Current Science
CS 5(4), 3847-3864 (2025)
Received 15 May 2025 | **Revised 10 June** 2025 | **Accepted 11 July**. 2025 | **Online Available 06 August** 2025
https://doi.org/ 10.52845/CS/2025-5-4-43

Current Science

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OPEN ACCESS

ISSN(O)2795-8639

Original Article

Tourism Destination Efficiency Measurement and Improvement -A Case Study of Guangxi, China

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Abstract:
Measuring operational efficiency and improving management levels are meaningful goals for regional tourism destinations to attract more tourists and occupying a larger market share. The objective of this study is to evaluate output-oriented managerial efficiency of tourism destinations and to provide insights towards improving overall efficiency by removing impacts of environment variables and statistical noise. The tourism destination efficiency is assessed with the three-stage Data Envelopment Analysis (DEA), and effects of environment and statistical noise are purged from initial efficiency with Stochastic Frontier Analysis (SFA). This case study is based on 14 prefectural-level cities of Guangxi autonomous region, China, in which five inputs and three output variables, and three environmental variables are chosen for efficiency measurement. The results show that managerial inefficiency explains half of the variation in tourism consumption slack variables, and statistical noise explains the remaining 50% of the variation. As to output slack variables of employees in the tourism industry and the number of visitors, the variation of efficiency are mainly due to external environmental and statistical noise. This study finds that there is room to improve the destination tourism industry operational efficiency of Guangxi by 20.4%, after controlling for the effects of the external environment. Finally, the optimal combinations of inputs and outputs of each city are suggested to improve managerial efficiency.

Keywords: Tourism destination efficiency; three-stage DEA; output-oriented; environmental effects; optimal combination; Guangxi

Introduction

Tourism has recently become the most common tertiary industry because of the increasingly important role on economic growth and its impacts on environmental protection and social integration of many countries and regions(Cracolici et al., 2007). With rising income levels, convenient transportation options, more geographical mobility and international openness, tourism has become a desired economic growth engine nowadays. The expectation of sustainable growth of outputs from the tourism industry has prompted tourist destinations to attract more tourists and strive to occupy a larger market share. Current studies show that 70% of tourists prefer taking a trip to the top 10% of destinations, thus intensifying the overall competition among tourism destinations(Morgan et al., 2002). Consequently, tourism destinations that have demonstrated capability of significantly increasing tourist flow have become the hot research topic in tourism theory and applied research.

Current studies focus on tourists' behavior on either the demand-side or destination supply-side to inform policy at destinations for attracting more tourists. Maximizing tourism destination utility can be best achieved by optimizing both of the demand and supply sides(Zha et al., 2020). Therefore, the measurement of destination tourism efficiency and testing of the matching of input and output factors is crucial to policymakers for improving destination tourism operation performance(Chaabouni, 2019). Current research on tourism efficiency mainly focuses on micro-tourism industry such as hotels and travel agencies. Among earlier studies of tourism efficiency, Morey and Dittman evaluated the performance efficiency of managers at 54 American hotels by using DEA with seven input and four output factors(Morey & Dittman, 1995). Hwang and Chang measured the management efficiency of 45 hotels and studied dynamics of the efficiency using DEA and the Malmquist index from 1994 to 1998 in which they drew a conclusion that the management styles and sources of customers result in a significant difference in efficiency dynamics of hotels(Hwang & Chang, 2003). Barros and Mascaren analyzed the technical efficiency of 43 hotels using DEA with three input and three output factors in Portugal (C.P. Barros & Mascarenhas, 2005). Other studies also have shown that the traditional DEA models are useful tools for evaluating tourism hotel efficiency(Arbelo-Perez et al., 2017; Arbelo et al., 2018; Arbelo et al., 2017; Assaf & Agbola, 2011; Assaf & Barros, 2013; Assaf & Tsionas, 2018; Botti et al., 2009; Chatzimichael & Liasidou, 2019; C. F. Chen, 2007; L. F. Chen, 2019; Chiang, 2004; Chiu & Lin, 2018; Cho & Wang, 2018; Guo et al., 2019; Huang, 2017; Kularatne et al., 2019; R. Lado-Sestayo & Fernandez-Castro, 2019; Rubén Lado-Sestayo & Fernández-Castro, 2019; Lee et al., 2019; H. W. Liu et al., 2018; Maha et al., 2018; Mak & Chang, 2019; Mendieta-Penalver et al., 2018; Oukil et al., 2016; Ramanathan et al., 2016; Sellers-Rubio & Casado-Diaz, 2018; Shieh et al., 2017; Tzeremes, 2019; Vives et al., 2018; Xu & Chi, 2017). In addition to tourism hotel efficiency, research has also tackled travel agency operational efficiency. Köksal and Aksu analyzed 24 A-group travel agencies operation efficiency in Turkey using DEA, and the results showed that there was no significant difference in operation efficiency among the travel agency groups(Köksal & Aksu, 2007). Nonetheless, they provided recommendations on how to improve the rating of travel agencies and management efficiency of managers with low efficiency score. With the development of tourism industry efficiency studies, increasingly more researchers are paying close attention to destination tourism efficiency from earlier efficiency studies on the micro-tourism industry.

