A Study on Static and Dynamic Provincial-level Measurements of Tourism Industry Efficiency in China -Based on Malmquist-Luenberger Index and SBM-DEA models

Yuyao Liu

The University of Hong Kong

yuyaoliu6@gmail.com

**Abstract:** While existing studies have considered economic inputs and outputs into the industrial efficiency measurement models for eco-tourism industries in China, few of them have put environment inputs such as natural resources and outputs such as carbon emission into account. This study applies the tourism stripping factor method to measure provincial tourism carbon emissions and innovatively employs the Malmquist-Luenberger and SBM-DEA models with unfavorable outputs to evaluate the eco-efficiency of China's provincial tourism industry by adding input and output variables reflecting environmental factors. The study found that, unlike the results from traditional models without unfavorable outputs, which showed a slight downward trend in pure economic efficiency, the industrial efficiency including the environmental factors of 31 Chinese provinces showed an upward trend through the static analysis, representing an increase in the eco-efficiency of the tourism industry. The tourism industrial efficiency values in each region evaluated dynamically are less volatile than the results from traditional models, which may support the moderating effect of the technological upgrading of China's green industry on the efficiency of the tourism industry. Theoretical and empirical findings of this research are also illustrated.

**Keywords:** Industry efficiency, Malmquist-Luenberger Index, SBM-DEA model, Tourism stripping Factor method, Eco-tourism, China

# Introduction

Data from the China Bureau of Statistics 2019 shows that the value added of China's tourism and related industries was RMB 449.89 billion in 2019, accounting for 4.56% of gross domestic product (GDP), with tourism and entertainment, tourism and accommodation, and integrated tourism services growing rapidly by 12.9%, 10.4% and 10.0% respectively. However, the rapid growth of tourism has also burdened on the environment. The report released by the World Tourism Organization in 2019 shows that global carbon emissions from tourism transport are expected to climb to 1,998 million tonnes by 2030, up from 1,697 million tonnes in 2019. These figures imply that carbon emissions from tourism transport will reach 5.3% of total man-made carbon emissions and account for around 23% of carbon emissions from the transport sector. China's tourism sector accounts for 3.17% and 5.76% of China's carbon emissions and the world's carbon emissions from tourism respectively (Zhang, 2016). In the context of China's double carbon policy, improving the environmental and economic efficiency of the tourism industry is an important part of promoting the sustainability of Chinese economies.

Nevertheless, existing measures of tourism industry efficiency in China mainly focus on the pure economic efficiency of the tourism industry, considering only economic input and output variables, without including variables reflecting the environmental impact of the tourism industry. Furthermore, while many existing literatures put attentions on regional changes in tourism industry efficiency, few of them analyzed the dynamics of industrial efficiency change at the provincial level in China. This paper aims to refine and optimize the model used by existing studies measuring tourism industry efficiency by taking into account environmental factors in terms of inputs and outputs, and innovatively uses the SMB-DEA model with unexpected outputs and the Malmquist-Luenberger index to measure static and dynamic changes in tourism industry efficiency at the provincial level respectively. Empirical findings of this paper may contribute to the macro-level analysis of tourism industry efficiency in China. The measurement methods of this study may also bring theoretical references to quantify the eco-efficiency of the tourism industry in China.

# Review of Literature

Existing studies measuring tourism industry efficiency can be categorized, in terms of the geographical dimension of the study area, into the following two groups: international (transnational) tourism, and domestic tourism in China.

## International (transnational) tourism

Meng-Chun et al. (2011) were among the first researchers to statically analyze the efficiency of international tourism development in 31 regions of China through a non-parametric data envelopment analysis (DEA) model. They employed the number of travel agents and employees as input variables and variables such as the number of international tourists and foreign exchange earnings as output variables. These researchers found that among 31 regions in China, Beijing, Shanghai and Guangdong exhibit economies of scale in terms of static tourism efficiency. Assaf et al. (2011) also expanded the findings of Meng-Chun et al. (2011) to the broader context by measuring the efficiency of the international tourism industry in 120 countries worldwide. The study further explored the factors that determine the performance of the tourism industry in each country through truncated regression using a DEA model, and identified crime rates, fuel prices, hotel prices, carbon emissions per capita, and visa requirements as the most important factors that negatively affect the performance of the tourism industry in each country. Similar to the previous researchers, Hadad et al. (2012) also used DEA model to measure and compare the efficiency of the international tourism industry in 105 countries and regions and suggested that globalisation and accessibility are important factors in improving the efficiency of the industry in developing countries. Joun and Kim (2020) used the DEA-Malmquist index to measure and assess ecotourism, cultural industries and sustainable development in 16 large-scale cities in the South Korean region and concluded that tourism industries are more efficient in less urbanised areas and that tourism could be a direction for sustainable economic development in less developed regions.

