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Evaluation of Operational Efficiency in China's Provincial Tourism Based on the SBM-DEA Model

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Abstract: *As China's tourism industry transitions toward a high-quality development, evaluating operational efficiency (OE) is critical for ensuring long-term industry sustainability. Using the Slacks-Based Measure (SBM) model, this study assesses the operational efficiency of 30 Chinese provinces from 2017 to 2023. The input indicators include the number of hotels, tourist attractions, travel agencies, and employees, while the outputs comprise tourism revenue and tourist arrivals. The empirical results indicate that overall efficiency leaves significant room for improvement in resource utilization. Temporally, the industry demonstrated a robust recovery, characterized by a pronounced efficiency rebound in 2023. Spatially, distinct heterogeneity exists: the central and western regions maintained relatively stable performance levels, while the Eastern region exhibited high revenue despite input redundancies. The Northeast consistently lagged behind. Furthermore, the analysis identifies multi-dimensional inefficiencies, specifically input redundancy in developed provinces and output insufficiency in other regions. Consequently, policy interventions should prioritize optimized resource allocation and enhanced regional cooperation to bridge these efficiency gaps.*

Keywords: *Tourism Operating Efficiency, SBM-DEA Model, Input-Output Analysis*

1. Introduction

The tourism industry has evolved into a strategic pillar of China's national economy, playing a pivotal role in optimizing industrial structures and stimulating domestic consumption. According to the 14th Five-Year Plan for Tourism Development issued by the State Council, the sector is currently transitioning from high-speed growth to high-quality development. Despite the severe shocks imposed by the global health crisis, the industry has demonstrated remarkable resilience. Recent data from the Ministry of Culture and Tourism of the People's Republic of China indicates a robust recovery[1]. In 2024, domestic tourism trips reached 5.615 billion, representing a year-on-year increase of 14.8%, while domestic tourism revenue surged to RMB 5.75 trillion, a 17.1% increase compared to the previous year[2]. Given this context, evaluating the operating efficiency of tourism across different provinces is not merely an academic exercise but a practical necessity for enhancing regional competitiveness and ensuring sustainable growth.

In this study, the operational efficiency (OE) is defined as the economic capability of a region to maximize tourism output under a given level of resource investment. This definition aligns with the perspective of Assaf and Josiassen, who characterize efficiency as the optimal transformation of inputs into market-valued outputs[3]. Furthermore, recent scholars emphasize that efficiency is not solely about numbers but also about resource allocation. As noted by Chaabouni (2019), operational efficiency in the tourism sector reflects the comprehensive ability of a region to utilize its natural and man-made endowments effectively to generate economic value[4]. In this study, the operational efficiency of tourism is specifically evaluated based on the input-output ratio within the provincial administrative framework.

In existing studies, the focus on tourism efficiency has expanded significantly, with Data Envelopment Analysis (DEA) emerging as the dominant methodological tool. For example, Li et al. utilized traditional DEA models to map the efficiency of China's star-rated hotels[5]. More recently, researchers have shifted towards non-radial models to account for slack variables. For instance, Wang and Zhou applied the Slacks-Based Measure (SBM) model to evaluate the operating efficiency and spatial-temporal evolution of tourism across China's three major economic belts, revealing pronounced

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regional imbalances[6]. Although the existing research content is quite extensive, there is still an urgent need for new empirical evidence to meet the timeliness requirements of tourism efficiency research. This study, by strictly focusing on the heterogeneity of operational efficiency across Chinese provincial tourism from 2017 to 2023, provides a detailed perspective on how different provinces adjust their resource allocation to improve efficiency.

2. Literature Review

2.1 DEA Method

Data Envelopment Analysis, first introduced by Charnes et al., has evolved into a widely adopted method for evaluating relative efficiency among decision-making units (DMUs) using linear programming[7]. The foundational framework, known as the CCR model, was later extended by Banker et al. with the BCC model to account for variable returns to scale (VRS), allowing researchers to distinguish technical efficiency from scale efficiency[8]. However, these traditional radial models inherently overlook slack variables due to their assumption of proportional adjustments, which can compromise evaluation accuracy. To overcome this limitation, Tone proposed the SBM model[9]. Unlike its predecessors, the SBM model explicitly incorporates input and output slacks, enabling a more precise quantification of non-proportional inefficiencies. Consequently, the SBM approach provides a more rigorous basis for performance evaluation and has been increasingly applied within the tourism sector[10-11].