Efficiency measurement and investigation of the matching of outputs and inputs of tourism are helpful for destinations to attract more tourists and command a larger tourism market share, factors that encourage competition in tourism destinations. While tourist destinations often perform as united enterprises with several inputs and outputs, many studies on tourism efficiency consider hotels and restaurants as separate united research objects. Cracolici et al. assessed the efficiency of 103 tourism destinations in Italy using output-oriented DEA. They found that there was little difference in the competitiveness rank of destinations, an indication that the change in tourism destination efficiency is minimal over the years(Cracolici et al., 2007). The aforementioned study is one of the earliest to evaluate tourism destination efficiency using the DEA model. Peypoch evaluated destination tourism industry efficiency in France using the Luenberger productivity indicator with two inputs and one output(Peypoch, 2007). The results showed that the change of tourism destination efficiency was mainly due to the change of the supply since demand-side was not modified. The reorganized tourism product made destinations more attractive which then motivated the tourists to spend more. The change in supply-side included the investment in innovation procedures and techniques which then increased tourist expenditure. Daskalopoulou and Petrou measured tourism industry performance of Patras City, Greece using the DEA method, and the results indicated that entrepreneur perceptions and destination networks within the city were the main determinants of the tourism destination efficiency(Daskalopoulou & Petrou, 2009). Barros et al. assessed the tourism destination efficiency in France with the two-stage DEA method, where the efficiency score was calculated in the first stage, and then a bootstrapped truncated regression method was used to calculate efficiency, incorporating the effects of environmental variables(Carlos Pestana Barros et al., 2011). They proposed policy recommendations to improve the performance efficiency of tourism destinations based on discovery and escape attraction. Assaf and Josiassen measured the performance of international tourism destinations and ranked the determinants of tourism performance by using the DEA procedure and the bootstrap truncated regression models(Assaf & Josiassen, 2012). Assaf and Dwyer benchmarked international tourism destinations efficiency with DEA model, and the results showed that the tourism industry productivity growth of North American and European were higher than that of African countries(Assaf & Dwyer, 2013). Alzua-Sorzabal et al. proposed a new way to verify tourism destination efficiency with internet data by using DEA method, and the efficiency was recorded in a ranked list in which the effects of input variables on tourism destination efficiency could be analyzed(Alzua-Sorzabal et al., 2015). Liu et al. evaluated tourism efficiency in 53 cities of China with DEA-Tobit model, and the results indicated that the mean tourism destination efficiency was 0.860 and only a few destinations were run effectively while most destinations had room to improve operation efficiency(J. Liu et al., 2017). Pham measured multifactor productivity, labor productivity and capital productivity of Australian tourism industry with DEA method(Pham, 2020). These studies have promoted the research theory and application on the efficiency of destination tourism. Current studies in tourism destination efficiency are mainly based on input-oriented DEA analysis in which environment effect and statistical noise are included. In contrast with input-oriented DEA procedure, the output-oriented destination tourism efficiency with both environment effects and statistical noise removed, will be a more suitable choice as it answers the question of “How many outputs will be increased if inputs remain unchanged?”; thereby enhancing managerial efficiency which is helpful for tourism destination policymaking.

The objective of our research is to evaluate the output-oriented regional tourism destination efficiency with the three-stage DEA procedure. The article is organized as follows. The three-stage producer performance evaluation model and the materials for conducting the model are introduced in Section 2. The results of the study are presented in Section 3 and the discussions are shown in Section 4. Conclusions are described in Section 5.

2. Methods and Materials

2.1 Methods

The key of the three-stage DEA procedure is to eliminate environment effects and statistical noise from traditional producer performance and highlight the assessment of managerial efficiency. An initial assessment of producer performance is calculated with the raw output and input data in the first stage DEA procedure. In the second stage, the producer performance metric from the first stage is decomposed to managerial inefficiency, environmental effects and statistical noise with stochastic frontier analysis (SFA)(H.O. Fried et al., 1999). Thereafter, the outputs of producers that result from environment variables and the statistical noise are purged from original outputs based on the decomposition in the second stage(H. O. Fried et al., 2002). Finally, the traditional DEA procedure is rerun with adjusted outputs and original inputs data. The final evaluation of producer performance improves measures of managerial efficiency since the effects of environmental variables and statistical noise have been purged from outputs with the SFA regression models.

2.1.1 Stage 1: the initial efficiency measurement with DEA procedure

The initial producer performance is measured with traditional BCC (Banker, Charens and Cooper, 1984) model by using output quantity data and input quantity data(Banker et al., 1984). For each producer, the envelopment problem of output-oriented efficiency, variable return to scale (VRS), can be represented using a linear programming problem:

$$\begin{aligned} &\max_{\phi,\lambda} \phi, \\ &st \quad -\phi y_i + Y\lambda \ge 0, \\ &\qquad x_i - X\lambda \ge 0, \\ &\qquad N1'\lambda = 1 \\ &\qquad \lambda \ge 0 \end{aligned} \qquad (1)$$

Where $y_i \geq 0$ is output vector of producer, $x_i \geq 0$ is input vector of producer, $Y=[y_1,y_2,\ldots,y_I]$ and $X=[x_1,x_2,\ldots,x_I]$ is matrix of output vector and input vector in the comparison set, respectively, and $\lambda=[\lambda_1, \lambda_2,\ldots, \lambda_I]$ is a vector of intensity variables.

The initial performance efficiency of optimal solutions to problem (1) is represented with the optimal results of $1\leq\phi<\infty$ of producer, and the value of ϕ-1 is the increased proportion in outputs, known as slack, which could be achieved with constant input quantities for a producer. The value of $1/\phi$ is called technical efficiency which varies from zero to one. In initial efficiency measurement, the pure technical efficiency VRS, scale efficiency and the overall technical efficiency (constant return to scale, CRS) are calculated in DEAP2.1 software(Coelli, 1996a).

The producer performance obtained from the first stage is affected by environment variables, statistical noise and management efficiency, hence the purging of environmental effects and statistical noise necessitated in the second stage.

2.1.2 Stage 2: decompose stage 1 slack with SFA and purge environmental effects and noise

In stage 2, the first step is to decompose the slack calculated from the first stage into environment effects, statistical noise and the management efficiency with the SFA method. Based on the research design, each output slack from stage 1 is set to be the dependent variable while environmental variables are set to be independent variables, meaning that *M* separation regression models need to be estimated when running SFA models(H. O. Fried et al., 2002). The form of SFA regressions are presented as formula (2):

$$s_{mi} = f^{m}(z_i;\beta^{m}) + v_{mi} + \mu_{mi}, m=1,\cdots,M, i=1,\cdots,I, \tag{2}$$

Where S_{mi} represents the slack value of the *m*th output for destination *i* from the first stage. The function of f^m is the *m*th regression equation of dependent variable S_{mi} and independent variables (environment variables) $z_{i,}$ and the value of $v_{mi}+\mu_{mi.}$ is the regression error, respectively. β^m is the parameter which can be estimated with the regression model, and M and I is the number of slack variables and producers, respectively. S_{mi} can be calculated with formula (3):

$$S_{mi}=Y_m\lambda-y_{mi}\geq 0, \tag{3}$$

Where Y_m is vector of Y, and $Y_m\lambda$ is the optimal projection value of y_{mi} with input vector x_i.