## Domestic tourism in China

Research on the efficiency of China's domestic tourism industry began after 2005. Liang and Yang (2012) decomposed China's tourism industry efficiency into pure technical efficiency and scale efficiency through a DEA model and demonstrated the overall lag and incremental payoffs of scale in China's tourism industry efficiency at the current stage. Zhang et al. (2014) combined the SFA method and the Durbin model to measure and analyse the factors influencing the efficiency of the tourism industry in China's provinces from 2004 to 2010, pointing out that the overall level of provincial tourism industry efficiency in China is low and regional differences are evident. Han et al. (2015) brought carbon emissions into the analysis of tourism industry efficiency and used an unexpected output DEA model to conduct a static analysis of tourism industry efficiency in five Chinese provinces. The conclusion reached was that the combined technical efficiency of tourism changed to varying degrees when carbon emissions were taken into account compared to that of tourism without carbon emissions, which was determined by the joint effect of pure technical efficiency and scale efficiency. Unlike the previous static model analysis, Wang and Zhao (2019) used the DEA-Malmquist model to analyse the efficiency of the tourism industry in Hunan Province in a spatial and temporal dynamic manner, pointing out that the efficiency of the tourism industry in Hunan Province has gradually increased, and that the efficiency of the tourism industry and decomposition efficiency show obvious characteristics of circle agglomeration, among other conclusions. In contrast to previous more macro-level analyses of regional tourism efficiency, Liang and Shi (2019) focused on the efficiency of China's rural ecotourism industry through a DEA model and data from Guangxi province as an example. They also identified the low technical efficiency in northwest China and the importance of more government support and investment to improve the efficiency of the tourism industry in the future.

Although research on the efficiency of the tourism industry has been intensifying in recent years both within China and abroad, the main shortcomings of current scholarly research are as follows: 1. The existing research models do not consider input and output variables comprehensively. Most literature only considers labour (e.g. the number of people employed in the tourism industry) inputs and economic output (e.g. annual income from tourism), while little literature considers input factors of production such as capital and natural resources. Most of the literature is dominated by basic research models that only consider purely positive economic outputs, without fully considering non-desired outputs such as pollution and carbon emissions generated by the tourism industry. 2. Few of the current domestic tourism efficiency analyses in China have systematically analysed the efficiency of China's provincial tourism industry in a spatial-temporal dynamics and even fewer have considered dynamic models that reflect non-desired outputs. 3. The majority of the existing literature uses traditional DEA or Most of the existing literature uses traditional DEA or SFA models and does not consider the impact of differences in the payoffs of scale in the tourism industry between provinces on the model's measurement results.

To filling the aforementioned research gaps and contribute the understanding on the tourism industry efficiency in China, this paper will conduct a dynamic and static analysis of the efficiency of the tourism industry in 30 Chinese provinces from 2014-2019 through the Malmquist-Luenberger (M-L) index of unexpected output and the SBM-DEA model (due to the lack of data this paper does not analyze Hong Kong, Macao, Taiwan and Tibet) to provide more comprehensive analysis data for the study of the efficiency of the tourism industry within China. This paper will analyze the results of the SBM-DEA model, which takes into account the unexpected outputs of carbon emissions, to further understand the impact of unexpected outputs, such as carbon emissions, on the measurement of industry efficiency, by using the concept of 'tourism consumption stripping factor' to calculate carbon emissions in the tourism industry. On this basis, this paper will also explore the impact of the differences in industry scale payoffs by province on the measurement results by comparing the results of the traditional DEA CCR and BCC models, and thus provide a measure of tourism industry efficiency for each province in China.

