forests

Article

Decline or Rejuvenation? Efficiency Development of China's National Scenic Areas

Linlin Xu [1,2], Hu Yu [1,2,*] and Bin Zhou [3]

[1] Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; xull.20s@igsnrr.ac.cn
[2] College of Resources and Environment, Chinese Academy of Sciences, Beijing 100049, China
[3] East China Sea Research Institute of Tourism, Ningbo University, Ningbo 315211, China; njuzhoubin@163.com
* Correspondence: yuhu@igsnrr.ac.cn

Abstract: The decline is one of the essential issues for developing tourism destinations. The rapid adoption of appropriate policies will enable them to reverse the decline and enter the rejuvenation stage in time. This study advocated establishing an operational evaluation model of tourism efficiency with DEA and the super-SBM model to estimate when China's mass tourism destinations are in decline and rejuvenation based on the tourism area life cycle (TALC) theory regarding China's national scenic areas (NSAs) samples. The results show that the development of China's mass tourism destinations can be divided into three phases, in which there is a clear process of persistent decline and rejuvenation. Different types of NSAs vary in terms of efficiency level and change trends. Human landscape, caves, and wetland and lakes all have distinct phases of persistent decline, but humanistic landscapes show a significant rejuvenation trend. These findings provide an innovative re-interpretation of the TALC model.

Keywords: national scenic areas (NSAs); efficiency; decline; rejuvenation; TALC; China

check for updates

Citation: Xu, L.; Yu, H.; Zhou, B. Decline or Rejuvenation? Efficiency Development of China's National Scenic Areas. *Forests* **2022**, *13*, 995. https://doi.org/10.3390/f13070995

Academic Editors: Chi-Ming Hsieh and Wan-Yu Liu

Received: 26 May 2022
Accepted: 22 June 2022
Published: 24 June 2022

1. Introduction

For more than four decades, tourism destination development has been a focal subject area in tourism research. Relevant theories and models have emerged to explain how tourism destinations develop and what factors or dynamics drive the expanding body of knowledge on tourism destinations [1,2]. A tourism destination keeps evolving through internal-external dynamics and macro-micro conditions [3]. The fungibility and homogeneous competition, which may lead to decline, are evident with the rapid growth of tourism destinations [4]. Mass tourism destinations have a higher risk of decline, especially those that have reached the mature stage. However, literature in the tourism field is not enough to study post-maturity destinations [5], although many tourism destinations in the Northern Hemisphere stagnate at various stages of stagnation and decline, notably in the Mediterranean [6]. Over the past decade, the coming of the experience consumption era and the change of the national consumption concept have made alternative tourism more and more popular in China [7]. The emergence of alternative tourism, to some degree, has blurred the boundary of tourism destinations in the traditional sense and exerted an influence on early tourism destinations [8]. On the other hand, tourism destinations' development in China has its complexity and background, often suffering from existing institutional conflicts, unclear government authority, the difference between government and enterprises or corporate functions, and ambiguous benefit distribution [9]. The government-oriented system reform is one of the leading forces to promote the development of tourism destinations, which is quite different from the development of western tourism destinations [10].

Butler's tourism areas life cycle (TALC) provides a stage-by-stage framework for analyzing the evolution of tourism destinations. The sixth stage of the model includes both decline and rejuvenation [11]. Although TALC has been widely used in tourism area planning and management projects, it has often been criticized for the difficulty of determining specific stages in practice [12]. Different stages of mass tourism destinations development have dominant influences, respectively. The initial stage of tourism destinations development requires extensive capital investment to build tourism facilities [13]. The mature stage of tourism destinations development requires more investment in management and technical elements to maintain the attractiveness and avoid falling into a decline "trap" [14]. Some mass tourism destinations are under serious threat of decline [15,16]. As early as the end of the last century, First-generation European mass tourism resorts showed impending declines as predicted by the TALC model (Knowles & Curtis, 1999). Leisure and recreation based on tourism are one of the core symbols of mass tourism [17]. In China, national scenic areas (NSAs) have a particular model and representativeness as the case of mass tourism destinations. NSAs account for 2.23% of China's total land area and 20% of the total number of tourists, making them essential goals for the masses to develop tourism activities [18]. Therefore, NSAs can serve as a lens to reflect the development of China's mass tourism destinations.