In equation (2), the composed error $v_{mi}\sim(0, \sigma^2_{vm})$ reflects the statistical noise, and the error $u_{mi}\sim M^{+}(u^m, \sigma^2_{um})$ represent managerial inefficiency. In each SFA regression model, the parameters $(\beta^m, u^m, \sigma^2_{vm}, \sigma^2_{um})$ can be estimated with the maximum-likelihood method. In the regression model, the parameters vary with the slack variables hence the three effects exerting different impacts across outputs.

The adjusted outputs are then calculated with the parameters in the second stage as follows(H. O. Fried et al., 2002):

$$y^A_{mi} = y_{mi} + \left[\max_i\{z_i\hat{\beta}^m\} - z_i\hat{\beta}^m\right] + \left[\max_i\{\hat{v}_{mi}\} - \hat{v}_{mi}\right], m=1,2,\cdots,M, i=1,2,\cdots,I \tag{4}$$

Where y^A_{mi} is the adjusted output and y_{mi} is the initial output. The first adjustment places all producers into the same environmental condition and another adjustment puts all producers into the same luck situation (a common state of nature) encountered in the sample. These adjustments vary both across producers and outputs.

To implement equation (4), the effects of statistical noise need to be separated from managerial inefficiency in the SFA regression results from equation (2). This can be accomplished using the Jondrow methodology(Jondrow et al., 1982) with which statistical noise estimators can be residually derived as follows:

$$\hat{E}[v_{mi}|v_{mi}+\mu_{mi}] = S_{mi} - z_i\hat{\beta}^n - \hat{E}[\mu_{mi}|v_{mi}+\mu_{mi}], m=1,2,\cdots,M, i=1,2,\cdots,I \tag{5}$$

Where managerial inefficiency residual $\hat{E}[\mu_{mi}|v_{mi}+\mu_{mi}]$ can be calculated as follows(Jondrow et al., 1982):

$$\hat{E}[\mu_{mi}|v_{mi}+\mu_{mi}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\varepsilon_i\lambda/\sigma)}{\Phi(\varepsilon_i\lambda/\sigma)} + \frac{\varepsilon_i\lambda}{\sigma}\right] \tag{6}$$

Where ε_i is the error of SFA regression model of equation (2), and $\varepsilon_i = v_i + \mu_i$, $\sigma^2 = \sigma_{vm}^2 + \sigma_{um}^2$, $\gamma = \frac{\sigma_{um}^2}{\sigma_{vm}^2 + \sigma_{um}^2}$, $\lambda = \frac{\sigma_\mu}{\sigma_v}$, $\phi(\cdot)$ and Φ $(\cdot)$ is the density function and distribution function of standard normal distribution. Since σ^2 and γ is known from SFA regression model, σ_{um}^2 and λ can be calculated too. Equation (6) is then solved, and the statistical noise is purged from SFA regression results. The adjusted outputs y_{mi}^A are then calculated using equation (4). The SFA regression model is run with Front41 software(Coelli, 1996b).

2.1.3 Stage 3: run traditional DEA with adjusted data

In Stage 3, the traditional BCC DEA model is rerun with the adjusted output data from the second stage and the initial input data from the first stage. The efficiency of the third Stage based on the measurement of producer efficiency resulting from managerial inefficiency since environment effects and statistical noise are put in the same situation.

2.2 Materials

2.2.1 Study Area

Guangxi Zhuang autonomous region sits in the southern of China with an area of 237,600 square kilometers. The region includes 14 prefectural-level cities namely the southern cities of Nanning, Qinzhou, Chongzuo, Fangchenggang and Beihai; the northern cities of Guilin, Hezhou and Liuzhou; the eastern cities of Wuzhou, Yulin, Guiyang and Laibin; and the western cities of Hechi and Baise (Figure 1).

Hilly basin landform covers 40% of total land area in Guangxi. The Xunjiang River plain is the largest alluvial river plain in Guangxi, covering an area of 630 square kilometers. Located in the marginal of the basin, Maoer Mountain is the highest peak in south China at 2,141 meters above sea level. Limestone formations are chronically eroded by the heavy precipitation of the warm humid climate regions, resulting in large-scale karst landforms which cover 37.8% of total land area of Guangxi.

As a multiethnic inhabited region, Zhuang is the main minority of Guangxi including other 10 native ethnic groups such as Miao, Yao and other 44 ethnic groups such as Manchu, Mongolian. Multi ethnic groups have formed rich and colorful cultural tourism resources. Special karst landforms, caves, hills and mountains form rich natural tourism resources in Guanxi. Moreover, the exhibition tourism has becoming a popular activity that attracts more tourists, since Guangxi is a long-term host of the China-ASEAN Expo. The rich cultural and glorious natural tourism resources have become the best tourism attraction of Guangxi.

