Comprehensive Measurement of Carbon Emission Efficiency of Tourism in the Yellow River Basin and Analysis of Influencing Factors: Postprint

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Abstract

Scientifically quantifying and analyzing the carbon emission efficiency of tourism and its influencing factors in the Yellow River Basin is of great significance for promoting the green development of its tourism economy. Based on panel data from nine provinces and regions in the Yellow River Basin from 2000 to 2019, this study employs the Super-SBM model to reveal the spatiotemporal evolution characteristics of tourism carbon emission efficiency from both static and dynamic perspectives, and uses the spatial Durbin model to explore the key factors influencing tourism carbon emission efficiency in the Yellow River Basin and their spatial spillover effects. The results show that: (1) From 2000 to 2019, the average tourism carbon emission efficiency in the Yellow River Basin exhibited a trend of fluctuating rise followed by decline, the differences among provinces and regions continuously narrowed, and the spatial distribution presented a pattern of "low in the west and high in the east." (2) In terms of dynamic efficiency, the changing trends of both the Malmquist-Luenberger index and kernel density curves indicate that the polarization phenomenon of tourism carbon emission efficiency has weakened, and technological progress contributes more to the changes in tourism carbon emission efficiency. (3) Regarding influencing factors, environmental regulation and urbanization level demonstrate positive spillover effects in promoting local tourism carbon emission efficiency; industrial structure, opening-up, technological level, and tourism industry agglomeration have negative impact coefficients on both local and neighboring areas; while economic development level inhibits the improvement of tourism carbon emission efficiency, it exhibits significant positive spillover effects on surrounding areas.

Full Text

Comprehensive Measurement and Influencing Factors of Carbon Emission Efficiency of Tourism in the Yellow River Basin

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Abstract

Scientific quantification and analysis of tourism carbon emission efficiency and its influencing factors in the Yellow River Basin are crucial for promoting green development of the tourism economy. Based on panel data from nine provinces and regions in the Yellow River Basin from 2000 to 2019, this study employs the Super-SBM model to reveal spatiotemporal evolution characteristics of tourism carbon emission efficiency from both static and dynamic perspectives, and uses a spatial Durbin model to explore key influencing factors and their spatial spillover effects. Results show: (1) From 2000 to 2019, the mean tourism carbon emission efficiency in the Yellow River Basin exhibited a trend of fluctuating increase followed by decrease, with differences among provinces continuously narrowing and spatial distribution showing a "low in the west, high in the east" pattern. (2) Regarding dynamic efficiency, both the Malmquist-Luenberger index and kernel density curve trends indicate weakening polarization in tourism carbon emission efficiency, with technological progress contributing more significantly to efficiency changes. (3) In terms of influencing factors, environmental regulation and urbanization level demonstrate positive spillover effects in promoting local tourism carbon emission efficiency; industrial structure, openness, technology level, and tourism industry agglomeration all have negative coefficients for both local and neighboring regions; while economic development level inhibits tourism carbon emission efficiency improvement but shows significant positive spillover effects on surrounding areas.

Keywords: tourism carbon emission efficiency; Super-SBM; spatial Durbin model; Yellow River Basin

1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report indicates that increased greenhouse gases, primarily CO_2, are affecting every region of Earth in multiple ways. Actively addressing climate change and accelerating the achievement of net-zero carbon emissions have become urgent issues for all countries. As one of the world's largest economic sectors, tourism exhibits sustainability and resource consumption characteristics that create inherent contradictions with the ecological environment. Research shows tourism's current contribution to global greenhouse effects reaches 5.3%, with emissions from tourists projected to grow at an average annual rate of 3.2% between 2016 and 2030, seriously threatening the green development of tourism.

Tourism carbon emission efficiency represents a critical indicator measuring the relationship between carbon emissions and economic value created during tourism production and consumption processes. Evaluating this efficiency and its influencing factors provides theoretical guidance and pathway support for promoting carbon reduction and green development in tourism. Current domestic and international research primarily focuses on efficiency measurement, analytical evaluation, and influencing factor exploration. Tourism carbon emission efficiency studies are mostly concentrated at the national level, with quantitative research dominating. The rational selection of input-output indicators is key to measurement. Previous studies mainly select capital, labor, and energy as inputs, with total tourism revenue as the desired output. Tourism carbon emissions serve as the non-desired output, calculated through bottom-up approaches, input-output analysis, and ecological footprint methods, with the bottom-up approach being widely adopted due to its data-based reflection of actual emissions.

