have more mature tourism development, while others, such as Chizhou and Tongling, lag behind, leading to notable within-region gaps. Northern and Central Anhui also exhibit within-region divergence due to differences in economic foundations and government support. The relatively small between-region disparity may, to some extent, indicate enhanced provincial coordination in tourism development. In recent years, provincial-level measures—such as integrated planning, regional cooperation, optimization of cross-regional tourism routes, and strengthened ecological supervision—may have provided policy support for narrowing inter-regional gaps. In addition, continuous improvements in expressway and high-speed rail networks have enhanced accessibility and may have facilitated coordinated tourism development.

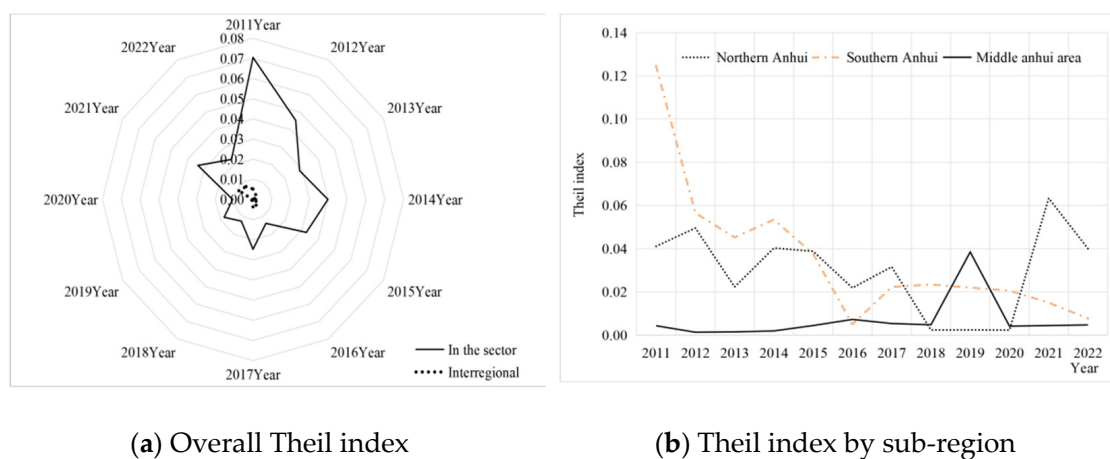


Figure 3. Spatial Distribution of Tourism Eco-efficiency.

From the sub-regional results (Figure 3b), the Theil index differs notably across Northern, Southern, and Central Anhui. Northern Anhui's Theil index is relatively low in most years, but exhibits stage-specific peaks in 2017 (0.032) and 2021 (0.063), possibly indicating instability during its TEE improvement process. Southern Anhui's Theil index is relatively stable and remains low in most years, decreasing from 0.125 in 2011 and stabilizing around 0.02, suggesting a relatively balanced TEE development trajectory. Central Anhui's Theil

index shows some fluctuations but stays at a low level overall, rising and falling slightly from 0.004 in 2011, which may reflect relatively steady TEE development.

A map produced using ArcGIS (Version 10.8, ESRI, Redlands, CA, USA) (Figure 4) shows the spatial distribution of average TEE for the 16 cities over 2011–2022, characterized by “higher in the south, lower in the north, and a central uplift.” In Southern Anhui, Huangshan and Xuancheng have the highest values, likely benefiting from abundant natural and cultural resources and relatively mature development and management mechanisms, enabling better coordination between tourism development and ecological protection. Huangshan may rely on world-class landscapes and brand effects, while Xuancheng may leverage sound ecological environments and cultural characteristics, together forming relatively sustainable tourism development patterns. In Central Anhui, TEE is relatively high with Hefei as the core, potentially due to the provincial capital’s economic strength, innovation capacity, and policy agglomeration effects that support smart tourism and green transition; Lu’an and Chuzhou may also benefit from close linkages with Hefei [45]. In contrast, Northern Anhui cities such as Suzhou, Huaipei, Bengbu, Bozhou, Fuyang, and Huainan tend to have lower values. This region is more reliant on traditional heavy industries such as coal; the industrial structure is relatively single, resource dependence is strong, tourism investment is insufficient, and development levels are relatively low. Tourism resources are also relatively less diversified, and high-quality products are insufficient to attract high-end demand, which may jointly constrain TEE improvement [21].