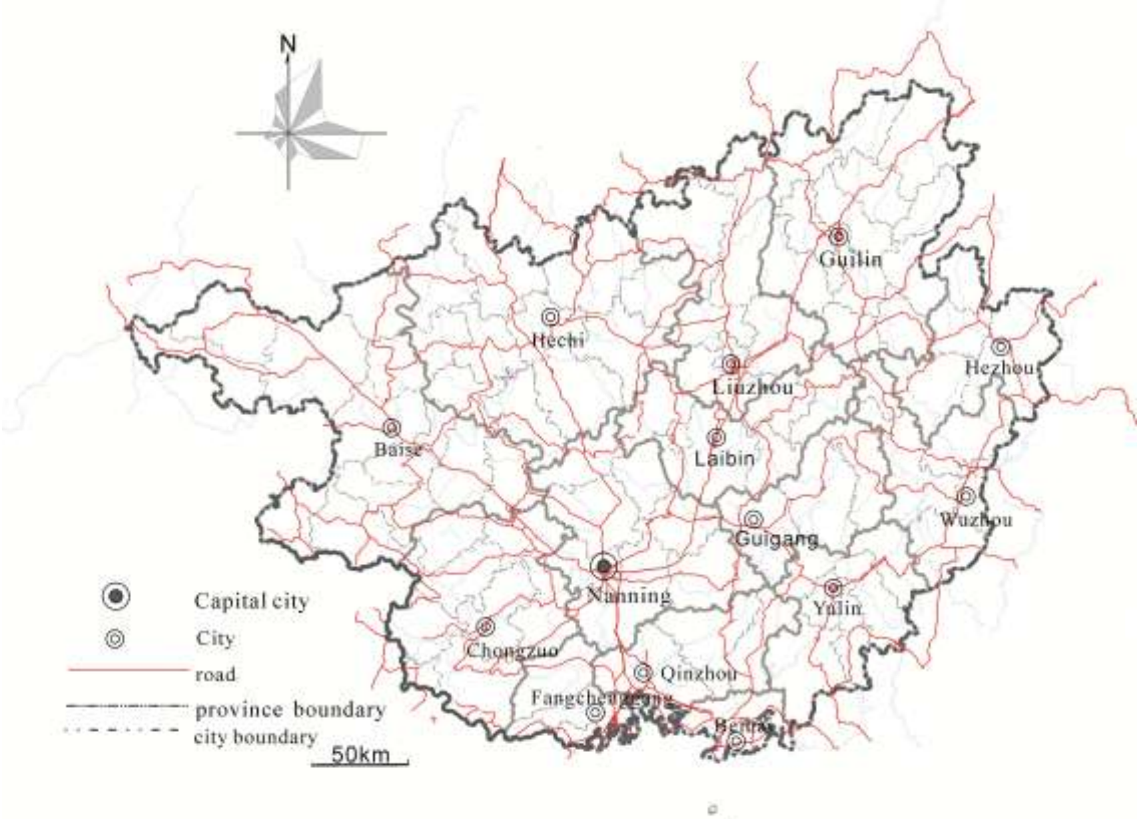

Figure 1 The Study Region

The rapid development of the tourism industry in Guangxi has led to the significant improvement of the inputs and outputs. Overall, A-class tourist attractions have been at the forefront of China. As of 2023, there were 422 A-class tourist attractions with 5 5A-class, 173 4A-class, 230 3A-class and 14 2A-class tourist attractions. Consistent with the development of tourist attractions, the tourism service industry has seen major improvements as well. There were 722 travel agencies and 473 star-rated hotels with 12 5 stars hotels, 88 4-star hotels and 276 3-star hotels of Guangxi in 2023. Moreover, the development of high-speed railways and highways has promoted the development of tourism infrastructure. These increase in inputs has led to great development in tourism outputs. Tourism consumption within Guangxi was up to 1024.114 billion Yuan with 34.4% annual growth and the number of tourists was up to 876 million with an annual growth of 28.2% in 2023. Tourism consumption within Guangxi accounts for 27.36% of GDP, a proportion of which is higher than China nationwide (11.04%). Furthermore, tourism consumption in Guangxi accounts for 68.12% of the added value of the tertiary industry, a figure that is also higher than that of China (21.38%). The number of employees working in the tourism industry account for almost 10% of total employees in Guangxi. Tourism has become one of the most important industries in the Guangxi tertiary industry (Department of Cultural and Tourism of Guangxi Zhuang Autonomous Region, http://wlt.gxzf.gov.cn/, last accessed Nov.11.2023). All in all, it is necessary to study the tourism industry efficiency of Guangxi for improving tourism outputs further.

2.2.2 The Output and Input Variables of Traditional DEA

The first procedure of the DEA is to choose input and output variables based on the research areas. When conducting destination tourism efficiency assessment, most scholars choose tourism consumption and number of visitors as the output variables, with the number of A-grade scenic spots and the number of star-rated hotels as the input variables. Some scholars choose employees of the tourism industry as input variables, while others consider them as output variables. In this study, taking into account the labor absorption ability of the tourism industry, the employees of tourism industry are regarded as output variables since the demands of employees could be driven by the grade of the scenic tourist spots, travel agency and star-rating of hotels. Therefore, we classify the scenic spots and hotels into different grades when assessing destination tourism industry efficiency. We do so by classifying scenic spots and hotels into two groups by A-grade and star-rating respectively. There are three output variables and five input variables of destination tourism industry in the traditional DEA model (Table 1).

Table 1. The output and input variables of the tourism industry of traditional DEA model

Output Variables	Input Variables
Employees at hotel and catering trade industry (person)	Number of AAAAA and AAAA grade scenic spot (unit)
Tourism consumption (100 million Yuan)	Number of AAA and AA grade scenic spot (unit)
Number of visitors (10 000 persons-times)	Number of travel agencies (unit)
	Number of 4 star and 5 star grade hotels (unit)
	Number of 2 star and 3 star grade hotels (unit)

2.2.3 Environmental Variables Influencing Destination Tourism Operation Efficiency

In three-stage DEA model, one key stage is to choose environmental variables which affect destination tourism industry operating efficiency while the environmental effects on operating efficiency cannot be controlled by local government and(or) tourism enterprises. In the tourism industry, one of the environmental variables is tourist markets which can affect the outputs of the destination tourism industry. A destination close to tourist markets could have a significant number of tourists and overall consumption because of the suitable travelling distance, while a destination far away from main tourist market has fewer tourists. In this study, each city has three types of tourist markets based on the spatial distribution and travel habits of tourists around cities. The first tourist market is the one in the Pearl River Delta, Guangdong Province in which most tourists travel to Guangxi Autonomous region by high-speed rail or car. The second tourist market is one in each city where many tourists usually have a day-trip during the weekend. Although tourists in that second market may not need to stay at a hotel, they usually spend money on transportation, admission and meals whenever they have a trip in their city. The third tourist market is the one in Nanning City, the capital of Guangxi Autonomous region. The Nanning City stands at the geographical center of Guangxi, thus convenient for the permanent population to travel to other cities. Since the permanent population of Pearl River Delta and Nanning are similar, the time they spend traveling to each city is calculated for the market points. Taking into account travel path, the time to a destination by high-speed rail and car are calculated with the weighted summation method. The weight for high-speed rail time is set to 0.6 and for car time is set to 0.4 for Guangzhou while the weight for high-speed rail time and car time is set to 0.4 and 0.6 for Nanning, respectively. There are three environmental variables including the permanent population of each city, Guangzhou points that represent the tourist market of Pearl River Delta, and Nanning point that represent the tourists market of Nanning City.