# Research Methodology

## Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a common non-parametric model used in economics to estimate the efficiency of industries on the production frontier which is used to evaluate several production or non-production sectors of the same type with multiple inputs and outputs (Charnes et al, 1978), i.e. Decision Making Units (DMUs). Models can be divided into output-oriented ones and input-oriented ones. When controlling certain input factors and seeking to maximise output, the output maximisation model is used. If output is controlled to minimise the input variables, then the input-oriented model is chosen. The choice of orientation is therefore based on the ability to control both input and output variables, but the results of both orientations are generally consistent. This paper is concerned with the efficiency of the tourism industry, as the output variables such as the number of tourist attractions served and hotel turnover are difficult to control manually, the output-oriented model will be chosen. Assuming that there are n decision units, j=1,2,⋯,n, including s input elements x, t output variables y, xj=(xij,x2j ,⋯,xtj) and yj=(yij,y2j,⋯,ysj), with slack variables s+ and s−, then the relative efficiency of decision unit α in the DEA base model is shown as follows:

j in the formula represents the weight variable for indicator n, αd represents the combined efficiency of the decision unit in the CCR model and αd represents the pure technical efficiency of the decision unit in the BBC model. Data Envelopment Analysis can be divided into the CCR model for constant returns to scale (CRS) and the BCC model for variable returns to scale (VRS), depending on the returns to scale of the decision-making unit (DMU) (as shown in Figure 1). Assuming that each of the n decision units corresponds to a combination of input and output vectors (xn,yn) decision units with valid inputs and outputs, the CCR model expression is as follows:

The formula for the BCC model with variable output-oriented returns to scale is as follows:

As shown in Figure 1, five data points (A, B, C, D and E) are used to estimate the effective frontier and the level of capacity utilisation under two scale assumptions, with the frontier indicating maximisation of output and utilisation for a fixed level of inputs. With constant returns to scale (CRS), point A on the CSR frontier indicates input fully utilised, while point CDB indicates underutilisation. In the variable country model payoff (VRS) case (with increasing and decreasing scale), points ADC are inputs fully utilised and point B is underutilized.

Figure 1. Schematic comparison of CRS and VRS frontiers (output oriented)

Outputs

CSR frontier

C



A

VRS frontier



B

D



Fixed input

Source：Author’s

Shi and Smyth (2012), studying the tourism industry in Western countries through the Cobb-Douglas production function, point out that transportation, retail transactions and entertainment services in the tourism industry show increasing returns to scale, while for accommodation, the bias is more towards constant returns to scale. Based on data from 31 provinces and regions in China, Wang Kai et al. (2016) estimated the current state of industrial agglomeration in the six factor sectors of the tourism industry in China, noting that the development of industry size varied across Chinese provinces and regions, with generally small and most provinces and regions in the incremental scale stage of the tourism industry (Wang et al., 2016). This means that the different shares of the transport, retail trade, entertainment services and accommodation sectors in the tourism industry affect the payoffs to scale in tourism industry efficiency to some extent. Therefore, this paper will use the output-oriented CCR and BCC models respectively and compare the results in order to provide a more comprehensive measure of the efficiency of the tourism industry in each province of China. However, both the CCR and BCC models can only take into account favourable output and positive economic returns, so this paper introduces the SMB-DEA model proposed by Tone (2001) to measure the efficiency of industries that take into account non-desired output and compares it with the desired output model.

## Malmquist and the M-L Index

While static models can only cross-sectionally compare the production efficiency of decision units at the same point in time, DEA-Malmquist index models can measure the dynamic changes in the efficiency of decision units over time in order to better analyse panel data. Färe et al. (1992) combined this theory with DEA and constructed the Malmquist index method based on a static DEA model to evaluate productivity dynamically from period t to period t+1. This method bridges the gap between the traditional DEA model and the inability to analyse changes in efficiency dynamically (Zhang & Zhao, 2020). The specific concept is as follows:

TFP = TEch×TECHch = PEch×SEch×TECHch

TEch indicates the change in technical efficiency from period t to period t+1. When TEch > 1, it indicates an increase in technical efficiency, otherwise vice versa; when TECHch > 1, it indicates an improvement in technology, otherwise vice versa. This paper focuses on the industrial efficiency of the tourism industry in 30 Chinese provinces from 2014-2019, therefore the use of the Malmquist index will better reflect the dynamic changes in industrial efficiency. With the inclusion of a consideration of unexpected output based on the traditional Malmquist index, the Malmquist-Luenberger (M-L) index is now used to assess environmental productivity growth versus undesirable output by applying the directional distance function (DDF) to the standard Malmquist Productivity Measure (M-L) index (Du et al., 2018). This paper will therefore also use the (M-L) index to measure and compare the dynamics of industrial efficiency in selected provinces that contain unexpected outputs.

## Measurement of carbon emissions from tourism

Although much scholarly attentions have been put on the issue of carbon emissions from tourism, answers to the question of how to accurately measure carbon emissions from tourism remains unclear. The tourism industry is a comprehensive industry that combines transport, retail, entertainment services and accommodation. In order to accurately calculate the carbon emissions of the tourism industry in different regions, the carbon emissions of the various elements of the industry need to be taken into account. Based on the existing carbon emissions statistical yearbooks in China, there is no data available to test the carbon emissions of the tourism industry in different regions, but the existing studies on carbon emissions can provide a reference for the measurement of tourism carbon emissions.

Han et al. (2015) used carbon dioxide emissions from tourism industry-related sectors as the main object of carbon emissions consideration, stripped the energy consumption of tourism from tourism-related sectors, and derived the carbon emissions of various sectors included in the tourism industry through the correlation coefficient of energy consumption converted to carbon emissions, and finally summed the carbon emissions of related sectors to arrive at tourism-specific carbon emissions. Also based on the tourism stripping factor method, Cha et al. (2017) stripped the energy consumption of the tourism sector from the total energy consumption of the sector under the existing statistical caliber and Yue et al. (2020) calculated the carbon emissions of tourism by provinces and municipalities by referring to the emission factor method of the IPCC Guidelines for Greenhouse Gas Emission Inventories (2006) (IPCC (2006)). Wang et al. (2015) estimated municipal tourism carbon emissions in Shandong Province using IPCC (2006) with the tourism stripping factor method (Wang et al., 2015).

As the tourism stripping factor method has been widely used by scholars and can produce more accurate results, this paper will adopt the above-mentioned research method and adopt the tourism stripping factor method and IPCC (2006) to measure the provincial tourism carbon emissions in China. The steps are as follows:

1. The formula for calculating the "Tourism Spending Stripping Factor" for each province is:

i denotes the relevant industry corresponding to the second sector of tourism, i.e. transport, storage and postal services, wholesale and retail, accommodation and catering. j denotes different types of energy, e.g. crude oil. Eij refers to the energy consumed by the corresponding second sector of tourism i. Ti is the value added of the second sector of tourism corresponding to industry i; Vi is the value added of industry i. VAi is the value-added rate of industry i; TRi is the revenue of the second sector of tourism corresponding to industry i. E\*ij is the total energy consumption of industry i; Ri is the tourism stripping factor.

1. Based on the IPCC (2006) emission factor method, the formula for calculating carbon emissions (Cs) from energy consumption in the tourism secondary sector s is shown below:

fj is the reference factor for the conversion of energy category j into standard coal, referring to the China Energy Statistics Yearbook, which aims to convert various energy sources into standard coal; CEj is the carbon emission factor of energy category j (IPCC, 2006). NCFj is the average low-level heating value of energy category j, referring to the China Energy Statistics Yearbook; CCj and COFj refer to the carbon content and carbon oxidation factors of energy category j respectively (Cha et al., 2017). By aggregating the carbon emissions of the secondary sector of the tourism industry, the total carbon emissions of the tourism industry are calculated as C = ∑Cs. C is the total carbon emissions of the tourism industry; Cs is the carbon emissions of the secondary sector of the tourism industry s. The measured results are consistent to results of Han et al. (2015) and Cha et al. (2017).