In the evolution of tourism destinations, the input-output curve of factors is constantly changing and intensified by the dual effect of the rapidly evolving external environment and the shift towards experiential and leisure-oriented tourist consumption demand. Recognizing the symptoms of destination decline at an early stage helps to provide faster feedback to stop or slow down the trend of destination decline by developing effective recovery policies [16,19]. An emerging body of literature has contributed to identify and forecast the development phase of various tourism destinations [16]. Most studies choose the number of tourists or business performance as the measure index, but these indicators lack comprehensiveness and are weak in identifying potential decline risks. Tourism efficiency is an indicator that characterizes the ratio of inputs to outputs of a tourist destination. Tourism efficiency has become an essential guarantee for the sustainable development of the tourism economy, as a critical indicator to measure the effectiveness of resources and the industry's overall development [20]. However, efficiency has not been used to reflect the decline and rejuvenation of tourism destinations.

This study attempts to fulfil this research gap by offering new viewpoints on the rejuvenation or decline of NSAs from the perspective of efficiency. In line with the current research status, two main questions need to be addressed: How should the development stages of China's mass tourism destinations be classified? What are the differences in mass tourism destinations' efficiency and development process in different regions and types?

2. Theoretical Background and Literature Review

2.1. Rejuvenation or Decline of Tourism Destinations

The tourism area life cycle (TALC) proposes that the development process of tourism destinations can be conceptually divided into six successive stages: exploration, involvement, development, consolidation, stagnation, decline, and rejuvenation [11]. TALC is widely used in tourism planning and management due to its simplicity and ease of understanding. Some studies have extended the TALC model to overcome the limitations of the original model. Xu (1997) proposed the doubly-periodic model to divide the life cycle into long and short processes [21]. The long cycle refers to the whole cycle from the initial stage to the final decline. The short cycle refers to tourism destinations' fluctuation when the tourist attraction environment remains unchanged. This extended model enhances TALC's ability to respond to different contexts. Later studies built on the TALC model give more insight into destination evolution's complex and non-linear nature [22,23]. TALC is also frequently combined with other theoretical models to jointly interpret realistic problems of high complexity, such as sustainable tourism and stakeholder engagement. For instance, Holladay (2018) focuses on a heuristic model that adapts Butler's (1980) TALC with Holling's Adaptive Cycle, and this heuristic model is intended to stimulate theories on destination resilience within the context of sustainable tourism [24]. Nazneen, Xu, and Ud Din (2020) proposed an integrative model that combined the TALC model and stakeholder theory to examine the perceived impacts of cross-border mega-infrastructure development [25].

The decline stage represents the area losing its appeal and cannot contend with the competition from newer destinations [26]. The existence of a decline phase has been highly debated in academic circles. Some scholars have found that specific tourism destinations (e.g., the internationally renowned World Natural and Cultural Heritage) can stabilize in a mature stage over time, combining the development, consolidation, rejuvenation, and decline phases [26,27]. However, with the widespread decline of tourism destinations in Europe, North America, and Asia, perhaps high-quality destinations can only resist the decline and maintain a consolidation state for a relatively long time [28,29]. A variety of factors can lead to the decline of tourism destinations, including outdated tourism facilities, inadequate tourism operations, changes in tourists' preferences, and competition from other destinations [30]. Agarwal (2002, 2005) argues that the decline of destinations is due to the interaction of the internal and external environment. The internal environment manifests itself as a weakening of the destination's competitiveness, while external competition is becoming increasingly intense [31,32]. In addition, TALC proposes a variety of scenarios for post-stagnation, with re-development, market repositioning, or as a result of public-private sector intervention for the rejuvenation stage alone. Prideaux (2004) proposed a resort development spectrum, arguing that destinations have multiple life cycles in the development process of serving tourism markets at different scales and in other countries [33].

