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Measuring sustainability and competitiveness of tourism destinations with data envelopment analysis

Dongdong Wu[a], Hui Li[a] and Yuhong Wang[b]

[a]College of Tourism and Service Management, Nankai University, Tianjin, P.R. China; [b]School of Business, Jiangnan University, Wuxi, P.R. China

ABSTRACT

This study analyses sustainability and competitiveness through measurements of efficiency, using data envelopment analysis. It constructs a meta-frontier non-radial directional distance function (meta-frontier NDDF) approach, which is then used to define a tourism development index and a tourism sustainability index. Using these indexes, the paper evaluates the efficiency of the tourism sector and its dynamic evolution for 27 cities in the Yangtze River Delta, China, (YRD) from 2010 to 2019. Considering regional heterogeneity, this paper analyzes the meta-frontier, group-frontier efficiency and technology gap ratio of urban tourism in the YRD, and explores the competitiveness of the cities. The results show that the more traditional measure of tourism efficiency, namely the tourism development index, which does not take account of the sector's undesirable output (i.e., the negative impacts of carbon emissions from travel), produces overestimates. This study highlights the following practical implications: The increasing competition among tourism destinations requires tourism industry managers to determine the appropriate allocation of resources to promote the sustainable development of urban tourism. In the context of the need for global 'carbon neutrality', more consideration should be given to the negative impact of tourism on the natural environment to enhance the competitiveness of tourist destinations.

Abbreviations: DEA: Data envelopment analysis; SFA: Stochastic frontier analysis; DMUs: Decision-making units; YRD: Yangtze River Delta; SDF: Shephard distance function; DDF: Direction distance function; NDDF: Non-radial direction distance function; CRS: Constant return to scale; VRS: Variable return to scale; TDI: Tourism development index; TSI: Tourism sustainability index; TGR: Technology gap ratio; MTE: Technological efficiency under the meta-frontier; GTE: Technological efficiency under the group-frontier

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Tourism destination; sustainable development; competitive analysis; meta-frontier NDDF; data envelopment analysis; Yangtze River Delta

Introduction

Cities are the core of national economic growth and tourism plays a vital role in urban economic growth. In recent years, urban tourism development in China has received increasing attention from policy makers and academic researchers. In 2019, China's 40 major tourism cities accounted for 35.4% and 38.2% of the national tourism sector in terms of tourist reception and income,

CONTACT Hui Li lihuihit@nankai.edu.cn College of Tourism and Service Management, Nankai University, Tianjin, P.R. China.
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respectively. It is evident that cities have become major tourism destinations. At the same time, the urban tourism infrastructure, construction projects and other investments in fixed assets has increased year by year. However, the negative impact of tourism, for example on the environment, such as carbon dioxide emissions, also deserves further attention (Zha et al., 2019).

Greater efficiency in the utilization of resources is one goal of urban tourism development, and so is of considerable importance for the design of policies (Lu et al., 2019). Tourism, as an important economic sector with a significant impact on resources, is closely aligned with the concept of sustainable development (Sharpley, 2020). There is a need to rethink tourism's role in promoting development while seeking to reduce its impact on the environment. Nevertheless, performance is still deemed to be the meaningful measurement of tourism competitiveness (Croes & Kubickova, 2013). The competitiveness of urban tourism depends on the efficiency with which a city's resources are exploited (Mendieta-Peñalver et al., 2018). It can reflect the comparative advantages of a given city. The greater a city's competitiveness is, the greater will be its potential for further development.

The Yangtze River Delta (YRD) is one of the most developed regions in China, in social and economic terms. The integrated economic development of the YRD has been promoted as a national strategy and is a matter of great research interest. The efficiency of urban tourism can be measured by taking the city as the production unit of the tourism economy, which has the goal of maximizing the output and total surplus of stakeholders for a given amount of factor input (Ma & Bao, 2010). Tourism competitiveness can be defined as the 'ability to increase tourism expenditure, to increasingly attract visitors while providing them with satisfying, memorable experiences, and to do so in a profitable way, while enhancing the well-being of destination residents and preserving the natural capital of the destination for future generations' (Ritchie & Crouch, 2003). The determination of the efficiency and competitiveness of the tourism industry in the YRD cities can provide the basis for decisions on the allocation of resource inputs for tourism development and allow direct comparisons to be made between destinations.

A city can be regarded as a complex tourism destination, which contains many inputs, and both desirable and undesirable outputs in the tourism production process. According to the tourism carrying capacity theory, over-tourism has a negative impact on sustainable development. For example, against the background of global 'carbon neutrality', carbon emissions are a typical undesirable output generated by tourism activities. Data envelopment analysis (DEA) (Charnes et al., 1978) and stochastic frontier analysis (SFA) (Aigner et al., 1977) are commonly used to measure efficiency in frontier analysis theory (Assaf & Josiassen, 2016). DEA is a nonparametric linear programming technique, which can be used to analyze the efficiency of decision-making units (DMUs) with multiple input and output indicators. DEA does not make assumptions about functional form, and so avoids one source of error in statistical analysis. In addition, the weights assigned in the DEA method are not affected by subjective factors, and efficiency can be evaluated by comprehensive indexes. Therefore, DEA is chosen in this paper as the technique for the assessment of efficiency.

As a commonly used data-driven tool, DEA has been adopted by a variety of scholars to analyze efficiency in different research fields (Emrouznejad & Yang, 2018), and especially in tourism (Assaf & Tsionas, 2019). The evaluation of the performance of the tourism industry and regional tourism has mainly focused on efficiency. This research has looked at hotels (Altin et al., 2018), the tourism supply chain (Huang, 2018), and tourist destinations (Gómez-Vega & Herrero-Prieto, 2018). Tourism efficiency has been researched at the provincial or regional level (Chaabouni, 2019), the city level (Zekan et al., 2019), and the industry or sector level (Mariani & Visani, 2019). However, previous studies have ignored the sustainability and regional heterogeneity of urban tourism development. This paper focuses on the development of urban agglomerations, and analyzes the efficiency, competitiveness and sustainability of tourism by taking the city (as a tourism destination) as the DMU.

The research objective of this paper is to evaluate the efficiency of urban tourism and analyze cities' competitiveness in the YRD over 10 years from the perspective of sustainable development and regional heterogeneity. As an extension of non-parametric frontier analysis (i.e., DEA), this paper uses the non-radial direction distance function (NDDF) approach to assess undesirable outputs in a comprehensive evaluation of the efficiency of urban tourism. In addition, from the perspective of high-quality integrated development of the YRD, the meta-frontier and group-frontier efficiency and the technology gap ratio (TGR) of cities in the YRD are calculated and the competitiveness of the cities is analyzed.

The main contributions of this paper are as follows. (1) We evaluate the sustainable development of urban tourism. In traditional research on the efficiency of urban tourism, development is evaluated solely in terms of income generation, even though it may not be sustainable. The NDDF approach used in this paper, in contrast, accounts for undesirable outputs. (2) Integrated economic development is evaluated from the perspective of regional heterogeneity. Previous research on urban tourism efficiency has been conducted at the provincial level. Here, however, to allow for the heterogeneity of DMUs within provinces, the efficiency of the urban tourism sector is determined with reference to the group-frontier.

The paper is structured as follows. Section 'Literature review' reviews the literature on the directional distance function approach and the evaluation of tourism efficiency. The research design and methodology are laid out in Section 'Research design and methodology'. Section 'Research area and indicator selection' presents the research area and data description. The empirical results and discussion are provided in Section 'Empirical results and discussion'. Section 'Conclusion' presents the conclusion.

Literature review

Meta-frontier directional distance function approach

The traditional DEA model, the CCR model (Charnes et al., 1978), makes a radial assumption in its evaluation of efficiency, which exaggerates efficiency scores. More importantly, the existence of undesirable outputs is not accounted for. That is, each DMU is assumed to generate its normal expected (good, desirable) output but it is also likely to generate a series of unexpected 'bad' byproducts (the undesirable output). In fact, the desirable and undesirable outputs are related to a certain degree. Many disposability methods considering undesirable outputs have been proposed, such as: strong disposability; weak disposability; the by-production model (Murty et al., 2012); natural and managerial disposability (Sueyoshi & Goto, 2012); and weak G-disposability (Hampf & Rødseth, 2015). Undesirable outputs are widely taken into account in research in the fields of energy, the economy and others, but as yet have been largely neglected in tourism research, especially in the context of sustainable tourism (Assaf & Cvelbar, 2015). Considering the practical significance of the tourism production process, the undesirable output in this paper (i.e., carbon emissions from tourism transportation) is modelled by assuming weak disposability and null-jointness (see below, Section 'Environmental production technology').