2.2 Domestic and International Research Review

International scholars initially utilized Data Envelopment Analysis (DEA) to assess the operating efficiency of specific tourism units, such as hotels and travel agencies, before expanding to regional destinations. Early studies focused on performance heterogeneity among service providers. For instance, Martín, Mendoza, and Román García evaluated regional tourism competitiveness in Spain using a DEA framework, finding that performance scores exhibited substantial spatial heterogeneity, with large coastal regions consistently outperforming smaller, inland areas[12]. More recently, the scope has widened to the efficiency of regional tourism. Niavis and Tsiotas evaluated the efficiency of Mediterranean coastal regions, revealing distinct performance gaps between different geographic clusters[13]. Their findings suggest that tourism efficiency is not spatially uniform; rather, it displays significant regional heterogeneity where certain clusters consistently outperform others due to superior resource utilization. In China, research on tourism efficiency has developed rapidly, with scholars extensively applying DEA models to map efficiency distributions across provinces. Chaabouni employed a DEA model to evaluate the tourism efficiency of Chinese provinces, confirming a distinct core-periphery structure[4]. These findings revealed that eastern coastal provinces consistently exhibit higher operating efficiency compared to the Central and Western regions.

However, despite these contributions regarding spatial patterns, existing literature mostly relies on datasets ending before 2020. Unlike previous research focusing on regression analysis to identify influencing factors, this paper delineates the evolutionary trends of efficiency disparities from 2017 to 2023. This approach enables a clearer depiction of how operational efficiency varies among different provinces under external pressures, thereby filling the research gap during this critical period.

3. Methodology

3.1 Input and output indicators

The identification of input and output indicators is a fundamental prerequisite for employing DEA to assess the operational efficiency of tourism accurately. Scholarly consensus indicates that the selection of these indicators varies significantly across different empirical contexts [14-18]. Synthesizing existing literature with the operation process of the tourism sector, this study utilizes the number of star-rated hotels, number of A-grade tourist attractions, number of travel agencies, and number of tourism employees as the primary input indicators. These factors are universally acknowledged as the essential determinants of production capacity and operational efficiency in tourism. Correspondingly, total tourism revenue and total tourist arrivals are considered as output indicators, serving as direct proxies for the economic effectiveness and service output magnitude of provincial tourism systems.

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3.2 Operational efficiency estimation in SBM-DEA model

To evaluate the OE of tourism across China's provinces, this study treats provinces as n independent Decision-Making Units (DMUs). The regional tourism operation process transforms resource endowments into market outcomes. Specifically, the input indicators comprise star-rated hotels (*XH*), A-grade tourist attractions (*XC*), travel agencies (*XA*), and tourism employees (*XL*). These inputs are utilized to yield two primary outputs: total operating tourism revenue (*YO*) and the number of tourists received (*YV*). This selection of input-output variables aligns with the prior tourism literature [16,18].

Regarding the methodological framework, the SBM model is adopted. Distinct from traditional radial DEA approaches, the SBM model is non-radial, allowing for the direct identification of inefficiencies by calculating the specific "input redundancy" and "output insufficiency" to maximize slacks[9]. Given its superior capability in revealing the true sources of inefficiency, the SBM model has gained extensive application in tourism performance assessment[4]. The specific efficiency evaluation model is presented as equation (1).

$$\begin{aligned}
&\theta_0 = \min \frac{1-\frac{1}{4}\left(\frac{s_{\mathrm{h}}^-}{XH_0}+\frac{s_c^-}{XC_0}+\frac{s_a^-}{XA_0}+\frac{s_l^-}{XL_0}\right)}{1+\frac{1}{2}\left(\frac{s_o^+}{YO_0}+\frac{s_v^-}{YV_0}\right)} \\
&\text{s.t.} \quad \sum_{j=1}^{n}\lambda_j XH_j + s_{\mathrm{h}}^- = XH_0, \qquad \sum_{j=1}^{n}\lambda_j XA_j + s_a^- = XA_0, \\
&\qquad \sum_{j=1}^{n}\lambda_j XC_j + s_c^- = XC_0, \qquad \sum_{j=1}^{n}\lambda_j XL_j + s_l^- = XL_0, \\
&\qquad \sum_{j=1}^{n}\lambda_j YO_j - s_o^+ = YO_0, \qquad \sum_{j=1}^{n}\lambda_j YV_j - s_v^+ = YV_0, \\
&\qquad \sum_{j=1}^{n}\lambda_j = 1, \\
&\qquad \lambda_j, s_h^-, s_c^-, s_a^-, s_l^-, s_o^+, s_v^+ \geq 0,\ j=1,2,...,n.
\end{aligned} \tag{1}$$