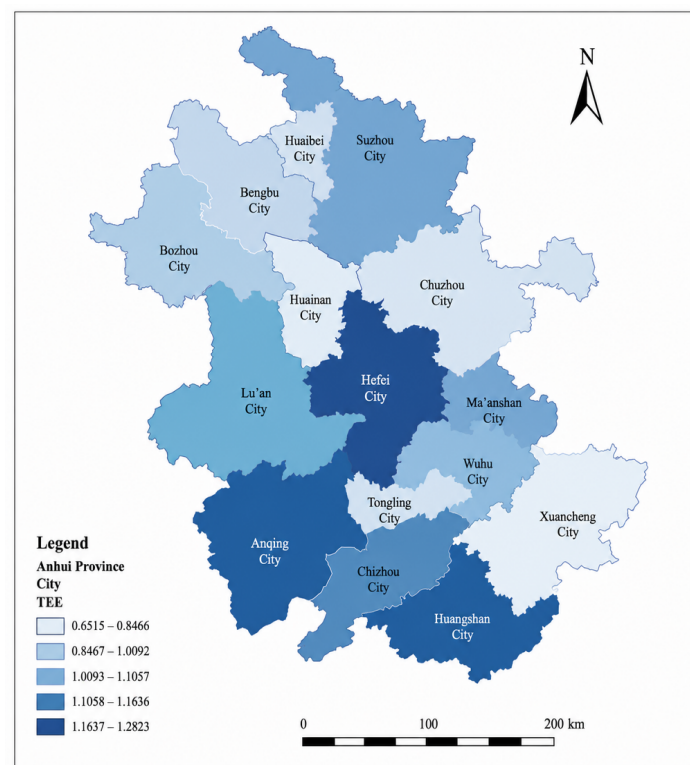


Figure 4. Spatial distribution of average Tourism Eco-efficiency across 16 cities.

3.3. Influencing Factors of Tourism Eco-Efficiency in Anhui Province

3.3.1. Model Tests

To determine the appropriate model specification, statistical tests are conducted for the panel model. The F-test indicates significant individual effects ($F = 11.770$, $p = 0.000$). The Hausman test rejects the null of random effects ($\text{Chi}(5) = 49.730$, $p = 0.000$). Therefore, a panel variable-coefficient fixed-effects model is adopted. After selecting the fixed-effects framework, additional diagnostics are performed for multicollinearity, heteroskedasticity,

and serial correlation to ensure reliable estimation and inference. Specifically: (1) variance inflation factors (VIF) are computed and fall within commonly used thresholds, suggesting no severe multicollinearity; (2) the Modified Wald test indicates groupwise heteroskedasticity; (3) the Wooldridge test indicates first-order serial correlation. Given these results and the prefecture-level panel structure, the baseline regressions use city-clustered robust standard errors (cluster-robust at the city level). All estimations and diagnostic tests were performed using Stata (Version 17.0, StataCorp, College Station, TX, USA). Diagnostic results are reported in Table 3.

Table 3. Diagnostic Test Results.

Test Type	Method of Calibration	Statistics	<i>p</i> Value	Conclusion and Treatment Approach
Multicollinearity	VIF	Mean: 3.42 Maximum: 6.18	—	Below the low threshold of 10; no severe multicollinearity exists
Heteroscedasticity	Modified Wald test for groupwise heteroskedasticity	$\chi^2(16) = 247.35$	0.000	The null of homoskedasticity is rejected; city-clustered robust standard errors are used
Serial correlation	Wooldridge test for first-order autocorrelation	$F(1, 15) = 12.84$	0.003	The null of no autocorrelation is rejected; city-clustered robust standard errors are used

3.3.2. Results Analysis

Under the above specification, the panel variable-coefficient fixed-effects model is estimated. The estimated results for the influencing factors of TEE in Anhui Province are reported in Table 4.

(1) Divergent effects of scale, affluence, and agglomeration: development stages and carrying constraints coexist

Table 4 suggests substantial heterogeneity across cities in how scale and affluence variables affect TEE: $\ln(\text{resident population})$, $\ln(\text{per capita disposable income})$, and $\ln(\text{GDP per capita})$ do not exhibit uniformly positive effects but rather diverge depending on development stages and resource–environment carrying capacities. In core cities such as Hefei, these variables show significantly positive relationships (e.g., Hefei: $\ln(\text{per capita disposable income})$ 0.673; $\ln(\text{resident population})$ 0.768; $\ln(\text{GDP per capita})$ 0.821), indicating that in cities with larger markets, higher incomes, and more efficient factor allocation, income growth and population concentration can be converted into improvements in TEE through market expansion, improved service supply, and enhanced management capacity.

By contrast, many cities show significantly negative coefficients on scale and affluence variables (e.g., Bozhou, Anqing, Chuzhou, Wuhu), implying that tourism development in these areas may still follow an “expansion–consumption” pattern: population and income growth primarily reflect demand expansion and rising resource use, without being matched by sufficient technological progress or governance improvement that would raise green productivity, thereby inhibiting TEE.

Notably, the agglomeration indicator $\ln(\text{population density})$ also varies in sign across cities. For example, Huangshan shows significantly negative coefficients on $\ln(\text{resident population})$ and affluence variables ($\ln(\text{resident population})$ -0.761 ; $\ln(\text{GDP per capita})$ -0.804 ; $\ln(\text{per capita disposable income})$ -0.586), but a significantly positive coefficient on $\ln(\text{population density})$ (2.023). This suggests that “scale expansion” and “agglomeration

effects” operate through different mechanisms: in cities with strong resource–environment constraints or high tourism development intensity, simple expansion may intensify environmental pressures, whereas higher spatial agglomeration may, under certain conditions, yield efficiency gains by improving public service provision efficiency, reducing transport and transaction costs, and strengthening industrial-chain coordination. Overall, the divergence in sign indicates that improving TEE in Anhui depends less on scale expansion or income growth per se and more on whether growth is transformed into efficiency-oriented structural optimization and governance upgrading.