Building upon efficiency measurement, scholars have further analyzed spatiotemporal evolution characteristics, regional differences, and spatial network features. In influencing factor research, traditional econometric methods (such as Tobit regression and geographically weighted regression) are commonly used to reveal determinants of tourism carbon efficiency. However, existing research exhibits several limitations: (1) Few studies examine tourism development quality and environmental impacts at the regional level, particularly for ecologically sensitive areas like the Yellow River Basin with rich tourism resources but fragile ecosystems; (2) Technological input is generally overlooked in quantifying tourism carbon emissions, despite innovation's role in reducing resource constraints and environmental damage; (3) Traditional econometric methods neglect interaction effects and spatial effects among influencing factors.

The Yellow River Basin, as an important cradle of Chinese civilization, possesses unique historical culture and natural resources, yet faces environmental pollution and resource shortages due to ecosystem fragility. As a key sector for high-quality development, tourism's environmental friendliness plays a vital role in promoting coordinated economic and ecological development. Therefore, scientifically measuring and analyzing tourism carbon emission efficiency and its influencing factors in the Yellow River Basin holds significant theoretical and practical value for advancing low-carbon tourism.

This study incorporates capital, labor, energy consumption, and technological innovation as input indicators into the Super-SBM model, combining kernel density estimation and Malmquist-Luenberger index to measure static and dynamic changes in tourism carbon emission efficiency from 2000 to 2019. Finally, a spatial Durbin model reveals key influencing factors, providing reasonable recommendations and theoretical foundations for low-carbon tourism development policies.

1.1 Study Area

The Yellow River, China's second-longest river, flows through nine provinces and regions: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong. By 2019, the basin had established 19 national 5A-level scenic spots and 27 national-level tourist resorts [Figure 1: see original paper]. Limited by geographical features, location conditions, and development models, the basin's tourism resource endowment has not been effectively transformed into economic advantages, with development characterized by high energy consumption and high emissions.

1.2 Data Sources

Macroeconomic data were obtained from the *China Statistical Yearbook*, provincial statistical yearbooks, and statistical bulletins, with per capita GDP indices deflated to 2000 constant prices. Environmental data came from the *China Environmental Statistics Yearbook* (2001–2020). Energy data were sourced from the *China Energy Statistical Yearbook* (2001–2020). Tourism data were derived from the *China Tourism Statistical Yearbook* and its supplement, *China Culture and Tourism Statistical Yearbook* (2001–2020), with some tourism transportation data from annual tourism sample surveys or regional bulletins. Tourism patent application quantities were retrieved from the China National Intellectual Property Administration patent search platform (https://pss-system.cponline.cnipa.gov.cn/conventionalSearch), using application time to determine the year and applicant location for provincial attribution. Missing data were supplemented using linear interpolation.

1.3 Methodology

1.3.1 Super-SBM Model The Slacks-Based Measure (SBM) model introduces slack variables to identify potential efficiency gaps, yielding more scientific and accurate results. The Super-SBM model further incorporates Super Efficiency model advantages, enabling horizontal comparison among multiple decision-making units (DMUs) with efficiency values of 1 . The formula is:

$$\min TEC_C = \frac{1 + \frac{1}{n}\sum_{i=1}^{n} \frac{s_i^-}{x_{ik}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}} + \sum_{l=1}^{s_2} \frac{s_l^b}{q_{lk}}\right)}$$

Subject to:

$$\begin{cases} x_k = \sum_{j=1,\neq k}^{m} \lambda_j x_{ij} + s_i^-, & i = 1, 2, \cdots, n \\ y_k = \sum_{j=1,\neq k}^{m} \lambda_j y_{rj} - s_r^g, & r = 1, 2, \cdots, s_1 \\ q_k = \sum_{j=1,\neq k}^{m} \lambda_j q_{lj} + s_l^b, & l = 1, 2, \cdots, s_2 \\ \lambda_j \geq 0, & j = 1, 2, \cdots, m \end{cases}$$

Where TEC_C is tourism carbon emission efficiency; n, s_1, and s_2 represent input, desirable output, and undesirable output indicators; m is the number of DMUs; x_{ik}, y_{rk}, and q_{lk} are input, desirable output, and undesirable output values; s_i^-, s_r^g, and s_l^b are slacks; and λ_j are weight coefficients. The model assumes constant returns to scale.