Regarding decline, available studies propose that it is pivotal to develop rejuvenation plans to regain attractiveness when tourism destinations have entered the stagnation stage or the decline stage [6,34,35]. In real situations, tourism destinations already in stagnation or decline are difficult to renew. This is because a true destination renaissance requires not only time and money investment, but also newer engines of attraction, such as famous festivals [36], new tourism projects [37], refurbished facilities [38] and new images [39]. Rodríguez-Díaz and Rodríguez-Díaz (2018) also highlighted the importance of the update of lodging offers and infrastructures [40]. The product rejuvenation strategies of organizations can be brought into tourism destinations, including external environmental factors, brand name, potential segments, and consumer value [41]. Regarding Chinese tourism destinations, the specific socio-economic and institutional space of tourism destinations enhances the dynamics and complexity of tourism development. Zhang and Xiao (2014) developed an RICI model (Resource, Institution, Capital, and Innovation) accounting for destination rejuvenation in China [42].

Different tourism destinations vary in rejuvenation modes, i.e., fishing values, resources, and ecological environments [41]. In contrast, city tourism destinations emphasize marketing by utilizing the Internet and social media [43]. Besides, rejuvenation strategies need to take complete account of the needs and preferences of the dominant market. Bali built a Chinatown to attract the Chinese tourism segmentation market's return and gradually formed Balinese Chinese culture, changing the local cultural landscape [44].

2.2. The Relationship between Efficiency and Decline or Rejuvenation

Efficiency refers to the ratio of production resource input to output effect and is an essential basis for measuring the rationality of tourism resource utilization and tourism development [45]. Efficiency was generally regarded as a measure of tourism competitiveness [46], tourism potential [47] or tourism performance [48] in the field of tourism destination research. For instance, Yi and Liang (2015) explained the temporal dynamics of tourism efficiency and proposed four models of tourism destinations' evolution, including the stable model, reciprocating model, progressive model, and radical model [49]. Nurmatov, Fernandez Lopez, and Coto Millan (2021) recommend that future studies consider the versatility of the DEA and broaden its scope to study [50]. Problems such as extensive development and utilization mode, vague understanding of investment environment, low technical innovation, and inferior development environment restrict the improvement of tourism efficiency, thus leading to the phenomenon of tourism destination decline [51,52].

Decline or rejuvenation may be measured in several ways, including the number of tourists; tourist satisfaction; business performance; investment in tourism facilities and infrastructure; social and environmental carrying capacity; and tourism-related employment [16]. Nonetheless, the above measurement indexes are all single dimensions and cannot examine the development stage of tourism destinations from a more comprehensive perspective. This problem has received limited attention in the literature.

Using efficiency to describe life cycle stages has a theoretical basis and research foundation. Not even a single study has shown a direct relationship between the efficiency, decline or rejuvenation of tourist destinations such as tourism and hospitality [53], business management [54], construction [55], energy [56] linked life cycles to efficiency. For instance, Yin et al. (2015) proposed a hotel life cycle model measured by the average efficiency change rate (AECR) and average efficiency (AE) [53]. AECR < 0 meant the recession and regeneration phase; when AE $\geq$ AE's average value of all DMU, it represented the recession stage; otherwise, it was the rejuvenation stage. Additionally, Koval et al. (2017) analyzed the possibilities of determining the impact of life cycle stages on the efficiency of investing in an enterprise [54]. Lozano, Iribarren, Moreira, and Feijoo (2009) used a joint application of Life Cycle Assessment (LCA) and DEA to establish a direct link between operational efficiency and environmental impacts [57]. Egilmez, Gumus, Kucukvar, and Tatari (2016) proposed an input-output-based life cycle assessment approach tackled with the proposed Fuzzy DEA framework [58]. On the other hand, it can be inferred that efficiency is an essential indicator of tourism performance and can be used as a comprehensive indicator to measure the development status of tourism destinations [59]. Due to the different scales of tourism destinations, it is biased to compare the number of tourists and tourism income. Efficiency can consider differences in scale of operation adequately and can be suitable to reflect the development level of a large number of NSAs of different scales. Consequently, this study measured the efficiency of NSAs through an input-output perspective to reveal the performance of tourism destinations and use it as an indicator of decline and rejuvenation.