Table 4. Estimated results of influencing factors for tourism eco-efficiency (TEE).

City	Influencing Factors							
	Ln(Per Capita Disposable Income)	Ln(Permanent Resident Population)	Ln(Share of R&D Expenditure in GDP)	Ln(Annual Electricity Consumption)	Ln(GDP per Capita)	Ln(Internet Users per 10,000 People)	Ln(Population Density)	Ln(Share of Tertiary Industry Value Added in GDP)
Bozhou city	−0.342 ***	−0.391 ***	−0.269 ***	0.385 ***	−0.337 ***	−0.723 ***	−0.747 ***	−1.048 ***
Lu'an City	0.089 ***	−0.02 ***	−0.04 ***	−0.565 ***	0.226 ***	−0.076 ***	0.048 ***	0.275 ***
Hefei City	0.673 ***	0.768 ***	0.556 ***	−0.792 ***	0.821 ***	−6.849 ***	−1.027 ***	1.258 ***
Anqing City	−0.228 ***	−0.281 ***	−0.024 ***	−0.008 ***	−0.176 ***	−1.331 ***	0.469 ***	−0.491 ***
Xuancheng City	−0.042 ***	−0.043 ***	−0.032 ***	0.169 ***	−0.125 ***	−0.898 ***	−0.047 ***	−0.379 ***
Suzhou City	−0.142 ***	−0.159 ***	−0.176 ***	0.321 ***	−0.264 ***	−0.125 ***	0.066 ***	−0.526 ***
Chizhou City	0.455 ***	0.407 ***	0.362 ***	−0.885 ***	0.652 ***	8.023 ***	−0.425 ***	1.87 ***
Huaibei City	−0.113 ***	−0.096 ***	−0.27 ***	0.955 ***	−0.579 ***	−7.742 ***	−0.585 ***	−0.467 ***
Huainan City	0.247 ***	0.292 ***	0.125 ***	−0.867 ***	0.679 ***	16.192 ***	−1.315 ***	0.696 ***
Chuzhou City	−0.144 ***	−0.171 ***	−0.111 ***	0.081 ***	−0.063 ***	−1.664 ***	−0.377 ***	−0.247 ***
Wuhu City	−0.057 ***	−0.065 ***	−0.053 ***	0.088 ***	−0.072 ***	−0.877 ***	−0.027 ***	−0.087 ***
Bengbu City	0.132 ***	0.16 ***	0.041 ***	−0.285 ***	0.311 ***	−0.621 ***	−0.124 ***	0.551 ***
Tongling City	0.662 ***	0.744 ***	0.651 ***	−1.73 ***	0.23 ***	6.367 ***	0.755 ***	1.69 ***
Fuyang City	−0.112 ***	−0.129 ***	−0.169 ***	−0.035 ***	−0.025 ***	−0.902 ***	0.264 ***	−0.106 ***
Ma'anshan City	−0.085 ***	−0.098 ***	−0.027 ***	0.157 ***	−0.122 ***	−0.386 ***	−0.147 ***	−0.186 ***
Huangshan City	−0.586 ***	−0.761 ***	−0.099 ***	0.954 ***	−0.804 ***	−12.908 ***	2.023 ***	−2.288 ***

Note: *** indicate significance at the 1% level. Values are coefficient estimates.

(2) More complex mechanisms in technology and structural dimensions: energy use and digital-to-green conversion efficiency as key constraints

For technology- and structure-related variables, ln(R&D intensity), ln(annual electricity consumption), ln(internet indicator), and ln(tertiary-industry share) exhibit stronger cross-city differences, reflecting issues of path dependence and conversion efficiency in technological inputs, energy utilization, and industrial upgrading.

First, the energy-consumption variable shows strong constraining effects. In many cities, ln(annual electricity consumption) is negative (e.g., Hefei −0.792; Chizhou −0.885; Tongling −1.73; Huainan −0.867), indicating that at the current stage, expanding energy use is often associated with higher environmental costs and thus suppresses TEE. However, three cities—Bozhou, Huaipei, and Huangshan—exhibit positive coefficients that caution

against overgeneralizing the “energy inhibits TEE” claim. For Bozhou and Huaibei, both located in Northern Anhui with relatively lower levels of economic development and electrification, the positive sign likely reflects a low-base energy catch-up effect: at early development stages, modest increases in electricity consumption accompany improvements in tourism infrastructure and service quality—such as upgraded accommodation, enhanced scenic area operations, and expanded digital services—that contribute positively to tourism revenue and efficiency before energy use reaches a threshold where marginal environmental costs dominate. For Huangshan, a leading tourism destination where the service sector dominates the local economy, the positive coefficient may reflect a sectoral composition effect: electricity consumption is disproportionately channeled into tourism-related services rather than energy-intensive manufacturing, meaning higher electricity use is more directly coupled with tourism output. These exceptions underscore that the energy–efficiency relationship is not uniform but is mediated by a city’s development stage and economic structure; the overall pattern—negative in most cities, positive in a few—reinforces rather than contradicts the finding that energy constraints are a common bottleneck, while highlighting that the nature of this constraint is conditional on local context.