2.2.4 Data Sources

The data of output and input variables of 2023 are obtained from Guangxi Statistical yearbook (2023) and the news from the website of the department of culture and tourism of Guangxi, and each city (Department of Cultural and Tourism of Guangxi Zhuang Autonomous Region, http://wlt.gxzf.gov.cn/, last accessed Nov.11.2023). Table 2 shows the original data and statistics of raw data. The data shows that the maximum value of output variables appear at Nanning City, the capital of Guangxi, and the maximum of input variables are appeared at Guilin City where most high-grade scenic spots and high-rate hotels of Guangxi are located.

Table 2. Data of output and input variables of tourism of traditional DEA model

City	Employ ees at	Touris m	Numbe r of	Number of	Number of AAA	Number of travel	Number of 4 star	Numb er of 2

	hotel and catering trade industry	consumption	visitors	AAAAA and AAAA grade scenic spot	and AA grade scenic spot	agencies	and 5 star grade hotels	star and 3 star grade hotels
Nanning	18810	919	9555	22	21	118	14	34
Liuzhou	3930	357	3316	22	21	53	12	36
Guilin	8038	637	5386	31	23	243	19	48
Wuzhou	1001	198	1748	4	8	24	1	33
Beihai	2734	288	2487	9	8	53	6	24
Fangchenggang	1004	129	1586	6	6	27	6	25
Qinzhou	1225	174	1807	4	18	40	1	17
Guigang	1058	179	1676	2	6	19	5	10
Yulin	1836	282	2800	7	16	29	5	16
Baise	1675	262	2725	11	10	21	6	25
Hezhou	686	217	1813	4	10	16	3	17
Hechi	1350	234	2165	12	22	39	9	42
Laibin	391	134	1809	7	14	11	4	13
Chongzuo	1315	183	2030	8	20	29	9	33
mean	3218	299	2922	11	15	52	7	27
SD	4894	219	2153	8	6	61	5	11
max	18810	919	9555	31	23	243	19	48
min	391	129	1586	2	6	11	1	10

As for the data of environmental variables, the local populations of each city in Guangxi are obtained from Guangxi Statistical yearbook (2023), and the times from Guangzhou and Nanning City to each city are obtained from Gaode map. Table 3 shows the detail data of environmental variables.

Table 3. Data of environmental variables of tourism at second stage

	Environmental Variables		
City	**Permanent population (10 000 persons)**	**Guangzhou** centroids	**Nanning** centroids
Nanning	706.22	5.08	2.03
Liuzhou	395.87	4.92	4.07
Guilin	500.94	3.90	4.74
Wuzhou	301.84	2.37	3.83
Beihai	164.37	5.94	4.30
Fangchenggang	92.90	6.12	3.95
Qinzhou	324.30	5.80	3.52
Guigang	303.20	4.08	3.01
Yulin	305.60	4.40	3.56
Baise	332.02	7.18	4.85
Hezhou	203.87	2.38	4.73
Hechi	349.90	7.30	4.90
Laibin	220.05	4.78	3.41
Chongzuo	206.92	7.60	4.24

In the variable of Guangzhou and Nanning centroids, the greater the value, the more travel time it takes since the value represents the time from Guangzhou or Nanning to the destination city.

3. Results

3.1. The First Stage: The Initial Efficiency Results

Based on the DEA assessment index system of the destination tourism industry, the efficiency (CRSTE), pure technical efficiency (VRSTE) and scale efficiency are calculated with DEAP2.1 software. The traditional DEA analysis efficiency results and returns to scale of 14 cities are summarized in Table 4.

Table 4. Efficiency of tourism industry of traditional DEA model

City	CRSTE	VRSTE	scale	Returns to scale
Nanning	1.000	1.000	1.000	--
Liuzhou	0.656	0.746	0.880	drs
Guilin	0.633	0.694	0.913	drs
Wuzhou	1.000	1.000	1.000	--
Beihai	0.823	1.000	0.823	irs
Fangchenggang	0.673	0.949	0.709	irs
Qinzhou	1.000	1.000	1.000	--
Guigang	1.000	1.000	1.000	--
Yulin	1.000	1.000	1.000	--
Baise	1.000	1.000	1.000	--
Hezhou	1.000	1.000	1.000	--
Hechi	0.491	0.612	0.802	drs
Laibin	1.000	1.000	1.000	--
Chongzuo	0.633	0.685	0.924	drs
mean	0.851	0.906	0.932	
SD	0.269	0.180	0.164	
Number of efficient cities	8			

Note: "--" represents constant returns to scale, "ins" represents increasing returns to scale and "drs" represents decreasing returns to scale

The mean of efficiency, pure technical efficiency and scale efficiency of the destination tourism industry is 0.851, 0.906 and 0.932, respectively. The results of the first stage DEA model indicate that there is still room to improve the overall operational efficiency of the tourism destination of Guangxi. The mean pure technical efficiency is 0.906 that means there is technical management inefficiency of the tourism industry in Guangxi. The average scale efficiency is 0.932, an indication that the average scale combination of input factors of the tourism industry in Guangxi is in good shape. The inefficiency of the tourism industry mainly results from pure techniques efficiency that means it is possible to improve management technical for maximizing destination tourism outputs. Moreover, the overall technical efficiency of cities such as Nanning, Wuzhou, Qinzhou, Guigang, Yulin, Baise, Hezhou and Laibin is significantly higher, meaning that they produce relatively more tourism outputs compared to other cities, with the input factors held constant. The destination efficiency of other cities in Guangxi call for improvement.