The distance function model can simultaneously consider desirable and undesirable outputs, which is a big advantage over the traditional DEA model. At the same time, it avoids the dilemma of choosing an input or output orientation. The Shephard distance function (SDF) assumes that desirable and undesirable outputs expand or shrink in the same proportion. In fact, the aim of any production process will be to get as much desirable output as possible and to reduce undesirable outputs, for any given amount of resource input. Unlike the SDF, the directional distance function (DDF) can consider both a decrease in undesirable output and an increase in desirable output within the allowable range of the technical feasible set (Chung et al., 1997). Such a balance is the key to sustainable tourism. For example, Niavis (2020) utilized the DDF model with weak disposability to measure the spatiotemporal performance of tourism destinations. In fact, the DDF model is a general expression of the traditional DEA model with a radial assumption. However, the increase in desirable output and the decrease in input and undesirable output are still treated in the same proportion in the DDF model. This radial assumption could lead to 'slack bias' (Fukuyama & Weber, 2009). In order to overcome this limitation of the DDF model, the NDDF model is widely used because it relaxes the assumption of constant proportional change. As a result, the NDDF model is considered a very suitable and developed approach for the evaluation of the efficiency of the tourism sector.

Due to geographical restrictions, resource endowments, policy factors and other reasons, there is usually production technology heterogeneity across geographical regions. The fundamental idea of the meta-frontier theory is to place a set of DMUs in various groups, and each group forms a production frontier, also known as the group-frontier. Then, a joint production frontier, also known as the meta-frontier, is formed by enveloping a number of group-frontiers. This analytical approach has been applied in research on the energy economy (Zhang & Choi, 2014), energy policy (Zhang et al., 2013), sociology (Ma et al., 2021), technology innovation (Wang et al., 2021) and other fields. It has only recently been applied to the tourism economy and the evaluation of hotel performance (Yu & Chen, 2020a, 2020b). Recently, Nurmatov et al. (2021) adopted the meta-frontier DEA technique and bootstrapping method to investigate regional tourism performance. Zha et al. (2020) developed meta-frontier DEA-based approaches for the decomposition of tourism growth, and further constructed a structural meta-frontier DEA model to evaluate tourism inefficiency in an analysis that accounted for tourism subsectors and regional heterogeneities (Zha et al., 2022).

Sustainable tourism and destination competitiveness

At present, studies evaluating tourism efficiency have focused on total factor productivity (Assaf & Tsionas, 2018; Walheer & Zhang, 2018). The paradigm for the evaluation of performance using frontier analysis has mainly involved the application of SFA (Arbelo et al., 2018; Liu & Tsai, 2021), DEA (Niavis & Tsiotas, 2019), the integration of DEA and SFA (Pulina & Santoni, 2018; Sellers-Rubio & Casado-Díaz, 2018). A single-stage static model or a multi-stage dynamic network model (Huang et al., 2017; Tan & Despotis, 2021) can be constructed to measure the performance of star-rated hotels and other tourism industries, or of tourism firms. In addition, scholars have used mathematical statistics, econometrics and GIS models to explore tourism eco-efficiency and its influencing factors (Liu et al., 2017), and the temporal and spatial differences in low-carbon tourism efficiency and total factor productivity (Zha et al., 2019). In relation to the measurement of the sustainability of the tourism sector, Ko (2001) put forward a framework based on a 'barometer of sustainability'. Further, Ko (2005) proposed a procedure for the assessment tourism sustainability. Asmelash and Kumar (2019) and Rasoolimanesh et al. (2020) provided a systematic review of sustainable tourism indicators based on the United Nations' Sustainable Development Goals.

Performance evaluation and competitive advantage share an underlying theoretical structure with the resource-based view theory (Hossain et al., 2021; Sharma et al., 2022). Following the competitiveness theory and comparative advantage framework, resource availability is the crux of creating advantage among DMUs (Croes & Kubickova, 2013). We can explain tourism destination competitiveness from this 'resource-based view', which encompasses resource competition and benchmarking competition. DEA has been seen as a balanced benchmarking method, and can therefore guide non-efficient DMUs to reach the 'benchmark', such as changing the 'slacks' identified by analysis of a set of input-output indicators. In this way, DEA can be viewed as a superior tool to explore the competitiveness of tourism destinations.

Zhang et al. (2011) measured destination competitiveness by adopting the TOPSIS and information entropy method. Font et al. (2021) investigated the impact of sustainable tourism

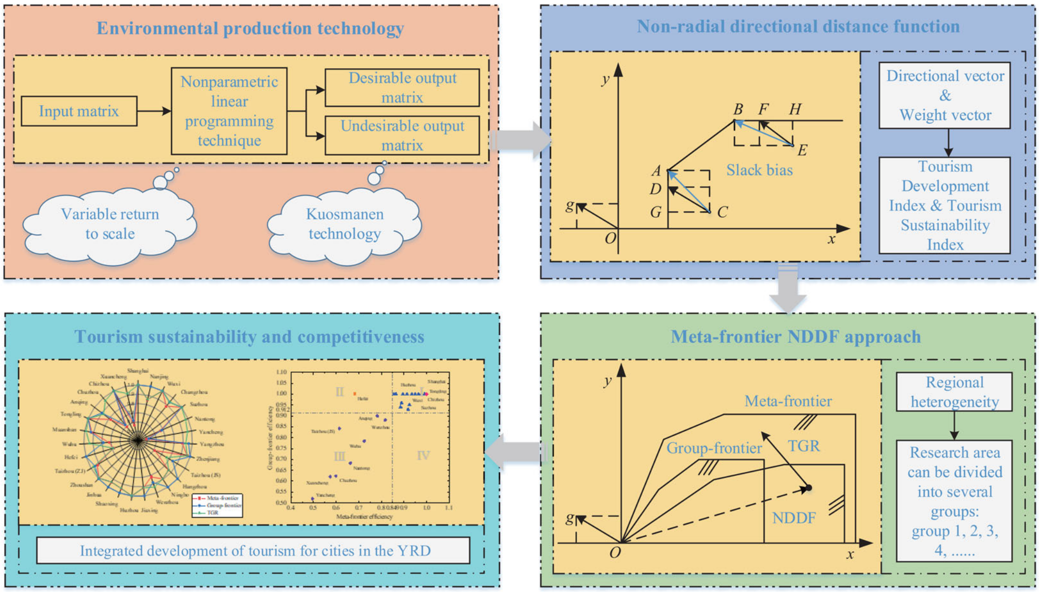


Figure 1. The analytical framework for tourism destination sustainability and competitiveness.

indicators on destination competitiveness. Goffi et al. (2019) demonstrated that sustainability plays a key role in fostering destination competitiveness. According to a comprehensive review of destination competitiveness, the new trend is for competitiveness to connect with concepts of sustainability (Cronjé & Du Plessis, 2020). However, previous studies have not considered both the sustainable development and the competitiveness of tourism destinations. In urban tourism as elsewhere, efficient DMUs have advantages over inefficient DMUs. More specifically, DMUs with a lower technology gap ratio (TGR) should have in place innovative technology that is closer to the overall optimal technology level. From the perspective of resource theory, such advantages will ensure the competitiveness of efficient DMUs.

Summary of the literature review

Although undesirable output has a great impact on efficiency, few articles consider it from the perspective of sustainability. In addition, the heterogeneity of production technology among various regions has not been considered in the research literature, and similarly evaluation of the efficiency of the tourism sector under a single production frontier in a region is also insufficient. Taking the YRD as a case study for the evaluation of the efficiency of urban tourism and for an analysis of destination competition (between cities), this paper attempts to fill the current research gap in tourism performance evaluation by constructing the meta-frontier non-radial directional distance function (meta-frontier NDDF).

On the one hand, the development of urban tourism needs to be closely combined with the theme of green and high-quality development. The evaluation of efficiency needs a more advanced and flexible method, and should include a consideration of sustainable development. On the other hand, the integrated development of the YRD has become a national strategy, and the development of regional tourism needs to break the restrictions of administrative boundaries. Considering meta-frontier and group-frontier production technology based on regional heterogeneity is of major importance for an evaluation of urban tourism's efficiency. The TGR is helpful for the analysis of competitiveness in the context of urban tourism.