# Data Sources

The data sources for this paper mainly include: China Tourism Statistical Yearbook Data 2015-2018, China Culture and Tourism Statistical Yearbook 2019-2020, China Energy Statistical Yearbook, IPCC Greenhouse Gas Emissions Inventory Guidelines (2006), etc. Combining the selection of variables from existing studies (Zhang et al., 2014; Wang & Zhao, 2019; Liang & Shi, 2020), the total number of people and total revenue (admission and business income) received by tourism scenic spots in each province in previous years were selected as the expected economic output variables. The provincial tourism carbon emissions measured by the tourism consumption stripping factor method were used as the unexpected environmental output variable.

To facilitate comparison of the impact of tourism carbon emissions, an unexpected environmental output variable, on the calculation of tourism industry efficiency, this paper will first measure the industry efficiency considering pure economic output variables, and then select six provinces (cities) with developed tourism industries, including Beijing, Zhejiang, Shandong, Hubei, Guangdong and Hainan, as the main reference objects for considering tourism carbon emission output variables based on data availability and the current development of tourism industry. By drawing on Hadad et al. (2012) method of considering natural parks as a response natural resource input variable, and drawing on Han Yuanjun (2015), and Yue et al.'s (2020) studies, this paper takes variables such as the number and area of natural tourism scenic spots, the number of people employed in the tourism industry (including, star-rated hotels, travel agencies, and scenic spots), the number of total tourism agencies, star-rated hotels, and fixed assets occupied per capita in scenic spots as the main input variables.

# Data Processing and Results

## Data Processing

The empirical part of this paper focuses on the calculation of tourism industry efficiency considering undesired output and desired output using the STATA 16 and DEAP2.1 data packages respectively, referring to the steps of Lee et al. (2011) for measuring the Malmquist index. Firstly, the differences between the combined technical efficiency measures of the tourism industry under different scale payoff premises are compared using the BCC and CCR static analysis models considering the radial direction using teradial and tenonradial commands. Then the unexpected output model of SMB-DEA is used to measure and compare the efficiency of the industry considering environmental output. To reflect the dynamic changes, this paper first measures the efficiency of the provincial tourism industry using the malq directive, and then uses Malmquist-Luenberger to measure the dynamic industrial efficiency that includes unexpected outputs and compares it with the results of the traditional Malmquist model. As tourism production activities, like other economic activities, are time-sensitive, tourism inputs do not immediately yield more significant tourism outputs, and it often takes some time for current inputs to reach current outputs. Studies have shown that the regional tourism industry output relative to tourism resources and factors of input, there is a certain time lag, that is, the current input does not necessarily in the current year to obtain output returns. On the basis of existing research findings, the lag period for tourism output is approximately one year (Lee et al., 2011; Wang & Zhao, 2019). Therefore, this paper measures the efficiency of the provincial and regional tourism industry by taking the current input data that corresponds to the next year's output data for calculation.

## CCR, BCC and SMB results

As shown in Table 1, using the measured results of the six major tourism regions in China (Beijing, Zhejiang, Shandong, Hubei, Guangdong and Hainan) in 2014 as an example, the BCC model with variable returns to scale under static analysis measures technical efficiency results smaller than the CCR model with constant returns to scale. For the same scale payoff, the non-radial technical efficiency is greater than or equal to the radial technical efficiency. "Radial" means that the evaluation of efficiency requires year-on-year variation in inputs or outputs, and when there is non-zero slack, radial measures will overestimate the efficiency of decision units, which in turn leads to poor differentiation of efficiency among all decision units (Li, 2013). However, little of the existing literature considers differences in returns to scale, and most studies do not explain why the BCC or CCR models were chosen. However, as variation in returns to scale affects the measurement of industry efficiency, it is important to first consider whether the returns to scale are variable in the industry under study when using static models to measure technical efficiency. Studies on the efficiency of the tourism industry in China, especially at the micro level, can further draw on Shi and Smyth (2012) industry share allocation method to first estimate the payoffs of scale for the tourism industry under study before choosing to use the CCR or BCC model. When carbon emissions from the tourism industry in each province are included as an unexpected output variable, technical efficiency is lower in both the variable and constant scale payoff cases than in the case where only the economic expected output variable is considered, while the variable scale case is still more efficient than the constant scale case.