3.2. The Second Stage: The Influences of Environmental Variables on Tourism Operational Efficiency

In the second stage, output slacks from the first stage are decomposed into environmental effects, management inefficiency and statistical noise from measurement error of output and input data. Consequently, the three output slacks are calculated with radial plus non-radial slacks, respectively (Table 5). Output slacks depict insufficient output compared with the best-practiced frontiers while the input slacks are regarded as a surplus. The results show that the highest insufficient outputs, employees of the tourism industry (slack 1), tourism consumption (slack 2) and tourists (slack 3), appear in Guilin City, since the input factors such as A-grade scenic spots, star-rated hotels and travel agencies of Guilin is the highest of Guangxi. The insufficient outputs of Liuzhou City and Hechi City are higher in Guangxi, and the insufficient outputs of Chongzuo City are lower while that of Fangchenggang City is the lowest.

Table 5. The slacks of output variables

City	slack 1 (employees in tourism)	slack 2 (tourism consumption)	slack 3 (number of visitors)
Nanning	0.00	0.00	0.00
Liuzhou	3397.78	121.72	1661.78
Guilin	10772.00	281.37	4169.29
Wuzhou	0.00	0.00	0.00
Beihai	0.00	0.00	0.00
Fangchenggang	54.00	49.93	90.02
Qinzhou	0.00	0.00	0.00
Guigang	0.00	0.00	0.00
Yulin	0.00	0.00	0.00
Baise	0.00	0.00	0.00
Hezhou	0.00	0.00	0.00
Hechi	3487.57	148.40	1736.66
Laibin	0.00	0.00	0.00
Chongzuo	1941.67	102.34	934.89

In the second stage, the three output slack variables are set to be dependent variables, respectively, and the environmental variables are set to be independent variables when running SFA regression. The results of SFA regression are summarized at Table 6. The likelihood ratio (LR) test rejects the null hypothesis to the second slack variable (tourism consumption) which indicates that the managerial efficiency makes contribution to the composed error term. The LR test accepts the null hypothesis to the first and the third slack variable (the employees in tourism, the number of visitors) which indicates that the managerial efficiency makes no contribution to the composed error term. The LR test results indicate that the managerial inefficiency makes no contribution to the variation of the employees of tourism (slack 1) and the number of visitors (slack 3) output. Consequently the parameters of employees of tourism (slack 1) and the number of visitors (slack 3) regression model are estimated based on a tobit specification(H.O. Fried et al., 1999).

The gamma of the second SFA regression model is 0.50 that indicates managerial inefficiency explains half of the variation in tourist consumption (slack 2) slack and statistical noise explains another 50% of the variation. As to output slack variables of employees in the tourism industry (slack 1) and the number of visitors (slack 3), the variation of efficiency can be completely explained with the effects of environmental variables and statistical noise, and regional tourism management plays no contribution to the efficiency variation of each city.

Table 6. Results of stochastic frontier estimation (standard errors in parenthesis)

	Dependent Variables		
Independent variables	**slack 1 (employees in tourism)**	**slack 2 (tourism consumption)**	**slack 3 (number ofvisitors)**

constant	-16029.24**	-140.91**	-6545.75**
	(6830.87)	(62.70)	(2772.50)
Permanent population (x_1)	10540.01*	200.11**	4239.69*
	(5898.58)	(70.46)	(2384.16)
Guangzhou centroids (x_2)	1985.30	19.76	1036.80
	(4440.08)	(52.98)	(1810.19)
Nanning centroids (x_3)	14308.07**	222.73**	5789.39**
	(6356.43)	(69.24)	(2564.50)
sigma-squared	3853.74**	4902.11**	1561.86**
	(1373.20)	(8.98)	(561.06)
gamma	N/A	0.50	N/A
		(0.42)	
log likelihood function	-52.12	-76.88	-47.67
LR test of the one-sided error		0.08	

Note:"**" represent significant at 5% level, and "*" represents significant at 10% level

The permanent population (x_1) has a significant positive coefficient of three output SFA regression models, suggesting that the three output slack variables will be greater if the permanent population of each city increases. The greater output slacks then result in reduction of operational efficiency. The effects of Guangzhou centroids (x_2) on three output equations are not significant, indicating that the Pearl River Delta tourism market has no significant effect on destination tourism operational efficiency. Nanning centroids (x_3) has a significant positive coefficient of three output equations, indicating that the three output slack variables will be grater if tourists spend more time traveling from Nanning City to destination. This suggests that it is unfavorable to destination tourism operational efficiency if tourists have to spend more time travelling to destination.

3.3. The Third Stage: The Final Efficiency Results

The significant parameters presented in Table 6 are then used to adjust initial output data according to equation (5). The adjusted data set are shown in Table 7.

Table 7. The adjusted output variables and input variables of tourism industry at second stage

City	Employees at hotel and catering trade industry	Tourism consumption	Number of visitors	Number of AAAAA and AAAA grade scenic spot	Number of AAA and AA grade scenic spot	Number of travel agencies	Number of 4 star and 5 star grade hotels	Number of 2 star and 3 star grade hotels
Nanning	33118	1171	15345	22	21	118	14	34
Liuzhou	8081	497	4996	22	21	53	12	36
Guilin	8836	637	5709	31	23	243	19	48
Wuzhou	6349	450	3912	4	8	24	1	33
Beihai	5747	541	3706	9	8	53	6	24
Fangchenggang	5753	350	3507	6	6	27	6	25
Qinzhou	8110	427	4593	4	18	40	1	17
Guigang	10477	440	5487	2	6	19	5	10
Yulin	8521	536	5505	7	16	29	5	16

Baise	1914	507	2821	11	10	21	6	25
Hezhou	1524	466	2152	4	10	16	3	17
Hechi	1350	344	2165	12	22	39	9	42
Laibin	7814	394	4812	7	14	11	4	13
Chongzuo	4608	349	2030	8	20	29	9	33

The final stage is to run the DEA procedure with the adjusted output and initial input data since the DEA is based on output-oriented analysis. This produces a composite efficiency index which incorporates the effects of environment variables and statistical noise and set them to the same level. Table 8 presents the efficiency of the third-stage results.