Research design and methodology

Firstly, we define the undesirable outputs and the returns to scale of the production technology (urban tourism). Then, we construct the NDDF model, and define the study's indexes of tourism development and sustainability according to the different choices of direction vector and weight. Finally, meta-frontier NDDF and TGR are analyzed. Figure 1 shows the analytical framework.

Environmental production technology

Tourism has an environmental impact and the sustainability of its development cannot be ignored. Suppose each DMU uses $x = (x_1, x_2, \ldots, x_M) \in \Re_+^M$ inputs to obtain $y = (y_1, y_2, \ldots, y_S) \in \Re_+^S$ desirable outputs but also $b = (b_1, b_2, \ldots, b_Q) \in \Re_+^Q$ undesirable outputs. Among those vectors, x_m, y_s and b_q are the m-th input, s-th desirable output, and q-th undesirable output associated with the DMU, respectively. We characterize the environmental production technology by $T = \{(x, y, b) : x \text{ can produce } (y, b)\}$ or $P(x) = \{(y, b) : (x, y, b) \in T\}$. In addition, it should satisfy the standard axioms of production theory (Färe & Grosskopf, 2003).

In this paper, null-jointness implies that the only way to eliminate all 'bad' outputs is to stop the production process (Shephard & Färe, 1974). That is, if $(x, y, b) \in T$ and $b = 0$, then $y = 0$. In addition, weak disposability indicates that it is possible to reduce both good and 'bad' outputs proportionally. That is, if $(x, y, b) \in T$ and $\theta \in [0, 1]$, then there must be $(x, \theta y, \theta b) \in T$. Alternatively, the strong (or 'free') disposability precludes production processes with 'bad' outputs that are expensive to dispose of. That is, if $(x, y, b) \in T$ and $(x, y^*, b) \le (x, y, b)$, then $(x, y^*, b) \in T$.

Constant return to scale (CRS) indicates that outputs increase (or decrease) in direct proportion to the inputs. Variable return to scale (VRS) can be divided into increasing or decreasing returns to scale. In this paper, considering the actual production process of urban tourism, the assumption of VRS is in line with reality and has scientific significance. Following D'Inverno et al. (2018) and Wu et al. (2020), this paper focuses on modelling weak disposability and VRS. The production possibility set with weak disposability and VRS can be denoted as (Kuosmanen, 2005):

$$T^* = \left\{ \begin{array}{c} (x, y, b) : \sum_{k=1}^{K} \lambda^k y_s^k \ge y_s, \forall s; \ \sum_{k=1}^{K} \lambda^k b_q^k = b_q, \forall q \\ \sum_{k=1}^{K} (\lambda^k + \mu^k) x_m^k \le x_m, \forall m; \ \sum_{k=1}^{K} \lambda^k + \mu^k = 1; \ \lambda^k, \mu^k \ge 0, \forall k \end{array} \right\} \tag{1}$$

where k is the number of DMUs (here, cities in the YRD); x_m^k, y_s^k and b_q^k are the m-th input, s-th desirable output, and q-th undesirable output associated with the evaluated k-th DMU. $\lambda^k + \mu^k$ denotes the intensity weights used to construct the convex combinations. The inequality constraints formalize the strong disposability of inputs and desirable outputs, while the equality constraints describe the weak disposability of undesirable outputs.

Non-radial directional distance function approach

Chung et al. (1997) introduced the DDF model into environmental efficiency evaluation. The DDF model aims to optimize desirable output while minimizing the undesirable output. Formally, it is defined as $\overrightarrow{D}(x, y, b; g) = \sup\{\beta : (x, y, b) + \beta g \in T\}$, where '$g$' is the vector of 'directions'; β represents the maximum possible proportions of desirable output, input and undesirable output. The DDF model assumes that the proportional change of each indicator in the input-output system is the same, so it may lead to 'slack bias' among the variables in the efficiency evaluation of specific economic and social sectors (Fukuyama & Weber, 2009).

Zhou et al. (2012) presented the NDDF model as a refinement of the DDF model. The limitation that all indicators in the DDF model must change in the same proportion is relaxed. Considering the above-mentioned Kuosmanen technology, the NDDF can be defined as:

$$\overrightarrow{ND}(x, y, b; g) = \sup\{(\beta_x, \beta_y, \beta_b) : (x, y, b) + g \times \mathrm{diag}(\beta_x, \beta_y, \beta_b) \in T^*\} \tag{2}$$

where $\beta = (\beta_x, \beta_y, \beta_b) = ((\beta_{x_m})_{m=1}^M, (\beta_{y_s})_{s=1}^S, (\beta_{b_q})_{q=1}^Q)$ is the scaling vector function, representing the percentage by which each variable can be increased or decreased; $g = (g_x, g_y, g_b) = ((g_{x_m})_{m=1}^M, (g_{y_s})_{s=1}^S, (g_{b_q})_{q=1}^Q)$ specifies the explicit directional vector used to scale the input-output combination; and $\mathrm{diag}(\cdot)$ is the diagonalization of vector β.

Following D'Inverno et al. (2018), the vector maximization problem, i.e., $\max\beta = (\beta_x, \beta_y, \beta_b)$, can be mathematically solved by maximizing a scalar function, i.e., $\max w^T\beta$. We define $w = ((w_{x_m})_{m=1}^M, (w_{y_s})_{s=1}^S, (w_{b_q})_{q=1}^Q)$ as the normalized weight vector, which satisfies $\sum_{m=1}^M w_{x_m} + \sum_{s=1}^S w_{y_s} + \sum_{q=1}^Q w_{b_q} = 1$ and $w_{x_m} \geq 0$, $w_{y_s} \geq 0$, $w_{b_q} \geq 0$, $\forall m, s, q$. Then, the optimal value of measured efficiency can be derived from model 3:

$$\begin{aligned}
&\max w^T\beta = w_{x_m}\beta_{x_m} + w_{y_s}\beta_{y_s} + w_{b_q}\beta_{b_q} \\
&s.t. \quad \sum_{k=1}^K (\lambda^k + \mu^k) x_m^k + g_{x_m}\beta_{x_m} \leq x_m, \ \forall m \\
&\qquad \sum_{k=1}^K \lambda^k y_s^k - g_{y_s}\beta_{y_s} \geq y_s, \ \forall s \\
&\qquad \sum_{k=1}^K \lambda^k b_q^k + g_{b_q}\beta_{b_q} = b_q, \ \forall q \\
&\qquad \sum_{k=1}^K \lambda^k + \mu^k = 1; \ \lambda^k, \mu^k \geq 0, \ \forall k \\
&\qquad \beta_{x_m} \geq 0, \beta_{y_s} \geq 0, \beta_{b_q} \geq 0, \ \forall m, \forall s, \forall q
\end{aligned} \tag{3}$$

Model 3 can be differently specified by varying β and g. The results suggest how inefficient DMUs might seek to improve their performance. In this paper, we consider two specifications:

Assumption 1: We assume that each DMU generate no undesirable outputs; that is, $\beta = (\beta_x, \beta_y)$ and $g = (-x, y, 0)$. The model is able to consider both input reduction and an increase in desirable outputs at the same time.

Assumption 2: We assume that each DMU does generate undesirable outputs; that is, $\beta = (\beta_x, \beta_y, \beta_b)$ and $g = (-x, y, -b)$. Here, the model is able to consider the situation where both inputs and undesirable outputs decrease, but there is nevertheless an increase in the level of desirable outputs.

The weight vector, w^T, assigns different weights to each input, desirable and undesirable output, which provides good flexibility. In the absence of prior information, it is reasonable to treat all indicators of the input-output system equally. In this paper, labor force (*L*), capital stock (*F*) and tourism resource endowment (*E*) are selected as inputs; total tourism income (*R*) and tourist reception (*T*) are treated as desirable outputs; carbon emissions from tourism transportation (*C*) is considered to be the (sole) undesirable output. Inputs, and desirable and undesirable outputs are assumed to be equally important and therefore given equal weight. Once the set of weights is established, we can derive the optimal value (i.e., the inefficiency value) by solving model (3).