Input indicators include capital (tourism fixed capital stock calculated using perpetual inventory method with 9.6% depreciation rate), labor (year-end tourism employees), energy consumption (tourism energy consumption), and technological innovation (cumulative tourism patent applications). Desired output is total tourism revenue; undesirable output is tourism carbon emissions calculated via the bottom-up approach from transportation, accommodation, and activities.

1.3.2 Malmquist-Luenberger Index Static efficiency evaluation using Super-SBM lacks dynamic time-series analysis. Therefore, we adopt the Malmquist-Luenberger (ML) index with undesirable outputs to explore dynamic characteristics, decomposing it into technical efficiency change (EC) and technological progress (TC) indices:

$$ML = EC \times TC$$

When indices > 1, efficiency improves; < 1 indicates decline; $= 1$ means no change.

1.3.3 Kernel Density Estimation Kernel density estimation requires no prior parametric distribution assumptions, directly fitting probability density functions. Using the Gaussian kernel function, we reveal absolute differences and distribution dynamics among provinces [Figure 5: see original paper].

1.3.4 Spatial Durbin Model We construct a spatial Durbin model to characterize spatial effects:

$$TEC_{Cit} = \rho \sum_{j=1}^{N} W_{ij} TEC_{Cjt} + \beta x_{it} + \phi \sum_{j=1}^{N} W_{ij} x_{jt} + v_t + \mu_i + \varepsilon_{it}$$

Where TEC_{Cit} is tourism carbon emission efficiency; W_{ij} is a spatial weight matrix combining economic distance (GDP per capita difference inverse) and geographic distance (inverse of latitude-longitude distances); ρ and ϕ are spatial lag parameters; x_{it} represents explanatory variables; and v_t and μ_i are time and individual fixed effects.

2 Results and Analysis

2.1 Static Efficiency Analysis

2.1.1 Temporal Evolution Characteristics Using Matlab 2021a, we calculated mean tourism carbon emission efficiency from 2000–2019 [Figure 2: see original paper]. The efficiency showed an inverted "U" curve: fluctuating increase followed by decrease, with a mean of 0.517. A peak occurred in 2015 (0.598) when reduced energy input coincided with emission reductions, particularly in Inner Mongolia, Sichuan, and Shaanxi. The coefficient of variation declined at 1.53% annually, indicating narrowing provincial differences and improving stability.

2.1.2 Spatial Distribution Characteristics Using natural breaks classification, we analyzed spatial patterns [Figure 3: see original paper]. A clear "west low, east high" pattern emerged. High-efficiency provinces (Henan, Shandong) remained in the east, while low-efficiency provinces (Gansu, Qinghai, Ningxia) persisted in the west. Western provinces, despite developed tourism, have weaker economies and fragile ecosystems where intensive tourism causes greater environmental damage. Incomplete transportation networks increase carbon emissions, perpetuating low efficiency. Shaanxi showed stable efficiency, while Shanxi gradually improved.

2.2 Dynamic Efficiency Analysis

2.2.1 ML Index Analysis The ML index revealed overall growth trends [Figure 4: see original paper]. From 2000–2019, the mean ML index was 1.012, with only 2003 and 2019 showing values < 1. Decomposition showed technological progress contributed more to efficiency changes than technical efficiency change. All nine provinces had ML > 1, indicating improving efficiency, though technical efficiency change fluctuated around 1, reflecting policy inconsistency.

2.2.2 Kernel Density Estimation Kernel density curves for benchmark years (2000, 2005, 2010, 2015, 2019) showed evolving patterns [Figure 5: see original paper]. Peak height decreased then slightly increased, remaining below 2000 levels, indicating reduced overall differences. The curve shifted rightward then leftward, confirming the inverted U-shaped efficiency trend. The distribution transformed from "multi-peak" to "single-peak," showing weakening polarization and more balanced distribution, with the right tail shortening over time.