Table 1. Summary of selected results of static technical efficiency analysis

Note: Remaining relevant annual data available on request

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Year | Region | Non-radial technical efficiency | | Radial technical efficiency | | SMB-DEA model | |
| CCR | BCC | CCR | BCC | TEVRS | TECRS |
| 2014 | Beijing | 1.125 | 1.032 | 1.321 | 1.304 | 0.90 | 0.88 |
| 2014 | Zhejiang | 1.000 | 1.000 | 1.287 | 1.043 | 0.75 | 0.74 |
| 2014 | Shandong | 1.093 | 1.047 | 1.275 | 1.232 | 0.89 | 0.88 |
| 2014 | Hubei | 1.101 | 1.058 | 1.260 | 1.244 | 0.85 | 0.84 |
| 2014 | Guangdong | 1.038 | 1.037 | 1.092 | 1.064 | 0.89 | 0.88 |
| 2014 | Hainan | 1.047 | 1.032 | 1.112 | 1.112 | 0.91 | 0.89 |

Figure 3. Comparison of model results for unexpected versus intended output models

Source: Author’s own

Figure 4. Number and operation of tourist attractions in China, 2014-2019

Source: Author’s own

As shown in Figure 3, in considering only economic input-output variables, the average value of the efficiency of the tourism industry in China's provinces is greater than the result of considering non-desired environmental outputs (SMB-DEA model) for both constant returns to scale (CCR model) and variable returns to scale (BCC model). Furthermore, in both model measurements considering purely economic variables, China's national average shows a small downward trend, which may be related to the increased market and natural resource inputs to the tourism industry. As shown in Figure 4, the number of scenic spots in China continued to rise during the period 2014-2019, reflecting the increase in natural resource and capital investment for the tourism industry. However, the relatively insignificant growth in tourism scenic area operating income and ticket revenue may be related to the time lag in the input of tourism resource elements and the change in the type of scenic area services from a single pursuit of economic returns to an emphasis on cultural tourism quality. In addition, according to the summary of the Tourism Green Book 2013-2014, it can be seen that since 2010, the revenue barrier of China's tourism industry has decreased, the tourism industry has become progressively more public-spirited and plebeian, and many scenic spots have reduced their ticket prices, which can partly explain the small decrease in the tourism industry efficiency measure that only considers economic output variables.

However, when the unexpected variable of carbon emissions from the tourism industry is added to the pure economic output model, as well as input factors that respond to environmental factors, the SMB-DEA model presents results that reflect a more significant increase in the mean efficiency of the tourism industry in all Chinese provinces over the period 2014-2016 for both the variable and non-variable payoffs of scale, in contrast to previous studies that have used traditional CCR and BCC models The trend is different from the smooth and small decline measured in previous studies using traditional CCR and BCC models. The change in trend reflects an increase in the average efficiency of China's tourism industry when environmental input and output factors are taken into account, which may be related to the green economy goals and energy saving and emission reduction plans implemented after the 12th Five-Year Plan. Without taking environmental factors into account, the trend in the traditional model indicates that inputs related to energy saving and emission reduction reduce pure economic efficiency, but have a positive impact on the eco-efficiency of the industry, which also reflects the effectiveness of green industry upgrading inputs in China. The results of the model considering unexpected outputs in the chart and the traditional model measurements both plateau and then converge after 2016, which is related to the continued implementation of green development measures and ideas such as the 10-year Made in China 2025 plan proposed in 2015 and the China Eco-tourism Development Plan (2016-2025) after 2016. With the importance attached to green and low-carbon development by society, the industry efficiency measurement with the inclusion of green environmental factors gradually converges with the results of the traditional model, with green industry upgrading and the use of clean energy leading to lower carbon emissions in the tourism industry and higher total factor productivity and technical efficiency in the industry. This is also a reflection of the reliability of the results of this study in incorporating indicators reflecting environmental factors into the traditional model. Furthermore, the gap between the results of these models narrowed after 2018, probably due to the policy of diversifying and integrating different industries in China's tourism industry such as leisure, culture and public welfare and environmental protection this year.