It is obvious that the higher the optimal value is, the lower will be the efficiency level of the evaluated DMU. It should be noted that the optimal (inefficiency) value lies in interval $[0, 1]$. A DMU is determined to be efficient when the optimal value equals 0. Using the obtained optimal value, we define two normalized efficiency indexes:

Definition 1: Tourism Development Index (TDI). Following Assumption 1, the TDI for the n-th DMU can be calculated by the following formula:

$$TDI_n = \frac{1 - \sum_{m=1}^{M} w_{x_m} \beta_{x_m}}{1 + \sum_{s=1}^{S} w_{y_s} \beta_{y_s}} \tag{4}$$

We set the weight vector $w = (w_L^x, w_F^x, w_E^x, w_R^y, w_T^y)$ to $\left(1/_6, 1/_6, 1/_6, 1/_4, 1/_4\right)$, where w_L^x, w_F^x, w_E^x, w_R^y and w_T^y are the weights on the indicators input L, input F, input E, desirable output R, and desirable output T, respectively. Also, we define the directional vector $g = (-x, y, 0)$ as $(-L, -F, -E, R, T)$. A TDI value of 1 indicates that the tourism sector has optimal performance, and the DMU is at the technology frontier; a value of 0 indicates the worst possible level of performance.

Definition 2: Tourism Sustainability Index (TSI). Following Assumption 2, the TSI for the n-th DMU can be calculated by the following formula:

$$TSI_n = \frac{1 - \left(\sum_{m=1}^{M} w_{x_m} \beta_{x_m} + \sum_{q=1}^{Q} w_{b_q} \beta_{b_q}\right)}{1 + \sum_{s=1}^{S} w_{y_s} \beta_{y_s}} \tag{5}$$

We set the weight vector $w = (w_L^x, w_F^x, w_E^x, w_R^y, w_T^y, w_C^b)$ to $(1/_9, 1/_9, 1/_9, 1/_6, 1/_6, 1/_3)$, where w_L^x, w_F^x, w_E^x, w_R^y, w_T^y and w_C^b are the weights on the indicators input L, input F, input E, desirable output R, desirable output T, and undesirable output C, respectively. Also, we define the directional vector $g = (-x, y, -b)$ as $(-L, -F, -E, R, T, -C)$. A TSI value of 1 indicates the tourism sector has the maximum level of sustainability and the DMU is at the technology frontier; and 0 indicates the worst possible level of sustainability and the DMU is far from the technology frontier.

Meta-frontier NDDF approach

The core of the meta-frontier theory is to analyze the distance between the meta-frontier and the group-frontier, which is measured as the ratio of the efficiency values of the meta-frontier and group-frontier, that is, the TGR. Following Battese et al. (2004), Zhang et al. (2013) and Liu and Liu (2020), we first construct the group-frontier and meta-frontier. In this paper, all DMUs are divided into H groups. According to Formula (1), the environmental production technology of group h can be defined as $T_h^* = \{\cdot\}$, $h = 1, 2, \ldots, H$. The NDDF of group h is defined as follows:

$$\overrightarrow{ND}_h(x, y, b; g) = \sup\left\{\left(\beta_x, \beta_y, \beta_b\right) : (x, y, b) + g \times \mathrm{diag}\left(\beta_x, \beta_y, \beta_b\right) \in T_h^*\right\}, \ \forall h \tag{6}$$

The meta-frontier is defined as the frontier that encompasses all different groups of technology levels, i.e., $T_o^* = \{T_1 \cup T_2 \cup \ldots T_H\}$. The meta-frontier NDDF is defined as follows:

$$\overrightarrow{ND}_o(x, y, b; g) = \sup\left\{\left(\beta_x, \beta_y, \beta_b\right) : (x, y, b) + g \times \mathrm{diag}\left(\beta_x, \beta_y, \beta_b\right) \in T_o^*\right\} \tag{7}$$

By solving Formula (3), the optimal value of the NDDF model of group h can be obtained. Assuming that group h contains N_h DMUs, the optimal solution can be obtained by solving Model (8).

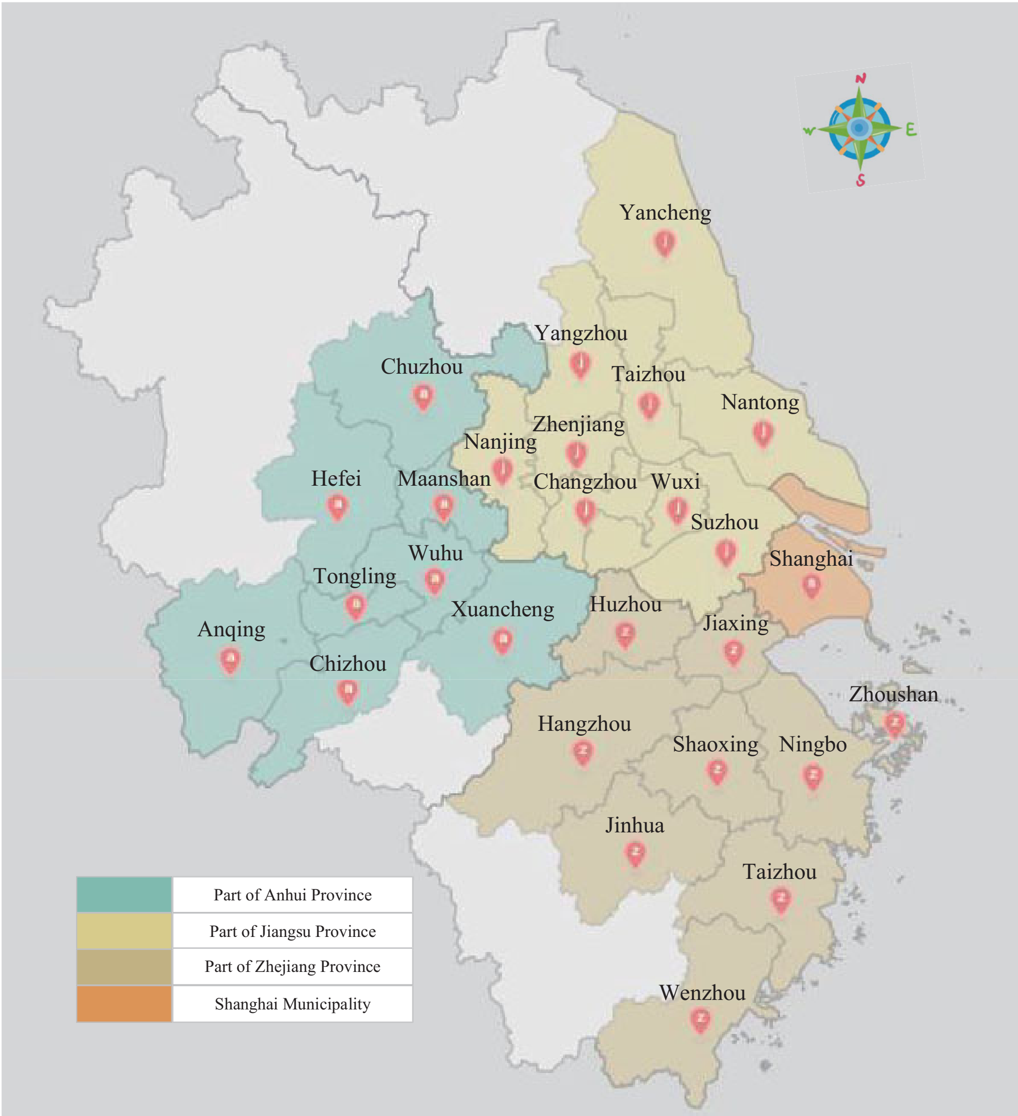


Figure 2. The geographical location of cities in the Yangtze River Delta.

$$
\begin{aligned}
&\max w^T\beta = w_{x_m}\beta_{x_m} + w_{y_s}\beta_{y_s} + w_{b_q}\beta_{b_q} \\
\text{s.t.}\quad &\sum_{h=1}^{H}\sum_{n_h=1}^{N_h}(\lambda^{n_h}+\mu^{n_h})x_m^{n_h} + g_{x_m}\beta_{x_m} \le x_m,\ \ \forall m \\
&\sum_{h=1}^{H}\sum_{n_h=1}^{N_h}\lambda^{n_h}y_s^{n_h} - g_{y_s}\beta_{y_s} \ge y_s,\ \ \forall s \\
&\sum_{h=1}^{H}\sum_{n_h=1}^{N_h}\lambda^{n_h}b_q^{n_h} + g_{b_q}\beta_{b_q} = b_q,\ \ \forall q \\
&\sum_{n_h=1}^{N_h}\lambda^{n_h} + \mu^{n_h} = 1;\ \ \lambda^{n_h},\mu^{n_h} \ge 0,\ \ \forall n_h, \forall h \\
&\beta_{x_m} \ge 0, \beta_{y_s} \ge 0, \beta_{b_q} \ge 0,\ \ \forall m, \forall s, \forall q
\end{aligned}
\tag{8}
$$

Table 1. Group division of 27 cities in the Yangtze River Delta.