In equation (1), the subscript 0 denotes the evaluated DMU. $s_h^-, s_c^-, s_a^-, s_l^-, s_o^+, s_v^+$ are slack variables, referring to *XH*, *XC*, *XA*, *XL*, *YO*, and *YV*. λ denotes the intensity variable, meaning the participation degree of each DMU in constructing the optimal production frontier. The objective value θ_0 denotes the operational efficiency for the evaluated DMU, ranging from 0 to 1. Notably, equation (1) is nonlinear, which makes it difficult to obtain the optimal solution. To address this issue, it can be transformed into a linear programming model.

4. Empirical Result

4.1 Sample and data source

To ensure research validity, data on hotels, tourist attractions, travel agencies, employees, and tourist arrivals are collected from the China Cultural and Tourism Statistical Yearbook, while data on tourism revenue is obtained from the Annual Tourism Reports of the provinces. Based on data availability, 30 Chinese provinces were ultimately selected as the research sample.

4.2 Overall analysis of operational efficiency

The OE results for the Chinese provinces from 2017 to 2023 are listed in Table 1. The data reveal year-on-year fluctuations and significant disparities between provinces. Overall, the mean operational efficiency during the observed period is 0.6220, which underscores considerable room for overall efficiency improvement.

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Table 1: Operational efficiency of 30 provinces from 2017 to 2023.

	2017	2018	2019	2020	2021	2022	2023	2017-2023
Beijing	0.1304	0.2869	0.1632	0.3749	0.5528	0.3876	1.0000	0.4137
Tianjin	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Hebei	0.1374	0.4435	0.4274	0.4737	0.4882	0.3752	0.8041	0.4499
Shanxi	0.6452	1.0000	1.0000	1.0000	0.6066	0.4148	0.4799	0.7352
Inner Mongolia	0.1665	0.1844	0.1569	0.3289	0.2369	0.2053	0.3227	0.2288
Liaoning	0.1208	0.3326	0.2988	0.3364	0.4406	0.3054	0.4849	0.3313
Jilin	0.6386	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9484
Heilongjiang	0.1072	0.2210	0.2153	0.3585	0.3071	0.2800	0.3869	0.2680
Shanghai	0.3054	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9008
Jiangsu	0.1812	1.0000	1.0000	1.0000	1.0000	1.0000	0.6818	0.8376
Zhejiang	0.1260	0.3752	0.2676	1.0000	0.3272	0.3173	0.2896	0.3861
Anhui	0.1578	0.4320	0.4051	0.5824	0.6154	0.6242	1.0000	0.5453
Fujian	0.1617	0.4225	0.3517	0.6304	0.5825	0.6215	0.6298	0.4857
Jiangxi	0.2971	0.5493	0.5422	1.0000	1.0000	1.0000	1.0000	0.7698
Shandong	0.1163	0.3165	0.2746	0.4058	0.4774	0.3842	0.3993	0.3392
Henan	0.1845	0.4809	0.3252	0.6338	1.0000	0.4584	1.0000	0.5833
Hubei	0.1627	0.3826	0.3149	0.5694	0.6952	0.7193	0.6418	0.4980
Hunan	1.0000	0.5168	0.4366	1.0000	0.6845	1.0000	0.6479	0.7551
Guangdong	0.1728	1.0000	1.0000	0.2620	0.2588	0.2008	0.2750	0.4528
Guangxi	0.0950	0.5158	0.5296	1.0000	1.0000	1.0000	1.0000	0.7344
Hainan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Chongqing	0.4812	0.6589	0.6991	1.0000	0.2067	0.2047	0.1833	0.4906
Sichuan	0.4272	0.6119	0.3794	0.6333	0.4706	1.0000	1.0000	0.6461
Guizhou	0.8100	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9729
Yunnan	0.0332	1.0000	0.6468	1.0000	1.0000	1.0000	1.0000	0.8114
Shaanxi	0.1625	0.4587	0.4042	0.4498	0.4362	0.4218	0.6183	0.4216
Gansu	1.0000	1.0000	1.0000	1.0000	0.3718	0.1693	0.3699	0.7016
Qinghai	0.0955	0.2722	1.0000	1.0000	1.0000	1.0000	1.0000	0.7668
Ningxia	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Xinjiang	0.0866	0.1736	0.1859	0.2227	0.2058	0.1615	0.2668	0.1861
Mean	0.3668	0.6212	0.6008	0.7421	0.6655	0.6417	0.7161	0.6220