1. Malmquist and ML index measurement results

While the above static analysis for national averages reflects the positive effect of green industry upgrading in China for the tourism industry considering unexpected output efficiency, the measurement of total factor yield needs to be differentiated for regions. This section therefore divides and analyses the 30 provinces within China (excluding Tibet) in terms of geographical location (as in Table 2.) and whether they are coastal or not (as in Table 3.) in two latitudes.

Table 2. Classification of Chinese provinces by geographical area

|  |  |
| --- | --- |
| Regional classification | Province |
| North China | Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia |
| Central China | Henan, Hubei, Hunan |
| South China | Guangxi, Guangdong, Hainan |
| East China | Shandong, Jiangsu, Anhui, Jiangxi, Fujian, Zhejiang, Shanghai |
| Northeast China | Heilongjiang, Jilin, Liaoning |
| Southwest China | Sichuan, Chongqing, Guizhou, Yunnan |
| Northwest China | Xinjiang, Qinghai, Gansu, Ningxia, Shaanxi |

Table 3. Classification of Chinese provinces by coastal areas

|  |  |
| --- | --- |
| Regional classification | Province |
| Major coastal areas | Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Hainan, Guangdong, Guangxi |
| Inland area | Beijing, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang |

The study summarises and compares the results of the Malmquist Index, which considers only the expected output of the economy, with the results of the ML Index, which considers unexpected output, over five time periods from 2014-2019 to Figures 5 to 8. Based on the overall results of the measurements, the two indices fluctuate in broadly similar trends, but the ML Index fluctuates less than the Malmquist Index, reflecting the moderating effect of technological upgrading of the green industry on The gradual convergence of the two indices between 2017 and 2019 also reflects the increasing integration of green and environmental factors in the total factor productivity of the tourism industry. The following section analyses and discusses the changes in the trend of the measurement results by region.

Figure 5. Malmquist index of change in total factor productivity

North China Central China Southern China Eastern China Northeast China. Southwest China Southwest China

Source: Author’s own

Figure 6. Malmquist-Luenberger index of change in total factor productivity

M-L index of change

Source: Author’s own

Figures 5 and 6 present the total factor productivity changes by region, with Figure 6 taking into account carbon rights, while Figure 5 does not. Firstly, in 2014-2015, the Malmquist measure for the southwest and northwest regions was slightly higher than the ML index that takes into account carbon emissions, probably related to the fact that the western region was driven by carbon-intensive industries at the time. Based on a 2012 report by the China Council for International Cooperation on Environment and Development (CICED), the western region emits more than 1.1 times the national level of "three wastes" per 10,000 yuan of industrial value added, while the output value of the energy and mining industry accounts for 63.41% of the total industrial output value in the western region. As a result, when the environmental factor is taken into account in the efficiency of industries in the West, the efficiency of unexpected industries was lower in the period 2014-2015. In the period 2015-2016, both indices show a significant upward trend. However, the rise in the index taking into account purely economic variables is greater, reflecting the rapid increase in tourism economic output in the western region between 2015 and 2016, which is related to China's plans for further development of the western region after 2014. "The revitalisation of cultural tourism along the Western Silk Road proposed during the 13th Five-Year Plan also further contributed to the growth of economic output in the tourism industry in the western region. 2017-2018 saw a significant decline in both indices, however the ML index fell less, reflecting the better performance of industrial efficiency than pure economic efficiency in that year, taking into account environmental factors, which the change in tourism efficiency in western China between 2016 and 2019 is related to the lag in the input variables used for ecological improvement and circular economy (Ma & Jin, 2015).

Secondly, the general trend in Northeast China is similar to that in North China, where the region's desired industrial efficiency declined significantly in 2015-2016. in 2014, the State Council proposed strategies such as consolidating the revitalisation of Northeast China and developing to the north, and emphasised promoting enterprise reform, encouraging investment and innovation, as well as increasing financial support for ecological and green industries and new energy and high-tech industries in the north. However, due to the fact that the industrial chain in the northern region is dominated by basic resources and heavy industries, and that tourism is developed in spring and summer, the transmission and effects of economies of scale in the northern region are reflected more slowly (Xu & Wu, 2011), so the pure economic efficiency declined between 2015 and 2016. But the unexpected efficiency, which takes into account carbon emissions, did not decline significantly, but increased slightly in northern China, which also reflects the positive effect on the eco-efficiency of the tourism industry of the investment in quality upgrading of the industry in the northern region. From the results, the difference between the efficiency measures considering unexpected and pure economic outputs is smaller in the more economically developed regions of Central and Southern China and Eastern China, probably due to the long-standing emphasis on low-carbon development and eco-economy construction in these areas.