Group	Province	City
Group 1	Shanghai	Shanghai
Group 2	Jiangsu	Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou (JS)
Group 3	Zhejiang	Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou (ZJ)
Group 4	Anhui	Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng

Note: Taizhou (JS) is denoted as a central city of Jiangsu Province; Taizhou (ZJ) is denoted as a coastal city of Zhejiang Province.

where $\lambda^k + \mu^k$ represent the intensity weights; $x_m^{n_h}$, $y_s^{n_h}$ and $b_q^{n_h}$ are the m-th input, s-th desirable output, and q-th undesirable output associated with the evaluated n-th DMU of group h.

Following O'Donnell et al. (2008), technological efficiency under the meta-frontier (MTE) can be decomposed into group technological efficiency (GTE) and TGR. In turn, TGR is the ratio of MTE to GTE. The TGR of group h can therefore be calculated as:

$$TGR_h(x, y, b; g) = \frac{\overrightarrow{ND}_o(x, y, b; g)}{\overrightarrow{ND}_h(x, y, b; g)} = \frac{T_o^*(x, y, b)}{T_h^*(x, y, b)} \tag{9}$$

The value of TGR lies in the interval $[0, 1]$, and it represents the gap between any given group and the overall optimal technology level. The closer it is to 1, the smaller is the gap between GTE and MTE, which implies that the innovative technology of that group of DMUs is closer to the overall optimal technology level.

Research area and indicator selection

Research area and group division

In 2019, the total tourism revenue of the YRD region was 3.9 trillion CNY, which represented 68.4% of national total tourism revenue (5.7 trillion CNY) and 9.8% of global total tourism revenue (5.8 trillion US dollars). The 'Yangtze River Delta Urban Agglomeration Development Plan' of 2016 aims to promote the coordinated development of the YRD urban agglomeration through reform and innovation. The 2019 'Outline of the Regional Integrated Development Plan for the Yangtze River Delta' further promoted the integrated development of regional tourism.

Geographically, the plan covers the whole region of Shanghai, Jiangsu, Zhejiang and Anhui provinces, with 27 cities, including Shanghai, Nanjing, Hangzhou and Hefei, as the central area. Figure 2 shows the geographical location of cities in the YRD. The division of the group directly affects the determination of the group-frontier, and thus the efficiency measurement. The general process uses a clustering method to determine the group to which each DMU belongs. Given that the level of production technology within a single province in the YRD is broadly similar, the cities are grouped by province in this analysis. Table 1 shows the group division of 27 cities in the YRD.

Indicator selection and data description

The choice of input and output indicators greatly affects the estimates of performance produced by DEA. For the selection of input indicators, the most basic factors of production in the economic sense include land, labor and capital. In the present context, tourism resource endowment or tourism attraction is also an important input (Ma & Bao, 2010). For the selection of output indicators, desirable outputs usually include domestic and inbound tourism revenues, as well as domestic tourism and inbound tourism receptions. This paper further considers the undesirable output of tourism and carbon emissions from tourism transportation are selected to measure the sustainability of urban tourism. The input and output variables selected in this paper are listed in

Table 2. Input-output variables of tourism efficiency evaluation.

Dimension	Criteria	Variable	Unit
Input	Labor input	Employed labor (*L*)	10 thousand persons
	Capital investment	Capital stock (*F*)	100 million CNY
	Resources input	Resource endowment (*E*)	Piece
Output	Desirable output	Tourism revenue (*R*)	100 million CNY
		Tourist reception (*T*)	10 thousand person-time
	Undesirable output	Carbon emission (*C*)	Tons

Table 2; they are similar to those used by Lu et al. (2019), Zha et al. (2019) and Zha et al. (2020), and partly reflect the urban context of the present research and the availability of data.

The resource input of tourism development differs from that of other sectors. This paper considers labor and capital factors, and the tourist resource endowment of the city. We choose the number of persons employed in the industry to represent the labor factor (Lu et al., 2019; Zha et al., 2019). This index includes all direct and indirect employment related to the tourism industry. We use investment in urban fixed assets to represent the capital factor, which is realized through urban tourism project construction and infrastructure improvement, as well as other factors (Ma & Bao, 2010; Zha et al., 2020). We take the number of star-rated hotels, the number of travel agencies and the number of A-level tourist attractions to represent the tourism resource endowment (Zha et al., 2020). In this paper, the entropy weight method is used to aggregate these three tourism resource indexes into a single overall index that reflects the cities' tourism resources.

This paper uses the perpetual inventory method to transform fixed asset investment into base capital stock. The calculation formula is $K_{i,t} = I_{i,t} + (1-\delta_{i,t})K_{i,t-1}$. Here, i and t represent the cities and years, respectively; $I_{i,t}$ represents the investment in fixed assets; $\delta_{i,t}$ represents the depreciation rate (9.6%); $K_{i,t}$ and $K_{i,t-1}$ represent the current and previous capital stock, respectively. The capital stock of the base year is calculated at 10 times the investment in fixed assets of the year. Finally, we use the fixed assets price index of each province to deflate the amount of investment in fixed assets. We choose the total number of inbound and domestic tourist receptions and the total revenue of inbound and domestic tourism to represent the desirable outputs (Lu et al., 2019; Zha et al., 2019). In order to eliminate the impact of price changes, we take 2010 as the base year for the fixed-price treatment of currency indicators. In this paper, the consumer price index of each province is subtracted to get the tourism revenue index.

Finally, we calculate a tourism carbon emission index to represent the 'green factor' in tourism economic development, and this is the undesirable output. The 'bottom-up' method is usually adopted to calculate tourism carbon footprints and energy consumption (Zha et al., 2020), whereby tourism as a whole is divided into three sectors: transportation, accommodation and activities. The carbon emission from tourism transportation accounts for 90% of the total emission equivalent of the tourism industry (Liu et al., 2011). Due to the availability of prefecture-level city data, the measurement of the carbon emissions from passenger transport focuses on highway and water transport, and are estimated by multiplying passenger turnover with the corresponding carbon emission coefficient (Lu et al., 2019).

The estimation formula is $C_T = \sum_{i=1}^{n}(P_{Ti} \times N_i \times D_i \times f_i)$, where C_T is the carbon emission of tourist passenger transport; P_{Ti} is the carbon emission factor of class i mode of transportation (kg/km), and the carbon emission factors of rail, road, water and aviation are 0.027, 0.133, 0.106, 0.137 kg/km, respectively; N_i is the number of passengers who choose class i as the mode of transportation; D_i is the transport distance of class i; $N_i \times D_i$ is the passenger turnover of class i where N_i is the total number of passengers transported in a certain period of time; f_i is the proportion of tourists in the total number of passengers using class i as their mode of transportation, and the values for rail, road, water and air are 31.6%, 13.8%, 10.6% and 64.7%, respectively (Lu et al., 2019).

Table 3. Descriptive statistics of the indicators from 2010-2019.

Variable	Min	Max	Mean	Std. Dev.
Employed labor (*L*)	3.83	528.97	47.75	75.28
Capital stock (*F*)	3496.85	59398.79	20648.85	13233.30
Resource endowment (*E*)	17.78	544.38	95.77	89.65
Tourism revenue (*R*)	22.80	3758.13	480.93	661.09
Tourist reception (*T*)	411.41	37038.23	6549.43	5801.36
Carbon emission (*C*)	13878.01	564744.05	129059.25	108133.36

We use panel data for the years 2010 to 2019 to evaluate the tourism efficiency of 27 cities in the YRD. The research data was derived from *China City Statistical Yearbook*, *China Tourism Statistical Yearbook*, the statistical yearbook of each province and city, and the statistical bulletin of national economic and social development. Some otherwise missing data were obtained by consulting the municipal statistics bureau, tourism bureau, yearbooks and other materials. The regional fixed asset investment price index, consumer price index and annual average CNY exchange rate were collected from *China Statistical Yearbook* and *China Price Statistical Yearbook*. Table 3 shows that there are large differences in the magnitude of the resource input and output indicators among the 27 cities in the YRD.