Second, innovation inputs do not have uniformly positive effects. $\ln(\text{R\&D intensity})$ is significantly positive in cities such as Hefei and Tongling (Hefei 0.556; Tongling 0.651) but significantly negative in cities such as Bozhou, Suzhou, Huaibei, and Huangshan (e.g., Bozhou -0.269 ; Suzhou -0.176 ; Huaibei -0.27 ; Huangshan -0.099). This suggests that the impact of R&D on TEE depends heavily on the direction of investment and the efficiency of outcome conversion: when R&D targets energy saving, emission reduction, cleaner production, and green service provision, positive effects are more likely; otherwise, if R&D is less aligned with tourism’s low-carbon transition or faces weak conversion, it may not translate into TEE gains.

Third, the digitalization variable is significantly negative in many cities (e.g., Hefei -6.849 ; Huaibei -7.742 ; Huangshan -12.908 ; while Huainan shows a positive coefficient that requires city-specific discussion). Overall, this implies that “expanding digital infrastructure” does not automatically increase TEE. It may increase resource–environment pressures by expanding travel and consumption and accelerating visitor concentration. It may also reflect insufficient depth of digital applications in energy management, smart governance, and green supply-side transformation, causing an unstable coupling between digitalization and greening.

Finally, the structural upgrading variable $\ln(\text{tertiary-industry share})$ is clearly heterogeneous. It is significantly positive in cities such as Hefei, Chizhou, and Tongling (Hefei 1.258; Chizhou 1.87; Tongling 1.69), suggesting that a higher service-sector share can improve TEE by improving factor allocation and lowering resource use per unit of output in some cities. However, it is significantly negative in cities such as Huangshan and Bozhou (Huangshan -2.288 ; Bozhou -1.048), indicating that “advanced industrial structure” does not automatically imply “green industrial structure.” The effect depends on the internal composition of the tertiary sector (e.g., the share of producer services and low-carbon services) and how it synergizes with tourism.

While the preceding analysis interprets R&D intensity and tertiary-industry share as exogenous determinants of TEE within the STIRPAT framework, the potential for reverse causality deserves explicit acknowledgment, particularly in core cities such as Hefei, Tongling, and Chizhou. In these cities, persistently high TEE may itself encourage further R&D investment by signaling profitable opportunities in green technology and cleaner production; likewise, a thriving, eco-efficient tourism sector can stimulate demand for modern producer services, thereby endogenously raising the tertiary-industry share. Be-

cause Table 4 reports significantly positive coefficients for both R&D intensity (e.g., Hefei 0.556; Tongling 0.651) and tertiary-industry share (e.g., Hefei 1.258; Tongling 1.69) in these cities, the estimated relationships likely capture a mixture of forward and reverse linkages rather than purely unidirectional causal effects. City and year fixed effects address time-invariant omitted variables and common macro shocks, but they do not fully resolve time-varying simultaneity. Readers should therefore interpret the influencing-factor coefficients as conditional associations indicative of co-evolutionary dynamics, and policy conclusions regarding R&D and industrial structure should be treated as suggestive rather than definitively causal.

3.3.3. Robustness Checks

To further validate baseline results, Driscoll–Kraay robust standard errors are reported to address potential impacts of heteroskedasticity and serial correlation on statistical significance, and a two-way fixed-effects model with common slopes is used as an alternative specification for sensitivity comparison. Robustness results are shown in Table 5. Notably, the common-slope specification in column (3) of Table 5 reports a negative coefficient for permanent resident population, whereas the city-specific estimates in Table 4 reveal markedly mixed signs (e.g., significantly positive in Hefei and Tongling but significantly negative in Bozhou, Anqing, and Xuancheng). This contrast illustrates that the common-slope FE masks substantial cross-city heterogeneity and underscores precisely why the variable-coefficient model is preferred for this analysis. Overall, the directions of effects for the other core explanatory variables remain consistent with the main conclusions, indicating satisfactory robustness.

Table 5. Results of Robustness Tests.

Variable	Varying-Coefficient FE		Two-Way FE with Common Slopes (Benchmark)
	(1) City-Clustered Robust SEs	(2) Driscoll–Kraay Robust SEs	(3) City-Clustered Robust SEs
Ln(Per capita disposable income)	0.142 *** (0.032)	0.142 ** (0.056)	0.118 ** (0.048)
Ln(Permanent resident population)	−0.056 (0.041)	−0.056 (0.058)	−0.039 (0.045)
Ln(Share of R&D expenditure in GDP)	0.089 ** (0.038)	0.089 * (0.049)	0.062 (0.042)
Ln(Annual electricity consumption)	−0.103 *** (0.029)	−0.103 *** (0.031)	−0.087 ** (0.035)
Ln(GDP per capita)	0.178 *** (0.045)	0.178 ** (0.072)	0.095 (0.068)
Ln(Internet users per 10,000 people)	0.065 * (0.034)	0.065 (0.048)	0.058 (0.039)
ln(Population density)	0.021 (0.028)	0.021 (0.035)	0.018 (0.030)
Ln(Share of tertiary industry value added in GDP)	0.092 ** (0.037)	0.092 ** (0.041)	0.076 * (0.040)
City fixed effects	Yes	Yes	Yes