From a temporal perspective, the annual OE can be categorized into three distinct phases that reflect major shifts in the tourism operating environment. During the pre-pandemic phase (2017-2019), the average OE demonstrated a fluctuating upward trend. Specifically, the OE value stood at 0.3668 in 2017, surged to 0.6212 in 2018, and subsequently stabilized at 0.6008 in 2019. During the pandemic disruption period (2020-2022), OE trends became more volatile. Despite adverse external conditions, the average OE peaked at 0.7421 in 2020, potentially due to the implementation of short-term adaptive strategies or a significant reduction in input redundancy. However, this progress was not sustained, as the OE declined to 0.6655 in 2021 and further to 0.6417 in 2022, indicating inconsistent performance under the prolonged impact of the public health crisis and regulatory restrictions. In the post-pandemic recovery phase, represented by 2023, a pronounced rebound in operational efficiency was observed. The average OE rose to 0.7161, standing as one of the highest values recorded over the seven-year period. This marked improvement suggests a robust recovery in operational effectiveness, driven by the resurgence of market demand, tactical operational adjustments, and enhanced managerial capabilities. This notable increase underscores the resilience and adaptive capacity of the tourism industry.

4.3 Efficiency analysis from a region perspective

According to the classification of the National Bureau of Statistics of China, the country is divided into four major regions: the eastern, central, western, and northeast regions. This geographical distinction enables a comprehensive analysis of regional disparities that influence the operational efficiency of provincial tourism.

The provinces examined in this study are categorized as follows: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan are located in the Eastern region; Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan are categorized in the Central region; Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang are situated in the Western region; and Liaoning, Jilin, and Heilongjiang comprise the Northeast region. Variations in operational efficiency across these four regions from 2017 to 2023 are illustrated in Figure 1.

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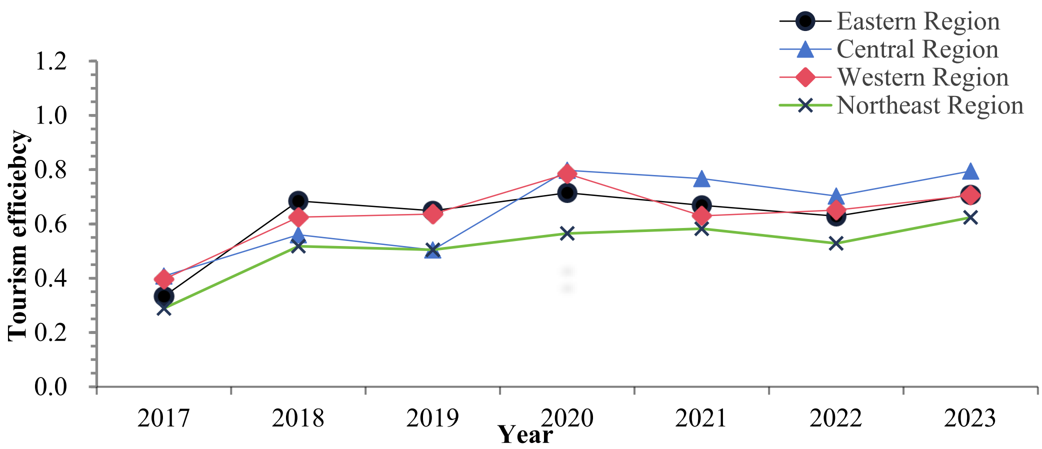

Figure 1: Average operational efficiency of provinces in four regions.

Throughout the observation period, regional disparities are evident. Contrary to typical economic patterns, the Central region exhibits the highest average efficiency (0.6477), slightly surpassing the Eastern and Western regions, while the Northeast region consistently lags (0.5159).

In the pre-pandemic phase, the Eastern and Western regions showed upward trends, whereas the Central and Northeast regions fluctuated. During the pandemic phase, the Central and Western regions demonstrated a strong initial recovery in performance, peaking in 2020 before declining, while the Eastern region suffered a continuous downturn due to stringent travel restrictions. In the post-pandemic phase (2023), a universal rebound occurred, driven by robust market recovery. The Central region maintained its leadership, rising to 0.7949, while the Eastern, Western, and Northeast regions also achieved significant improvements. Notably, the efficiency levels of the Eastern, Central, and Western regions are converging within a higher range, indicating that regional disparities among major tourism hubs are narrowing over time.