Empirical results and discussion

Efficiency refers to the output from a unit input, here in reference to the utilization of urban tourism resources. As set out in Section 'Research design and methodology' of the paper, Model (3) and Model (8) are calculated, and the optimal value under the group-frontier and the meta-frontier is obtained, respectively. According to Formula (4) and Formula (5), the TDI and TSI values are calculated. In this paper, these two indexes correspond to the urban tourism efficiency without and with consideration of the undesirable output, respectively. According to meta-frontier theory, the TGR between the MTE value and the GTE value is obtained by calculating Formula (9). Python 3 software and the 'pulp' module are used to calculate efficiency scores.

Tourism development index and tourism sustainability index

Table 4 shows the efficiency of urban tourism in different situations for the two frontiers. The efficiency of each DMU is the average value across the sample period (2010 to 2019). For the TDI, the calculated results represent the MTE value, GTE value and TGR without considering the undesirable output. For the TSI, the calculated results represent the MTE value, GTE value and TGR with consideration of the undesirable output. In general, the of TDI and TSI values of all the cities over the sample period are relatively high (indicating good performance), but there is nevertheless room for improvement.

Under the meta-frontier, Shanghai, Wuxi, Suzhou, Huzhou, Tongling and Chizhou all have TDI and TSI values of 1. They are on the meta-frontier and can be seen as a benchmark for other cities in their group (see Table 1) to increase their TDI or TSI values. Both the TDI and the TSI values of 18 cities (66.67%) of the 27 cities in the YRD were higher than the overall mean (0.849 and 0.805, respectively). Under the group-frontier, Shanghai is on the group-frontier of group 1; Nanjing, Wuxi, Suzhou and Zhenjiang are on the group-frontier of group 2; Hangzhou, Ningbo, Huzhou, Shaoxing, Jinhua and Zhoushan are on the group-frontier of group 3; and Hefei, Tongling and Chizhou are on the group-frontier of group 4. These cities can be used as benchmarks for other cities in their group to improve the TDI or TSI values. It is worth noting that the TDI value of Jiaxing is on the group-frontier, but the TSI value is not on the group-frontier. That is, consideration of the undesirable output leads to a different evaluation of the city's performance. The TDI value of 21 cities is higher than the overall mean (0.912), accounting for 77.78% of

Table 4. Tourism efficiency in different situations and with different frontiers.

		Without undesirable output			With undesirable output		
DMU	Group	Meta-frontier	Group-frontier	TGR	Meta-frontier	Group-frontier	TGR
Shanghai	1	1.000	1.000	1.000	1.000	1.000	1.000
Nanjing	2	0.856	1.000	0.856	0.858	1.000	0.858
Wuxi	2	1.000	1.000	1.000	1.000	1.000	1.000
Changzhou	2	0.885	0.941	0.942	0.842	0.878	0.959
Suzhou	2	1.000	1.000	1.000	1.000	1.000	1.000
Nantong	2	0.663	0.683	0.971	0.571	0.587	0.972
Yancheng	2	0.495	0.519	0.954	0.403	0.423	0.952
Yangzhou	2	0.889	0.960	0.928	0.850	0.923	0.923
Zhenjiang	2	0.965	1.000	0.965	0.943	1.000	0.943
Taizhou (JS)	2	0.614	0.842	0.767	0.524	0.809	0.711
Hangzhou	3	0.864	1.000	0.864	0.862	1.000	0.862
Ningbo	3	0.895	1.000	0.895	0.880	1.000	0.880
Wenzhou	3	0.817	0.880	0.933	0.822	0.899	0.918
Jiaxing	3	0.913	1.000	0.913	0.853	0.940	0.909
Huzhou	3	1.000	1.000	1.000	1.000	1.000	1.000
Shaoxing	3	0.949	1.000	0.949	0.929	1.000	0.929
Jinhua	3	0.935	1.000	0.935	0.956	1.000	0.956
Zhoushan	3	0.991	1.000	0.991	0.914	1.000	0.914
Taizhou (ZJ)	3	0.924	0.950	0.973	0.917	0.947	0.968
Hefei	4	0.685	1.000	0.686	0.598	1.000	0.598
Wuhu	4	0.724	0.784	0.937	0.615	0.641	0.962
Maanshan	4	0.918	0.931	0.984	0.731	0.761	0.955
Tongling	4	1.000	1.000	1.000	1.000	1.000	1.000
Anqing	4	0.782	0.899	0.877	0.731	0.828	0.889
Chuzhou	4	0.599	0.624	0.962	0.510	0.537	0.954
Chizhou	4	1.000	1.000	1.000	1.000	1.000	1.000
Xuancheng	4	0.573	0.621	0.922	0.430	0.481	0.890
Average		0.849	0.912	0.933	0.805	0.876	0.922

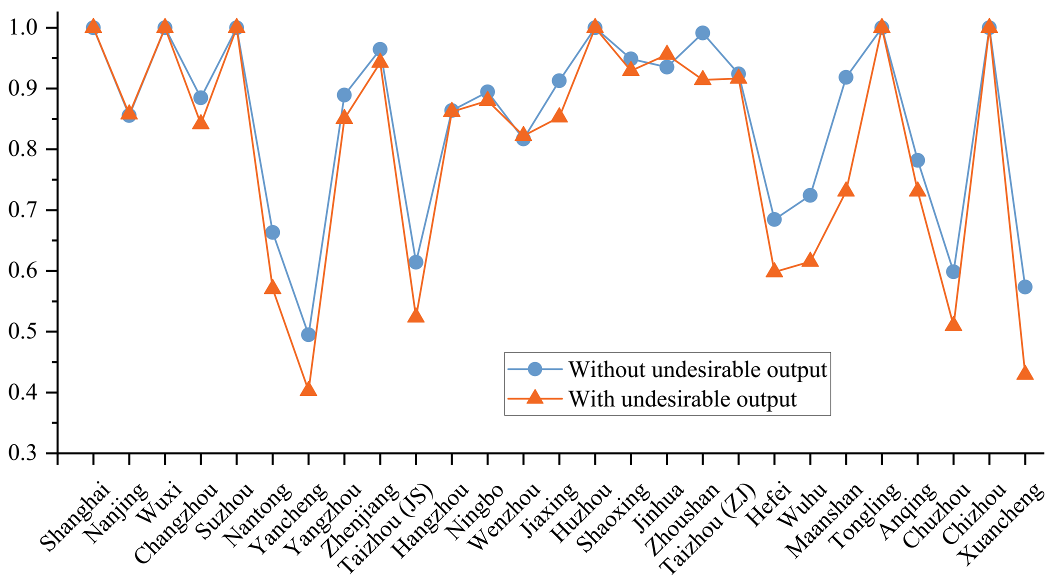


Figure 3. The comparison of TDI and TSI values under the meta-frontier.

the 27 cities in the YRD. The TSI value of 19 cities is higher than the overall mean (0.876), accounting for 70.37% of the 27 cities in the YRD.

The TDI and TSI values under the meta-frontier are compared in Figure 3. It can be seen that the TDI value (which does not incorporate the undesirable output) is mostly higher than the TSI

Table 5. Mean value of urban tourism efficiency of different groups in major years.

Item	Group 1	Group 2	Group 3	Group 4	Research area
Meta-frontier (2010)	1.000	0.815	0.899	0.781	0.840
Group-frontier (2010)	1.000	0.898	1.000	0.850	0.921
TGR (2010)	1.000	0.913	0.899	0.927	0.916
Meta-frontier (2013)	1.000	0.809	0.917	0.775	0.842
Group-frontier (2013)	1.000	0.916	0.986	0.891	0.935
TGR (2013)	1.000	0.885	0.931	0.874	0.901
Meta-frontier (2016)	1.000	0.807	0.916	0.804	0.849
Group-frontier (2016)	1.000	0.849	0.973	0.852	0.897
TGR (2016)	1.000	0.950	0.942	0.949	0.949
Meta-frontier (2019)	1.000	0.831	0.951	0.794	0.866
Group-frontier (2019)	1.000	0.870	0.969	0.846	0.901
TGR (2019)	1.000	0.960	0.981	0.940	0.963

value (which does consider the undesirable output). This also means that the traditional measure of urban tourism efficiency (i.e., the TDI value) overestimates efficiency. Therefore, this paper henceforth focuses on the TSI in the analysis of the efficiency of urban tourism.