Table 5. *Cont.*

Variable	Varying-Coefficient FE		Two-Way FE with Common Slopes (Benchmark)
	(1) City-Clustered Robust SEs	(2) Driscoll–Kraay Robust SEs	(3) City-Clustered Robust SEs
Year fixed effects	Yes	Yes	Yes
Observations	192	192	192

Note: Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (2) are variable-coefficient fixed-effects models, with column (1) using city-clustered robust standard errors and column (2) using Driscoll–Kraay robust SEs to correct for heteroskedasticity, cross-sectional dependence, and serial correlation; column (3) is a two-way fixed-effects model with common slopes as a comparison, also using city-clustered robust SEs. Given $T = 12$, Driscoll–Kraay SEs may have small-sample bias and are provided for robustness reference only.

4. Discussion

4.1. Overall Consistency of Results and Sources of Provincial Disparities

Based on the super-efficiency SBM results, TEE in Anhui Province exhibits an overall fluctuating upward trend and a spatial pattern of “higher in the south, lower in the north, with a central uplift.” This conclusion is broadly consistent with mainstream findings in prior research on tourism green/eco-efficiency at provincial and city scales in China, which commonly emphasize significant spatial imbalance and gradient-like distribution patterns [46]. In terms of mechanisms, existing studies often attribute such patterns to differences in resource endowments, industrial structure, and the strength of environmental regulation, as well as the advantages of central cities in factor agglomeration and public service provision [47]. Evidence from Anhui supports that these mechanisms remain relevant at the provincial scale.

More importantly, the Theil index decomposition indicates that overall disparity is driven primarily by within-region differences rather than between-region differences. Compared with studies emphasizing that “inter-regional gradient differences” (e.g., east–central–west or core–periphery) dominate [48], the present finding aligns more with studies arguing that “city differentiation within the same region” is decisive [49]. Possible reasons for differences across studies include: (i) differences in spatial scale (national multi-region vs. single province) affecting decomposition weights; (ii) differences in measurement methods and indicator systems (e.g., inclusion of undesirable outputs, use of super-efficiency, consideration of environmental constraints) altering relative city positions and disparity sources; and (iii) the possibility that during the sample period, the “speed of divergence” across cities within the province in terms of industrial transition and governance capacity exceeded the pace of convergence in inter-provincial disparities, increasing the contribution of within-group differences. The marginal contribution of this study is thus to provide evidence—under a measurement framework incorporating undesirable outputs—that “intra-provincial differentiation dominates,” implying that explanation and policy design should more explicitly identify city-level constraints that lead to “different efficiency within the same region.”

These findings can be contextualized by comparing them with tourism eco-efficiency studies in other Chinese regions. At the broader Yangtze River Delta (YRD) scale, Ma et al. documented that the YRD urban agglomeration exhibits a clear east-high, west-low spatial pattern characterized by “high–high agglomeration, low–low agglomeration,” with Anhui cities within the YRD concentrated in lower efficiency tiers during the earlier years of the study period [19]. Similarly, Fang et al. confirmed this YRD spatial configuration and further demonstrated that the Pearl River Delta urban agglomeration displays a distinct pattern centered on the eastern Pearl River estuary, reflecting a different spatial logic shaped

by core–periphery structures within each city cluster [20]. At the individual province scale, Zhao et al. found that Shaanxi Province TEE follows a central-plain > southern-mountain > northern-plateau gradient, while Wu et al. showed that Fujian Province TEE exhibits a northeast–southwest spatial orientation with Xiamen as the dominant high-efficiency core [22,23]. Studies on Henan Province report that within-region differences constitute the main source of overall TEE disparity—a decomposition pattern consistent with the Anhui finding [24]. At the national level, Fu and Zhang analyzed the spatial association network of tourism eco-efficiency across 30 Chinese provinces from 2011 to 2022, finding a persistent “dual-core” structure centered on the Beijing–Tianjin–Hebei and Yangtze River Delta regions, with eastern coastal provinces occupying core network positions while northeastern, northwestern, and southwestern provinces remain peripheral—a pattern reflecting profound regional imbalances in tourism resource allocation and technology diffusion [17]. Notably, Anhui was identified as one of only nine provinces consistently maintaining high closeness centrality in the national TEE network, serving as a key bridge node between the eastern core and central/western regions. This dual identity—a bridging province in the national TEE network yet internally characterized by a stark north–south gradient—reinforces the argument that spatial heterogeneity in tourism eco-efficiency operates at multiple scales and that single-province studies can reveal within-unit dynamics that national-level analyses necessarily overlook.