Table 8. The efficiency of tourism industry at third stage

City	CRSTE	three-stage CRSTE	three-stage scale	Returns to scale
Nanning	1.000	1.000	1.000	-
Liuzhou	0.393	0.688	0.571	drs
Guilin	0.379	0.544	0.696	drs
Wuzhou	1.000	1.000	1.000	-
Beihai	0.948	1.000	0.948	drs
Fangchenggang	0.795	0.795	1.000	-
Qinzhou	1.000	1.000	1.000	-
Guigang	1.000	1.000	1.000	-
Yulin	0.947	1.000	0.947	drs
Baise	0.920	1.000	0.920	drs
Hezhou	1.000	1.000	1.000	-
Hechi	0.317	0.547	0.579	drs
Laibin	1.000	1.000	1.000	-
Chongzuo	0.424	0.637	0.666	drs
mean	0.794	0.872	0.880	
SD	0.184	0.143	0.092	
Number of efficient cities	6			

After putting all tourism destinations to the same environment and the same luck, the mean overall efficiency, the pure technical efficiency and the scale efficiency of Guangxi is 0.794, 0.872, and 0.880, respectively.

4. Discussion

Current studies have researched destination tourism efficiency or specific tourism industry efficiency such as hotel and travel agency(Lee et al., 2019; Tzeremes, 2019). This study aims to measure output oriented destination tourism efficiency with purging environmental and statistical noise effects while the current studies mainly measure input oriented efficiency of destination tourism which usually pay more attention to reduce input surplus(Chaabouni, 2019; Charles & Zegarra, 2014). In the tourism industry, it is often difficult to reduce the number of scenic spots, hotels and tourism infrastructure after they are constructed. The output-oriented destination tourism efficiency could help answer how much outputs will be increased if the inputs are combined in the best situation, and the management level improved. This approach may serve as an alternative to traditional DEA model for making more informed regional tourism development policies.

Compared with the traditional DEA model, the average overall efficiency and the standard deviation in the third stage decreased (Figure 2.a). Meanwhile, the pure technical efficiency and the scale efficiency decreased as well (Figure 2. b, c). Moreover, the decreasing of overall technical efficiency of destination tourism in the final stage results mainly from the reduction of scale efficiency while the reduction of pure technical efficiency is small. The decrease in mean overall technical efficiency indicates that the benefit to tourism destination under favorable environmental conditions outweighed the penalty to tourism destination under disadvantageous environmental conditions, without adjusting the effects of environment variables. This shows that some destinations such as Nanning, Wuzhou, Qinzhou, Guigang, Hezhou and Labin that receive relatively high initial efficiency do so in part due to their relatively advantageous environments. Not all destinations are run as well as their initial efficiency indicated. The efficiency relation of stage 1 and stage 3 in this study is similar to that of Frieds' research(H. O. Fried et al., 2002).