4.4 Input and output improvement analysis

To further enhance operational efficiency, this study conducts a detailed input and output improvement potential analysis of 16 inefficient provinces in 2023. The corresponding results are presented in Table 2.

Table 2: Improvement ratios of input and output variables in 16 inefficient provinces in 2023.

DMU	Score	Input				Output	
		Hotels	Tourist attractions	Travel agencies	Employees	Tourism revenue	Tourist arrivals
Hebei	0.8041	-1.84%	0.00%	-12.48%	-30.44%	17.38%	3.51%
Shanxi	0.4799	0.00%	-11.89%	-3.68%	-11.33%	122.17%	66.54%
Inner Mongolia	0.3227	-6.73%	-12.78%	-11.07%	0.00%	172.12%	200.28%
Liaoning	0.4849	-8.50%	-28.86%	0.00%	-43.07%	88.93%	40.60%
Heilongjiang	0.3869	0.00%	-57.38%	-26.50%	-41.27%	88.44%	66.74%
Jiangsu	0.6818	0.00%	-6.97%	-44.30%	-50.24%	13.63%	5.27%
Zhejiang	0.2896	-27.32%	-34.11%	-41.29%	-45.25%	108.63%	126.59%
Fujian	0.6298	-2.59%	-8.31%	0.00%	-30.54%	48.98%	35.71%
Shandong	0.3993	-27.14%	-49.23%	-41.05%	-62.32%	48.25%	27.54%
Hubei	0.6418	-14.87%	-21.24%	0.00%	-41.37%	45.34%	5.90%
Hunan	0.6479	0.00%	-29.20%	-6.35%	-71.05%	8.60%	17.83%
Guangdong	0.2750	-54.91%	-37.41%	-61.81%	-74.07%	0.00%	112.33%
Chongqing	0.1833	0.00%	-15.86%	-18.37%	-32.63%	363.36%	345.14%
Shaanxi	0.6183	-25.53%	-25.47%	0.00%	-46.03%	45.01%	0.00%
Gansu	0.3699	-48.53%	-31.24%	-12.68%	0.00%	167.64%	48.05%
Xinjiang	0.2668	-54.03%	-50.08%	0.00%	-24.08%	173.82%	135.57%
Mean	0.4676	-17.00%	-26.25%	-17.47%	-37.73%	94.52%	77.35%

Table 2 shows distinct resource misallocation and multi-dimensional inefficiency across provinces. In general, the 16 inefficient provinces exhibit an efficiency score of 0.4676, there is significant room for improvement. The mean improvement ratios reveal that Employee redundancy is the most critical input issue at -37.73%, while Tourism revenue generation remains the primary output bottleneck, requiring a 94.52% average increase to reach the effective level.

On the input side, substantial redundancies exist in Hotels and Tourist attractions. Guangdong and Xinjiang exceed 50% overinvestment in hotels, while Heilongjiang shows severe redundancy in Tourist attractions. Conversely, Shanxi and Chongqing achieve optimal Hotels utilization. Regarding Travel agencies and Employees, Guangdong requires significant reductions, whereas Liaoning and Shaanxi demonstrate optimal Travel agencies allocation. On the output side, Tourism revenue generation remains a bottleneck for many regions. Chongqing requires a 363.36% increase to reach the efficiency frontier, contrasting with Guangdong's optimal performance. Similarly, Tourist arrivals lag in Chongqing and Inner Mongolia, while Shaanxi aligns with the frontier. These complex efficiency issues necessitate that each province identifies an optimal, customized solution tailored to its specific conditions.

5. Conclusions

Based on the SBM-DEA model, this study evaluates the tourism operational efficiency of 30 Chinese provinces from 2017 to 2023. The results reveal an average efficiency score of 0.6220, suggesting that there remains significant room for improvement. However, the efficiency score rebounded to 0.7161 in the post-pandemic phase, which highlights the inherent resilience of the tourism industry. To further enhance operational efficiency, provinces should draw on successful precedents such as the "Integrated Tourism Development of the Yangtze River Delta" and strengthen cross-regional cooperation. Such efforts are essential to narrow the disparity between high-efficiency regions and lagging ones, thereby ensuring a more sustainable growth trajectory.