Compared with these patterns, Anhui presents a distinct spatial configuration: its TEE gradient is north–south rather than coastal–inland, and the dominance of within-region over between-region disparities—while shared with some provinces—is a feature less emphasized in multi-province national studies. This suggests that within-province institutional and structural factors—such as differential industrial transition speeds, varying local government capacity for environmental governance, and uneven tourism infrastructure investment—play a more decisive role in shaping TEE heterogeneity in Anhui than in provinces with more homogeneous economic structures.

From an international perspective, comparable sub-national heterogeneity has been documented in tourism destinations across large emerging economies. Studies on Mediterranean mass tourism destinations in Spain have shown that even within a single coastal region, hotels exhibit substantially different resource efficiency levels depending on scale, facility configuration, and management models, with large high-rise hotels benefiting from economies of scale in resource use while smaller establishments face efficiency disadvantages [28]. This pattern parallels the core–periphery divergence observed in Anhui, where Hefei and other central cities achieve higher TEE partly through agglomeration economies, while peripheral cities struggle with resource conversion efficiency. However, the Anhui case reveals a deeper level of heterogeneity: within a single province, cities at different development stages exhibit fundamentally different efficiency responses to the same driving forces—a granularity of sub-national variation less commonly documented in European studies, which typically focus on national-level or regional-level averages. This finding underscores the importance of city-tailored policy approaches, a recommendation that may have relevance beyond China for other large emerging economies with substantial internal heterogeneity.

4.2. Divergent Directions of Scale and Affluence Effects: From “Average Effects” to “Conditional Effects”

The panel variable-coefficient results show that the effects of population scale and affluence-related variables on TEE are heterogeneous across cities and not uniform in direction. This directly engages with studies using traditional fixed-coefficient/average-effect models, which often reach a single-direction conclusion, such as “economic development promotes green efficiency” or “scale expansion suppresses green efficiency,” yet with un-

stable findings across samples and specifications [50]. The present results suggest that such “inconsistencies” do not necessarily imply estimation bias; they may reflect real conditional and stage-specific effects.

Consistent with research emphasizing economies of scale and agglomeration effects in improving green efficiency [51], the present study finds positive effects of scale and affluence on TEE in some core cities with relatively stronger economic bases and public service provision capacities, indicating that when governance capacity, environmental management capability, and industrial upgrading foundations are stronger, scale expansion can promote TEE through improved management efficiency, higher value-added supply, and technology diffusion, lowering environmental pressure per unit of output. Meanwhile, negative effects in other cities align with the “scale–pressure” logic (increased travel, higher energy use in accommodation and catering, stressed environmental carrying capacity) and associated negative externalities [52]. Therefore, the key contribution is not to label scale/affluence as “good” or “bad,” but to show that their impacts on TEE depend on three conditions: (1) development stage and governance capacity; (2) the intensity of environmental carrying constraints; and (3) whether demand upgrading is matched by high-quality supply and low-carbon governance capacity. In other words, the variable-coefficient evidence helps integrate seemingly contradictory conclusions in existing literature within a more interpretable framework: cities under different condition combinations exhibit different marginal effects in direction and magnitude. This conditional-effects perspective finds resonance in the international tourism literature. Research on environmental efficiency in European tourism destinations has increasingly moved away from uniform-effect assumptions, recognizing that the relationship between tourism scale and environmental performance is mediated by destination-specific characteristics such as infrastructure quality, energy mix, and governance capacity [9]. For instance, studies on water efficiency in Spanish Mediterranean hotels have demonstrated that larger establishments achieve higher per-guest resource efficiency through economies of scale in facility management—yet this scale advantage does not automatically translate to overall eco-efficiency unless accompanied by proactive environmental management practices [28]. Similarly, cross-national analyses of tourism eco-efficiency in European regions have found that the efficiency dividend of tourism growth is conditional on regional innovation capacity and environmental policy stringency, echoing the three conditions identified in this study: development stage, carrying constraints, and governance capacity. Anhui’s variable-coefficient evidence thus contributes to this international literature by demonstrating that such conditionality operates not only across countries or regions but also across cities within a single province, highlighting the importance of local absorptive capacity in mediating scale–efficiency relationships.

4.3. Constraints on “Green Conversion” of Technology and Structural Factors

Regression results show heterogeneous signs and significance for R&D, digitalization, and industrial structure variables across cities, while expansion of energy consumption (electricity use) exhibits a significant inhibiting effect in most cities. Prior studies differ on whether technological progress/digitalization necessarily promotes green efficiency: one view argues that innovation and digitalization improve resource allocation efficiency and reduce emission intensity, thus enhancing green performance [53]; another view highlights lagged effects, misalignment, and rebound effects, implying that in the short run, technology investment may induce scale expansion and offset energy-saving benefits [54]. The cross-city heterogeneity results provide “compatible evidence” for both: technology and digitalization are not inherently promoting or inhibiting; their impacts depend on whether a closed loop of “input–conversion–governance–performance” is formed.