As shown in Figure 7, the pure economic efficiency of the tourism industry in inland areas was significantly better than that of coastal areas during the period 2014-2016, which may be related to the strategies developed for the economic and industrial revitalization of inland areas and the development of urban scale during the period 2000-2012. However, according to China's National Territorial Plan (2016-2030) and the Strategic Urban Development Plan, the country's "five-in-one" strategy of integrating the economic benefits of inland areas and the sea, as well as the concept of greening, opening up and sharing, was comprehensively promoted after 2016, so the economic efficiency of the inland and coastal areas. The economic efficiency of the tourism industry is beginning to converge after 2016.

Figure 7. Malmquist index of change in total factor productivity for coastal and non-coastal

Coastal areas

Inland areas.

Malmquist index of change

Source: Author’s own

The overall outperformance of the coastal ML Index over the inland areas is related to the structure of the coastal areas, which is dominated by low carbon industries. While the inland areas ML Index first decreasing and then increasing also reflects China's transition from incremental development to the pursuit of low carbon and high-quality development for the inland areas.

Figure 8. Index of change in Malmquist-Luenberger total factor productivity for coastal and non-coastal areas

M-L index of change

Source: Author’s own

The trends in the measured results in Figure 7 and Figure 8 show that the expected industrial efficiency of the tourism industry declines slightly between 2014 and 2019 in both coastal and inland areas, while the unexpected industrial efficiency, which takes into account environmental factors, climbs slightly, which is consistent with the findings of the static analysis using the traditional model above.

# Summary and Discussion

This paper measures the carbon emissions of the tourism industry in each province of China by drawing on the tourism stripping factor method based on the tourism industry statistics of 30 provinces within China (excluding Tibet) from 2014-2019, and then adding tourism carbon emissions as an industry unexpected output variable to the traditional static and dynamic efficiency model measures. Two main innovations are found in this paper. Firstly, by deriving the unexpected output through the SMB-DEA model and the Malmquist-Luenberger (M-L) index, this paper provides a macro measurement of the efficiency of the tourism industry at the provincial level within China. Secondly, this paper adds input variables that respond to natural resources and output variables that respond to environmental burdens to tourism industry efficiency, thus taking environmental impacts into account in tourism economic efficiency. This study enhances the use of DEA models in measuring tourism industry efficiency and updates existing related studies in terms of model variables.

As shown by the results of the model, after adding carbon emissions and natural resources to the model, the average efficiency values of Chinese provinces show a significant upward trend under the static analysis, which represents an increase in the eco-efficiency of the tourism industry and is related to the promotion of green industrial upgrading and energy-saving and emission reduction policies in China. With dynamic analysis, the efficiency values of the tourism industry in each region show less fluctuation compared to the traditional measurement results, which laterally reflects the moderating effect of the technological upgrading of China's green industry on the efficiency of the tourism industry, as well as the effectiveness of green industry transformation investment. The innovations and findings of this paper can be used to support the future development of ecotourism and efficiency measurement in China, and offer theoretical reference and practical experience for international tourism industry efficiency measurement.

This paper also has some limitations to be acknowledged. Firstly, there are no detailed statistics on carbon emissions at the sectoral level in China, and as the stripping factor method is more mature and has already been compared in the literature, this paper uses the more traditional tourism stripping factor method and the IPCC (2006) to measure carbon emissions from tourism in China's provincial areas. However, as the method and the data used have been published earlier, there may be discrepancies between the estimated carbon emissions and the actual data, which may affect the estimation results. In addition, since this paper is one of the few recent papers to measure the efficiency of the tourism industry at the national level, there are currently few references available for the results, so the results of this paper need to be further compared with the results of future related studies.

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