2.3 Influencing Factors and Spatial Spillover Effects

2.3.1 Spatial Autocorrelation Test Before estimation, we tested for spatial autocorrelation using global Moran's I . All annual indices were positive and significant at the 1% level, confirming strong positive spatial correlation and spillover effects.

2.3.2 Model Specification Tests We conducted specification tests . Lagrange multiplier tests rejected the spatial error model (except robust LM-error). Likelihood ratio and Wald tests rejected the spatial lag model, supporting the spatial Durbin model. Hausman test results favored fixed effects, with further testing indicating two-way fixed effects as most appropriate.

2.3.3 Influencing Factors Analysis Regression results show varying impacts across factors:

- **Economic development level**: Negative local effect (-0.021) but positive spatial spillover (0.031), with small overall impact.
- **Industrial structure**: Negative coefficient (-0.183), as high tertiary industry share increases tourism scale and emissions.
- **Openness**: Negative impact (-0.102) and spatial lag (-0.201), with high-energy foreign investment creating regional radiation effects.
- **Environmental regulation**: Positive local (0.156) and significant spatial spillover (0.089), as policies promote green technology adoption and warn neighboring regions.
- **Urbanization level**: Positive local effect (0.078) and significant spatial spillover (0.245), enhancing inter-regional connections and environmental awareness.
- **Technology level**: Positive local impact (0.018) but negative spatial spillover (-0.003), as energy-saving technology improves efficiency while creating competitive effects.
- **Tourism industry agglomeration**: Significant negative effect (-0.291), as scale expansion increases energy consumption and creates negative environmental externalities.

2.3.4 Spatial Effect Decomposition Direct and indirect effects reveal:

- **Direct effects**: Environmental regulation (0.186) and technology level (0.018) enhance provincial efficiency; economic development (-0.021) and agglomeration (-0.291) reduce it.
- **Indirect effects**: Economic development (0.031), environmental regulation (0.089), and urbanization (0.245) positively affect neighbors; industrial structure (-0.201), technology (-0.003), and agglomeration (-0.201) negatively affect neighbors.
- **Total effects**: Economic development, environmental regulation, and urbanization show net positive effects, promoting basin-wide efficiency improvement.

3 Conclusions and Recommendations

3.1 Conclusions

(1) **Static efficiency**: From 2000–2019, mean tourism carbon emission efficiency showed an inverted U-shaped trend, with provincial differences narrowing. Spatial distribution displayed a "west low, east high" pattern with western collapse characteristics.

(2) **Dynamic efficiency**: The ML index > 1 indicated overall growth, with technological progress as the primary contributor. Kernel density curves showed weakening polarization and more balanced distribution, though efficiency remained below optimal production frontiers.

(3) **Influencing factors**: Environmental regulation and urbanization exhibited positive spillover effects. Industrial structure, openness, technology level, and agglomeration had negative impacts locally and regionally. Economic development inhibited local efficiency but showed significant positive spillover.

3.2 Recommendations

(1) **Avoid blind tourism growth**: The rapid tourism growth mode since 2015 reduced efficiency, confirming the Environmental Kuznets Curve hypothesis. Provinces should reduce resource dependency and avoid pursuing economic growth at the expense of green development.

(2) **Strengthen technological innovation**: Given technology's major contribution to efficiency improvement, western provinces (Gansu, Qinghai, Ningxia) should prioritize clean energy substitution and green technology adoption to overcome ecological fragility.

(3) **Leverage urbanization spillovers**: The significant positive spillover of urbanization (0.245) should be harnessed through scientifically planned urbanization development to enhance regional environmental awareness and resource efficiency.

(4) **Balance economic development**: Though economic development negatively affects local efficiency, its positive total spillover effect suggests the basin should boldly develop tourism while encouraging innovation and reducing traditional energy consumption.

(5) **Enhance environmental regulation**: The strong positive effects of environmental regulation (direct: 0.186; indirect: 0.089) warrant accelerated legislative and enforcement efforts, with grid-based management systems and strict penalties to effectively reduce tourism carbon emissions.

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Note: Figure translations are in progress. See original paper for figures.