Specifically, positive effects of R&D are more likely in cities where green-technology orientation is clear, conversion channels are smooth, and environmental regulation and performance assessment provide constraints. If R&D is less related to tourism's low-carbon governance, or if conversion is lagged, it may not show up statistically as improved TEE. Digitalization similarly operates as a double-edged sword: when it is mainly used for visitor organization and marketing expansion without synchronized energy management, transport dispatching, and capacity control, short-term effects may be negative or insignificant; when digitalization is embedded into "smart governance–energy saving and emission reduction–service upgrading," it is more likely to generate efficiency gains. This logic resonates with studies emphasizing "technology–institution synergy" or "governance-capacity thresholds" [55].

At the same time, the electricity-consumption variable is negative in Hefei, Tongling, Chizhou, Huainan, Bengbu, Fuyang, Lu'an, and Anqing. The magnitude of negative coefficients is generally larger than that of positive coefficients, and the direction remains consistent under robustness checks, indicating that energy consumption expansion remains a common bottleneck for tourism's green transition in the province. This is consistent with research treating energy constraints as a "hard constraint" for improving green efficiency [56] and helps explain why some cities do not show efficiency improvements even with increased technology/digitalization inputs: if energy structure and energy-efficiency improvements lag, the benefits may be offset by expanding energy use.

This "digitalization paradox" in tourism eco-efficiency has been observed internationally. Chen et al., using panel data from 275 Chinese prefecture-level cities, found that while the digital economy can enhance tourism eco-efficiency through technological, structural, and resource allocation effects, its benefits are heterogeneous and contingent on local absorptive capacity and complementary infrastructure [27]. Zeqiri et al. further argued that digital tourism platforms in the Industry 4.0 era generate dual environmental effects: on one hand, smart energy management and optimized logistics reduce per-unit resource consumption; on the other hand, algorithm-driven demand stimulation and reduced search costs can induce additional travel, expanding the aggregate environmental footprint [57]. Anhui's city-level evidence reveals an additional layer of this paradox: the negative digitalization coefficients observed in less-developed cities such as Huangshan and Huaibei suggest that where digital applications remain focused on marketing and booking rather than deep operational optimization, induced tourism demand may outpace environmental management capacity. This finding reinforces the emerging international consensus that digitalization's environmental benefits are not automatic but depend on whether digital tools are embedded into "smart governance–energy saving–service upgrading" closed loops—a precondition that mirrors the "technology–institution synergy" emphasized in European smart tourism research.

4.4. Differentiated Pathways Are More Effective than One-Size-Fits-All Policies

The above discussion indicates a coexistence of "common constraints + heterogeneous mechanisms" in enhancing TEE in Anhui: energy consumption expansion commonly suppresses TEE, while the effects of scale, affluence, and technology variables depend strongly on city-specific conditions and conversion chains. This aligns with regional green governance research emphasizing "classification-based and city-specific policies," as policy effectiveness hinges on whether it matches local development stages, industrial structures, and ecological carrying capacities [58]. The variable-coefficient evidence also supplements studies that still adopt "average effects–uniform prescriptions" in policy discussions: under substantial heterogeneity, uniform policies may lead to diminishing marginal returns or even directionally biased outcomes, making it difficult to explain divergence in local

performance after policy implementation. A more feasible policy logic is, at the provincial level, to establish a unified action direction centered on energy efficiency improvements and low-carbon substitution (e.g., tourism transport decarbonization and end-use energy optimization) to address common bottlenecks; at the city level, implement differentiated governance aligned with local development stages, carrying constraints, and industrial structures to improve policy matching and conversion efficiency.

5. Conclusions

5.1. Summary of Findings

Based on panel data for 16 prefecture-level cities in Anhui Province from 2011 to 2022, this study measures TEE using a super-efficiency SBM model incorporating undesirable outputs, decomposes disparity sources using the Theil index, and identifies cross-city heterogeneity in influencing factors using a panel variable-coefficient fixed-effects model. The findings indicate that TEE in Anhui Province shows a fluctuating upward trend over the observation period, but city-level disparities are substantial. The spatial pattern is characterized by higher TEE in southern and central cities and lower TEE in northern cities. Overall disparity is driven mainly by intra-regional city differentiation rather than inter-regional differences among Northern, Central, and Southern Anhui. In terms of driving mechanisms, explanatory variables exhibit pronounced heterogeneity across cities, with no uniform linear relationship across the province. Population scale, income, and affluence variables positively promote TEE in core cities such as Hefei but constrain or inhibit TEE in many other cities such as Bozhou and Anqing. Agglomeration and scale expansion operate through different mechanisms: agglomeration can, under certain conditions, improve service provision efficiency and thus generate gains, whereas scale expansion may simply increase resource consumption pressure. The effects of technology investment and structural upgrading depend heavily on local conversion conditions; increases in R&D, digitalization, and the service-sector share are not universally effective. By contrast, expanding electricity consumption is a suppressing factor in most cities and represents a more universal hard constraint within the province.