Furthermore, the findings reveal significant resource misallocation in certain provinces. Economically developed provinces exhibit substantial redundancy in infrastructure and labor, whereas other regions suffer from insufficient revenue generation despite a high number of tourist arrivals. Consequently, provinces should prioritize the optimization of factor allocation rather than the mere expansion of input scale. By implementing initiatives such as the “Night Economy” to stimulate tourist consumption, provinces can effectively improve the utilization efficiency of existing tourism resources.

Finally, although this study provides a rigorous quantitative analysis based on recent data, it acknowledges certain limitations regarding its predictive capacity. Future research should more comprehensively incorporate external environmental variables to elucidate their specific impacts and establish a predictive framework for the longitudinal evolutionary trends of provincial tourism efficiency.

References

[1] The State Council of the PRC. The 14th Five-Year Plan for Tourism Development [R]. Beijing: The State Council of the PRC, 2021.
[2] Ministry of Culture and Tourism of the PRC. 2024 Domestic Tourism Data Report [R]. Beijing: Ministry of Culture and Tourism of the PRC, 2025.
[3] Assaf A G, Josiassen A. Frontier analysis: A state-of-the-art review and agenda [J]. Tourism Management, 2016, 53: 45-56.
[4] Chaabouni S. China's regional tourism efficiency: A two-stage double bootstrap data envelopment analysis [J]. Journal of Destination Marketing & Management, 2019, 11: 183-191.
[5] Li H, Liu J, Tsai H. Total factor productivity growth and regional competitive analysis of China's star-rated hotels [J]. Tourism Economics, 2018, 24(4): 468-486.
[6] Wang H, Zhou B. Evaluation and spatial-temporal evolution of tourism efficiency in China's three belts using a super-efficiency SBM model [J]. Journal of Destination Marketing & Management, 2020, 17: 100454.
[7] Charnes A, Cooper W W, Rhodes E. Measuring the efficiency of decision making units [J]. European Journal of Operational Research, 1978, 2: 429-444.
[8] Banker R D, Charnes A, Cooper W W. Some models for estimating technical and scale inefficiencies in data envelopment analysis [J]. Management Science, 1984, 30: 1078-1092.
[9] Tone K. A slacks-based measure of efficiency in data envelopment analysis [J]. European Journal of Operational Research, 2001, 130: 498-509.
[10] Gao J, Shao C, Chen S. Evolution and driving factors of the spatiotemporal pattern of tourism efficiency at the provincial level in China based on SBM–DEA model [J]. International Journal of Environmental Research and Public Health, 2022, 19: 10118.

ISSN 2616-5902 Vol. 8, Issue 1: 163-169, DOI: 10.25236/AJBM.2026.080122

[11] Arana-Jiménez M, Lozano-Ramírez J, Sánchez-Gil M C, et al. A novel slacks-based interval DEA model and application [J]. Axioms, 2024, 13: 144.
[12] Martín J C, Mendoza C, Román García C. Regional Spanish tourism competitiveness: A DEA-MONITUR approach [J]. Region, 2017, 4(3): 153-173.
[13] Niavis S, Tsiotas D. Assessing the tourism performance of the Mediterranean coastal destinations: A combined efficiency and effectiveness approach [J]. Journal of Destination Marketing & Management, 2019, 14: 100379.
[14] Wang Y, Wang M, Li K, et al. Analysis of the relationships between tourism efficiency and transport accessibility: A case study in Hubei Province, China [J]. Sustainability, 2021, 13(15): 8649.
[15] Xue D, Li X, Ahmad F, et al. Exploring tourism efficiency and its drivers to understand the backwardness of the tourism industry in Gansu, China [J]. International Journal of Environmental Research and Public Health, 2022, 19(18): 11574.
[16] Liao Z, Liang S. Construction and evolutionary factors of spatial correlation network of China's provincial tourism resource conversion efficiency [J]. Heliyon, 2024, 10(2): e25032.
[17] Liao Z, Wang L. Spatial differentiation and influencing factors of red tourism resources transformation efficiency in China based on RMP–IO analysis [J]. Scientific Reports, 2024, 14(1): 10761.
[18] Yang C, Xia Y, Lam J F, et al. Analyzing the tourism efficiency and its influencing factors of China's coastal provinces [J]. PLOS ONE, 2024, 19(3): e0299772.