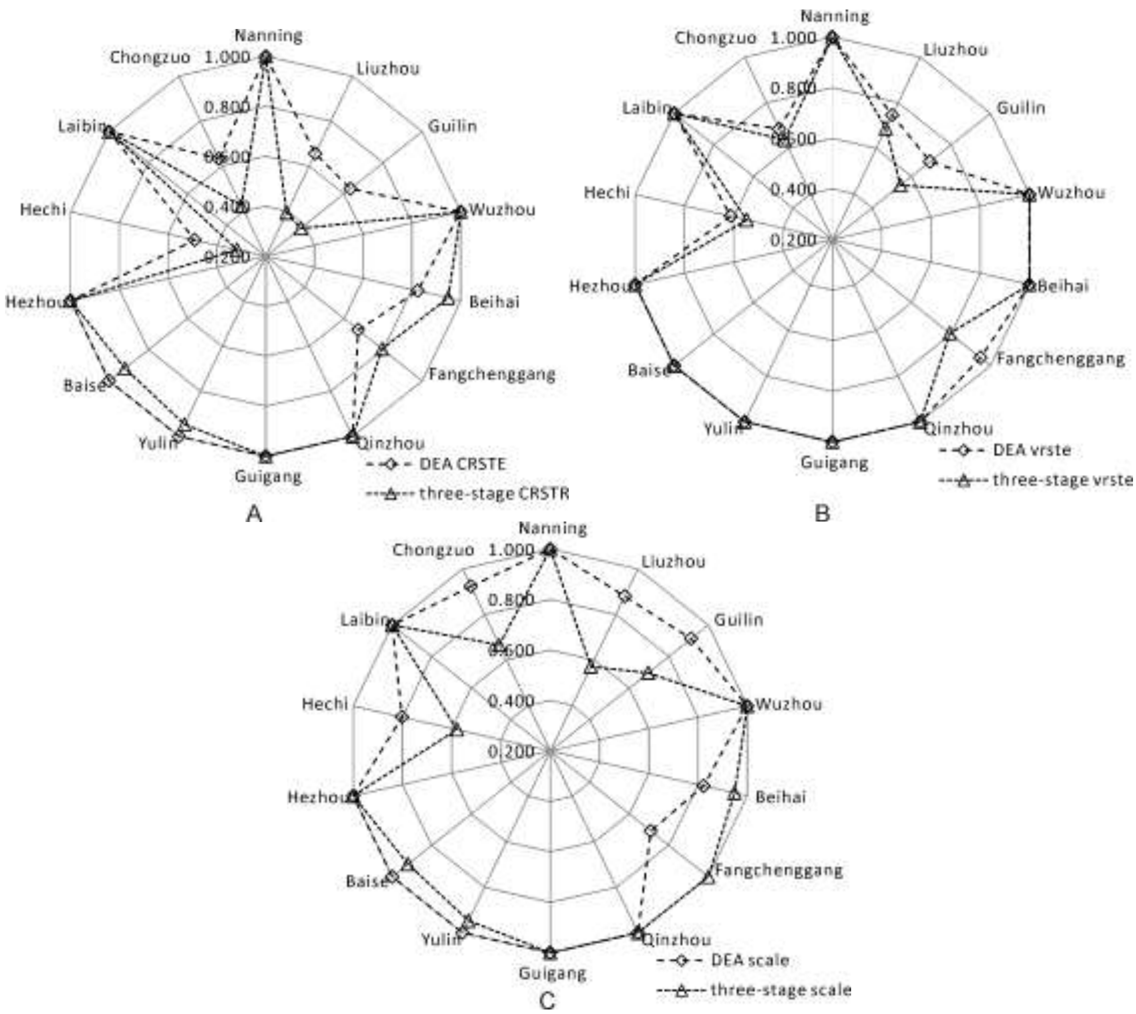

Figure 2. The difference of overall efficiency (A), pure technical efficiency (B) and scale efficiency (C)

The decrease of the number of efficient tourism destinations indicates that tourism destinations with advantageous environments are more efficient compared to tourism destinations with unfavorable environments, when the efficiency includes environment effects. The decrease of the standard deviation reflects that the efficiency of tourism destinations with favorable environments are biased up while the efficiency of tourism destination with unfavorable environments are biased down, without controlling for environmental effects. By adjusting the output data to put all tourism destinations in the same environment, this bias to the efficiency is removed, and the spread is narrowed.

The Kendall rank correlation coefficient between the first stage and the third-stage efficiency is 0.255 (p=0.059); the 95 percent confidence interval is 0.120 to 0.134. Controlling environmental effects makes a difference in terms of efficiency rankings at 10% level. This confirms the importance of purging environmental effects from tourism destination efficiency.

The efficiency of the destination tourism industry of Guangxi can be improved by 20.4%. The projected input and output combination of cities are shown in Table 9.

Table 9. The projected output and input variables of tourism industry based on three-stage DEA

City	Employees at hotel and catering trade industry	Tourism consumption	Number of visitors	Number of AAAAA and AAAA grade scenic spot	Number of AAA and AA grade scenic spot	Number of travel agencies	Number of 4 star and 5 star grade hotels	Number of 2 star and 3 star grade hotels
Nanning	33118	1171	15345	22	21	118	14	34
Liuzhou	22097	1264	12706	8	21	53	12	36
Guilin	39938	1683	20933	8	23	73	19	39
Wuzhou	6349	450	3912	4	8	24	1	33
Beihai	13073	571	6916	3	8	25	6	16
Fangchenggang	10477	440	5487	2	6	19	5	10
Qinzhou	8110	427	4593	4	18	40	1	17
Guigang	10477	440	5487	2	6	19	5	10
Yulin	11010	566	6129	3	12	29	5	16
Baise	6610	551	4384	4	10	21	5	17
Hezhou	466	2152	4	10	16	3	17	17
Hechi	8237	1086	6837	9	22	39	8	37
Laibin	7814	394	4812	7	14	11	4	13
Chongzuo	10864	823	7183	8	19	29	7	26
mean	13474	858	7480	7	15	36	8	23
SD	10908	544	5367	5	6	29	6	11
max	39938	2152	20933	22	23	118	19	39
min	466	394	4	2	6	3	1	10
increase	68%	69%	57%	-38%	0%	-30%	9%	-14%

The mean output of employees of the tourism industry, the tourism consumption and the number of visitors could be increased by 68%, 69% and 57%, respectively based on projections. Moreover, another finding is that the average number of travel agencies could be decreased by 30%, and it could be reduced mainly in Guilin, Beihai, Fangchenggang and Hezhou cities.

5. Conclusions

The objective of this study is to conduct the output-oriented regional tourism destination efficiency based on the three-stage DEA procedure on 14 prefectural-level cities of Guangxi Autonomous region of China. The key contribution is the employment of the tourist market as environmental variables, which is then used to eliminate the effects of environment and statistical noise from the traditional DEA procedure and to analyze the managerial efficiency of destination tourism. Therefore, the results go beyond the current studies that pay close attention on input-oriented efficiency.

In the traditional DEA procedure, the results indicate that the efficiency of the destination tourism industry of Guangxi can be improved by 10%. The inefficiency of the tourism industry mainly results from pure technical inefficiency. The results of the second stage indicate that managerial inefficiency explains half of the variation in tourist consumption slack variable and statistical noise explains another 50% of the variation. In reference to the output slack variables of the employees in tourism industry and the number of visitors, we note that the effects of environment and statistical noise explain the whole variation of the efficiency, and managerial inefficiency impacts tourism destination efficiency in each city. In the final stage, the results show that there is more room for improvement of the efficiency of destination tourism industry of Guangxi after eliminating the effects of environment and statistical noise. The inefficiency of tourism industry results from the pure technical and scale efficiency.

Compared with the traditional DEA procedure, the final stage average overall efficiency and standard deviation decrease. The pure technical and scale efficiency of the final stage decrease as well. The projected input and output combination of the tourism industry in cities show that the average output of employees, the tourism consumption and the number of visitors could be increased by 68%, 69% and 57%, respectively based on projections. Moreover, the average number of travel agencies could be decreased by 30%, and it could be reduced mainly at Guilin, Beihai, Fangchenggang and Hezhou cities. The conclusion of this study is that local governments should further develop the tourist market of the Nanning and other cities in Guangxi, improve operation levels and reallocate scenic spots, travel agencies and hotels in order to increase tourism efficiency. As a next step, a comparison of the tourism industry efficiency at the provincial level may lead to more meaningful policy recommendations based on this study.

Acknowledgments:

Conflict of Interest Statement: The authors declare no conflict of interest.

Funding Statement: This work was supported by the China Natural Science Fund Project under grant number 41501152.

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