5.2. Theoretical Implications

These findings carry several theoretical implications. First, the pronounced cross-city heterogeneity in driving factors challenges the widespread use of pooled-coefficient models in tourism eco-efficiency research: uniform average effects can mask real mechanism differences across cities, which may explain why prior studies using national or multi-province samples have reached inconsistent conclusions regarding the roles of economic development, industrial structure, and technology [19,22]. The variable-coefficient evidence thus supports moving from “average-effect” to “conditional-effect” frameworks in eco-efficiency research. Second, the finding that agglomeration and scale expansion operate through distinct mechanisms—with agglomeration potentially generating efficiency gains via improved service provision and knowledge spillovers, while simple scale expansion may increase resource-consumption pressure without commensurate efficiency dividends—adds conceptual precision to the tourism eco-efficiency literature, where “scale” and “agglomeration” have often been conflated. Third, the results caution against equating industrial upgrading (rising tertiary-industry share) with greening: structural transformation only improves TEE when accompanied by low-carbon governance capacity and energy-efficiency improvements, a condition that varies substantially across cities.

5.3. Practical Implications

From a practical standpoint, these findings suggest a two-tier policy approach. At the provincial level, the common constraint—energy consumption—warrants a unified action framework: strengthening energy-efficiency standards for tourism transport and accommodation, accelerating renewable energy penetration in tourism facilities, and establishing provincial-level monitoring platforms for tourism-related energy and emissions. At the city level, one-size-fits-all policies should be replaced by differentiated governance. Leading cities (e.g., Hefei, Huangshan) should prioritize consolidating efficiency gains through green technology diffusion and demonstration effects to neighboring cities. Cities where scale and affluence variables show negative TEE impacts (e.g., Bozhou, Anqing) require demand-side management coupled with investment in environmental infrastructure to decouple tourism growth from resource consumption. Cities where digitalization coefficients are negative or insignificant need targeted interventions to deepen digital technology integration beyond marketing applications—focusing on smart energy management, intelligent transport dispatching, and real-time environmental monitoring—so that digital tools contribute to efficiency improvement rather than merely expanding tourism volume. The overarching principle is that policy instruments must be matched to local development stages, industrial structures, and ecological carrying capacities; copying pathways from more developed areas may yield diminishing or even counterproductive outcomes. Although the empirical findings are specific to Anhui, the analytical framework—combining super-efficiency SBM measurement, Theil-index decomposition, and variable-coefficient identification of heterogeneous driving factors—is readily transferable to other Chinese provinces and emerging-economy regions characterized by pronounced internal developmental gradients (e.g., Henan, Sichuan, inland Brazil, northern India), where pooled-coefficient approaches are similarly likely to mask cross-unit heterogeneity. The policy principle derived from this study—that common energy constraints warrant provincial-level coordination while structural and technological interventions require city-specific calibration—may also inform green tourism governance in comparable contexts.

5.4. Limitations and Future Research

5.4.1. Limitations

Several limitations should be acknowledged. First, tourism-specific environmental indicators (wastewater, SO₂, smoke/dust emissions) and tourism education expenditure are estimated via proportional allocation rather than obtained from direct statistical reporting, which may introduce measurement error, particularly in cities where the emission intensity of tourism diverges from the city-wide average. Second, although the variable-coefficient model effectively captures cross-city heterogeneity, it estimates time-averaged city-specific slopes and cannot identify temporal shifts in the direction or magnitude of effects within individual cities. Third, the single-province focus, while enabling granular intra-provincial analysis, constrains external validity; the findings may not generalize directly to provinces with substantially different tourism structures or development levels. Fourth, the input indicator system does not include tourism-dedicated energy consumption or tourist transport fuel use—two variables central to the conceptual definition of eco-efficiency—owing to the absence of sector-disaggregated energy statistics at the prefecture level in China. While electricity consumption is examined as an influencing factor in the second-stage analysis, the inability to incorporate direct energy inputs into the DEA framework means that the measured TEE scores may overstate efficiency by not fully accounting for the energy dimension of tourism's environmental pressure. This limitation is shared by most city-level tourism eco-efficiency studies in China and represents a priority area for improvement as statistical systems evolve. Finally, the nonexperimental panel design limits causal

interpretation; despite robustness checks, residual concerns regarding omitted variables and reverse causality remain.

5.4.2. Future Research Directions

To address these limitations, several extensions are warranted. At the data level, future studies could incorporate micro-level or scenic-area-level energy and emissions data, or leverage emerging city-level tourism satellite accounts, to reduce reliance on proportional allocation and improve measurement accuracy. Methodologically, stronger causal identification strategies—such as instrumental variables exploiting exogenous policy shocks, difference-in-differences designs leveraging pilot low-carbon tourism policies, or spatial difference-in-differences to capture cross-city spillovers—would strengthen the evidence base. A dynamic panel framework allowing time-varying coefficients could further reveal whether city-level efficiency responses evolve over different development stages. Spatially, extending the analytical framework to other Yangtze River Delta provinces would enable cross-provincial validation of the conditional-effects perspective and provide comparative evidence for regional low-carbon tourism transitions. Finally, incorporating tourism-dedicated energy consumption data, should such data become available at the city level, would substantially improve the precision and policy relevance of future eco-efficiency assessments.

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