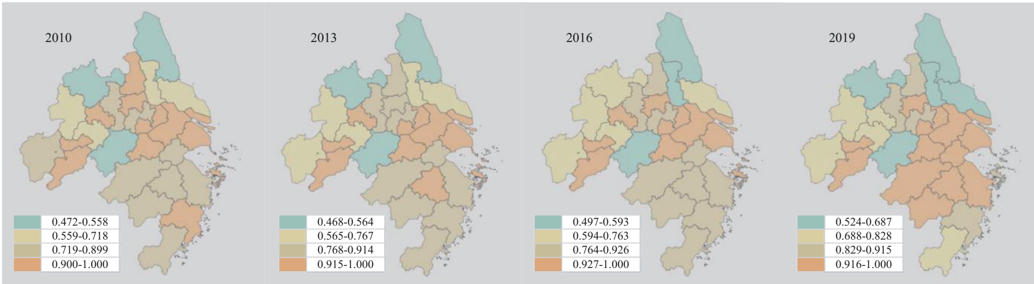
In addition, we can also see from Figure 3 that both the TDI and the TSI values of Nantong, Yancheng, Taizhou (JS), Hefei, Wuhu, Chuzhou and Xuancheng are low, and the difference between these two indexes is large. That is, consideration of the undesirable output leads to a large decline in their urban tourism efficiency. Therefore, when considering the optimal allocation of tourism inputs, it is important to pay attention to the undesirable output, that is, the carbon emission from tourism transportation.

The dynamic evolution of efficiency

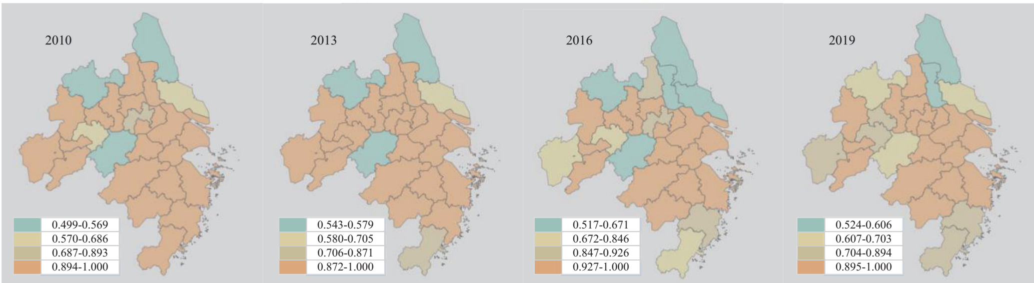
An analysis of urban tourism efficiency can directly point to the optimal development direction for each DMU. Table 5 shows the average urban tourism efficiency of the different groups in four major years, 2010, 2013, 2016 and 2019. From the perspective of the meta-frontier and group-frontier, group 1 and group 3 are both higher than the mean value of the overall study area, indicating that the development level of urban tourism of these two groups is relatively high. From the perspective of time evolution, the urban tourism efficiency of each group under the meta-frontier shows a of rising trend, indicating that the quality of urban tourism in the YRD is increasing. Under the group-frontier, the urban tourism efficiency of each group fluctuates without any obvious pattern; nevertheless, the DMUs within each group is developing steadily.

After the implementation of the 'Yangtze River Delta Urban Agglomeration Development Plan' in 2016, the TGR of group 1 is 1, which is the optimal technology level. The TGR for groups 2 and 3 increases, indicating that the gap between the group-frontier and the meta-frontier of groups 2 and 3 is narrowing. The TGR for group 4 decreased a little, indicating that the gap between the frontier of group 4 and the meta-frontier widened slightly. Therefore, group 4 needs to integrate into regional development as soon as possible, optimize the input-output slacks, and narrow the regional gap.

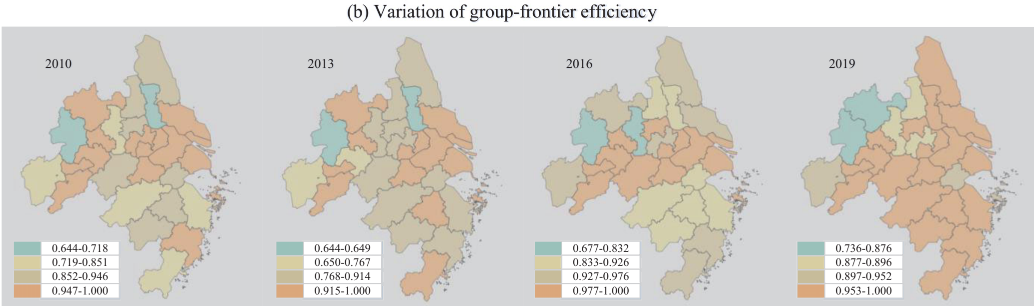
Figure 4 shows the evolution of urban tourism efficiency in the YRD in major years. According to the natural break point method in GIS research, four efficiency intervals are determined for each sub-figure. Python 3 software and the 'jenkspy' module are used to calculate the natural break point. As can be seen from Figure 4a, the number of cities in the first rank of MTE values is increasing, and the tourism development level of cities in the YRD is improving. As can be seen from Figure 4b, Yancheng in group 2 and Xuancheng in group 4 are always located in the fourth rank in their group-frontiers, which indicates that their tourism efficiency and overall development need to be improved urgently. As can be seen from Figure 4c, the TGR of most cities in the YRD is in the first rank, and the overall tourism development level is close to the optimal technological level.



(a) Variation of meta-frontier efficiency



(b) Variation of group-frontier efficiency



(c) Variation of technology gap ratio

Figure 4. Urban tourism efficiency and its evolution in major years.

Technology gap ratio and competitive analysis

According to the data analysis in Section 'Tourism development index and tourism sustainability index', Shanghai, Wuxi, Suzhou, Huzhou, Tongling and Chizhou all have a TGR of 1. This implies that the innovative technology of these cities is close to being optimal. Moreover, the TDI value in 18 cities in the YRD (66.67%) is higher than the overall mean (0.933), while the TSI value of 16 cities (59.26%) is higher than the overall mean (0.922). Figure 5 shows the MTE, GTE values and TGR under the framework of meta-frontier NDDF. According to the above analysis and the visualization in Figure 5, we can identify the following four groups of cities in terms of their types of urban tourism development.

1. Shanghai, Wuxi, Suzhou, Huzhou, Tongling and Chizhou. These cities are on both the group-frontier and the meta-frontier, and their innovative technology is optimal. The possible explanation is that these cities have good economic development, sufficient tourism resources, mature utilization of tourism development technology and rich experience in tourism planning and management. Therefore, they can not only promote the high-quality development of urban tourism in the YRD, but also promote the efficiency in the respective groups and narrow the regional gap.

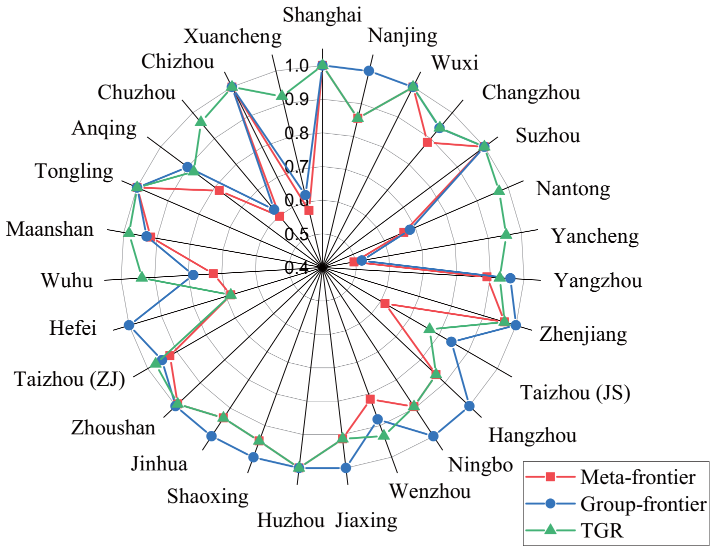


Figure 5. Analysis of TGR and competition of urban tourism.

2. Nantong, Yancheng, Wenzhou, Wuhu, Chuzhou and Xuancheng. The urban tourism efficiency in these cities is low under both the meta-frontier and group-frontier, but the TGR is relatively high, which means there is a large gap between their innovative technology and the overall optimal technology level. The possible explanation is that the tourism resources (e.g. attractions) of these cities are scarce. These cities have no competitive advantage in tourism under either the meta-frontier and the group-frontier, so it is necessary to comprehensively optimize tourism inputs and outputs.
3. Taizhou (JS), Hefei and Anqing. The efficiency values of these cities are lower in the meta-frontier, but higher in the group-frontier. Lower meta-frontier efficiencies drag down the TGR and widen the gap between them and the optimal technology level. Under the group-frontier, each DMU takes its own group technology frontier as the benchmark. Under the meta-frontier, the technological frontier of reference is the best level of overall tourism development. These cities should quickly promote the integrated development of their urban tourism and abandon the false 'location' based on the group they belong to.
4. Nanjing, Changzhou, Yangzhou, Zhenjiang, Hangzhou, Ningbo, Jiaxing, Shaoxing, Jinhua, Zhoushan, Taizhou (ZJ) and Maanshan. These cities have a better level of economic development, a higher degree of opening to the outside world, rich tourism resources and moderate development. Their innovative technology is close to the overall optimal technology level, and the tourism development level is high. From the perspective of sustainable development, these cities need to improve their tourism services, enhance the cultural appeal of tourism, and promote the integrated development of tourism.

Figure 6 shows the distribution of urban tourism efficiency under the meta-frontier and the group-frontier. The four quadrants are drawn according to the mean values of meta-frontier and group-frontier efficiency (0.849 and 0.912), respectively. The horizontal axis represents the mean value of meta-frontier efficiency, and the vertical axis represents the mean value of group-frontier efficiency in the sample period. It can be seen in Figure 6 that the distribution of urban tourism efficiency is basically consistent with the four types classified above. The six cities marked with pink diamonds belong to type 1 and are located in Quadrant I. Their urban tourism efficiency values in both the group-frontier and the meta-frontier are 1. The cities marked by the blue upper triangle have higher tourism efficiency under the group-frontier and the meta-

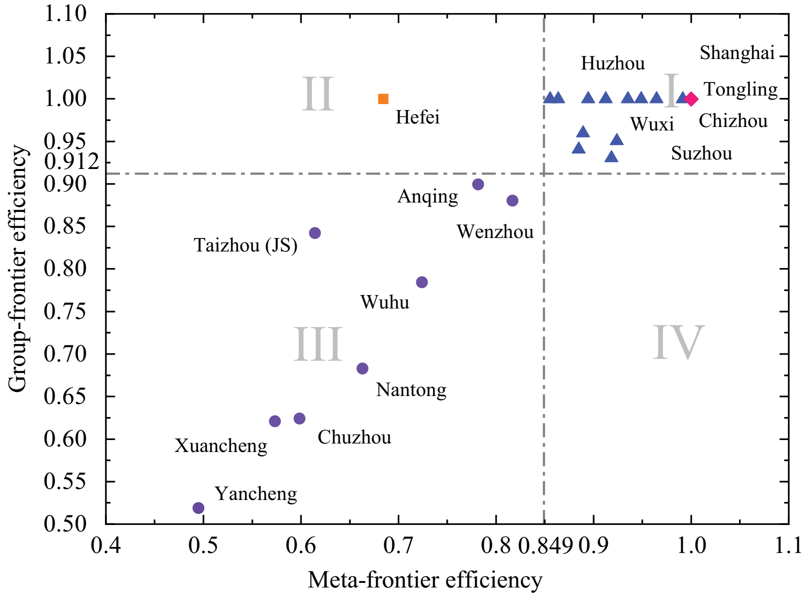


Figure 6. Urban tourism efficiency distribution under meta-frontier and group-frontier.

frontier, which is close to the optimal technology level. They belong to type 4 and are also located in Quadrant I.

Cities marked with orange squares and purple dots belong to types 2 and 3. Hefei is located in Quadrant II. Its meta-frontier efficiency is lower than average, while the group-frontier efficiency is higher than average. Anqing, Wenzhou, Taizhou (JS), Wuhu, Nantong, Chuzhou, Xuancheng and Yancheng are located in Quadrant III. The meta-frontier and group-frontier efficiency of these cities are both lower than the average level. It is worth noting that no DMU falls into Quadrant IV, which also indicates the rationale of the research design in this paper. If a DMU does not perform well in its own group and is not on the group-frontier, it will not be on the meta-frontier and reach the optimal technical level.

Conclusion

In this paper, the meta-frontier theory and the NDDF model are used to construct a comprehensive research framework for non-parametric frontier analysis. From the perspective of sustainable development, the direction vector and weights in the meta-frontier NDDF approach are selected to construct the TDI and TSI. The comparative study of these two indexes enables us to explore the impact of one undesirable output of tourism production activities on the economic efficiency of tourism. From the perspective of regional heterogeneity, the group-frontier and meta-frontier are constructed, and the TGR is obtained through the decomposition method. The TGR and competitive analysis enable us to explore the gap between each DMU and the optimal level of production technology, and investigate appropriate development strategies for urban tourism.

Based on the sample data of 27 cities in the YRD from 2010 to 2019, this paper analyzes the integrated development of tourism in the YRD. The main empirical results are as follows: (1) Through the comparative analysis of TDI and TSI values, we believe that traditional measures of tourism efficiency, which fail to consider undesirable outputs, overestimate the urban tourism efficiency. Specifically, cities such as Nantong, Yancheng, Taizhou, Hefei, Wuhu, Chuzhou and Xuancheng need to pay more attention to the undesirable outputs of their tourism sector. (2) According to the dynamic evolution of urban tourism efficiency, the TGR of most cities in the

YRD is located in the first rank, and the overall level of tourism development is close to being optimal in terms of technology. (3) By analyzing the TGR, this paper identifies four types of tourism development (or groups of cities) for the 27 cities in the YRD. Combined with the analysis of urban tourism efficiency under the meta-frontier and the group-frontier, we further analyze the appropriate strategies for the competitive development of urban tourism.

Destinations are the fundamental unit of analysis in tourism. However, the environment of tourist destinations is constantly changing. The findings reported here have some practical implications. (1) Tourism destinations are facing increasing competition, and this requires tourism industry managers to determine the appropriate allocation of resources to promote the sustainable development of urban tourism. More attention should be paid to coordinate the relationship between the input factors (i.e., resources, facilities, and infrastructure) and the output factors (i.e., social, economic, and natural environment). (2) In the context of the need for global 'carbon neutrality', more consideration should be given to the negative impact of tourism on the natural environment to enhance the competitiveness of tourist destinations. In particular, low-carbon tourism should receive more attention from local government managers.

This study does have some limitations. (1) Because of a lack of data, this paper uses the number of persons employed in the tertiary industry to represent the number of employees in the tourism industry. In addition, this paper ignores the differences in the use of urban fixed asset investment in different types of cities. (2) The division of urban groups needs to be improved. In this paper, the group division of cities by province fails to consider the clustering of cities by other attributes. (3) When TGR is calculated using the NDDF model, the technological efficiency under the meta-frontier may exceed the technological efficiency under the group frontier (Wang et al., 2018). Future studies are needed to make up for the disadvantage of the traditional TGR calculation method and to refine the proposed research design.

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Notes on contributors

Dongdong Wu is a PhD candidate at College of Tourism and Service Management, Nankai University, China. His research focuses on sustainable tourism, tourism firm management, text mining, and decision science. His research has been published in journals such as: *JCLP*, *CAIE*, *ITOR*, *TASM*, *GS*, etc. Email: dwu@mail.nankai.edu.cn.

Hui Li, PhD, is a Young Chang-Jiang professor and Associate Dean at College of Tourism and Service Management, Nankai University, China. His research focuses on tourism big data mining and prediction, tourism firm management and governance. He has published over 80 papers on tourism, management and information science, such as: *ATR*, *TM*, *JTR*, *IJHM*, *IJCHM*, *CIT*, *JHTM*, *APJTR*; *EJOR*, *COR*, *JORS*, *FOR*; *IEEE TSMCA*, *IAM*, *INFFUS*, *INS*, etc. Email: lihuihit@nankai.edu.cn.

Yuhong Wang, PhD, is a full professor majoring in Management Science and Engineering at School of Business, Jiangnan University, China. His research focuses on grey system theory, systems prediction and decision making. His research has been published in journals such as: *OMEGA*, *JORS*, *CAIE*, *ESWA*, *ITOR*, *TASM*, *JCLP*, *GS*, etc. Email: yuhongwang@jiangnan.edu.cn.

ORCID

Dongdong Wu http://orcid.org/0000-0002-9784-401X
Hui Li http://orcid.org/0000-0002-5822-2795

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