2.3. The Tourism Area Life Cycle Measured by Efficiency

This paper established a theoretical model referring to Yin et al. (Figure 1) based on the above analysis. Our model only focuses on the decline and rejuvenation phases and distinguishes the decline phase further. In this model, efficiency change rate (ECR) is taken as the main index to judge the life cycle stage. Specifically, ECR > 0 represents continuous efficiency growth. When ECR reaches the maximum value, efficiency grows fastest, and tourism destinations are usually in the development phase of their life cycle. When ECR < 0, the efficiency value decreases, which is judged as a declining stage in this study. r is the duration of ECR < 0. Due to the cyclical fluctuations in tourism efficiency generally, the decline phase was divided into fluctuating decline and persistent decline. Fluctuating decline is followed by a phase of fluctuating rise. Only after the continuous decline stage can tourism destinations have the chance to enter the rejuvenation phase. Furthermore, it should be emphasized that the curves in Figure 1 are only a stereotyped assumption, while the efficiency variation of tourism destinations in the actual situation is non-regular.

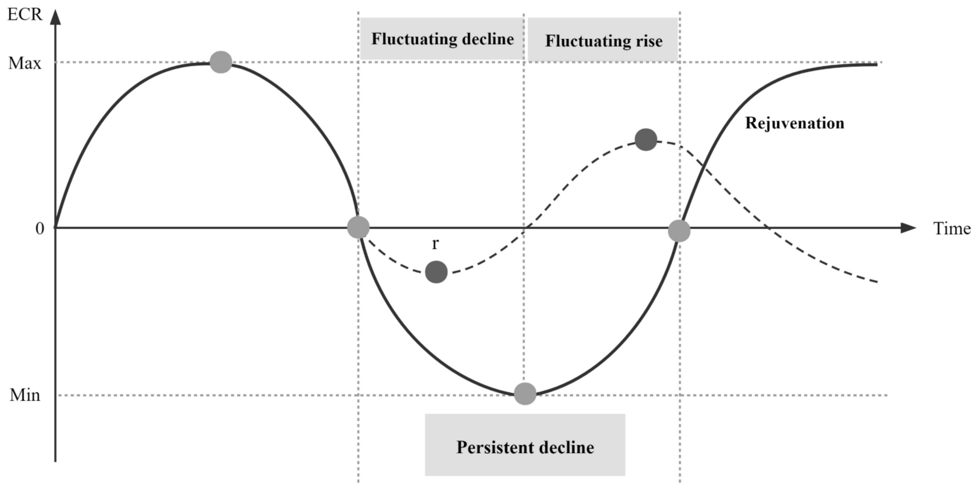

Figure 1. A model for tourism area life cycle measured by efficiency.

3. Methodology

3.1. Sample

NSAs are the spatial areas with concentrated scenic resources and wonderful natural environment that are available for sightseeing, recreation and scientific research [60]. In 1982, the Chinese government established the management system for National Scenic Areas. Until 2022, a total of nine batches with 244 sites were selected and they are distributed in 32 provincial-level administrative regions in China (Figure 2). NSAs are the main body of China's "World Natural and Cultural Heritage", representing China's most essential natural and cultural landscape [61]. In the *Classification Standard of National Scenic Areas(CJJ/T121-2008)*, NSAs are divided into Mountain, Cave, River & Waterfall, Coast, Wetland & Lake, Special landform, Historic heritage and Human landscape and Folk custom, etc. As most NSAs contain rich forest resources, Forest is not classified as a separate category. However, there is no denying that forest landscape is one of the most significant landscape types in NSAs.

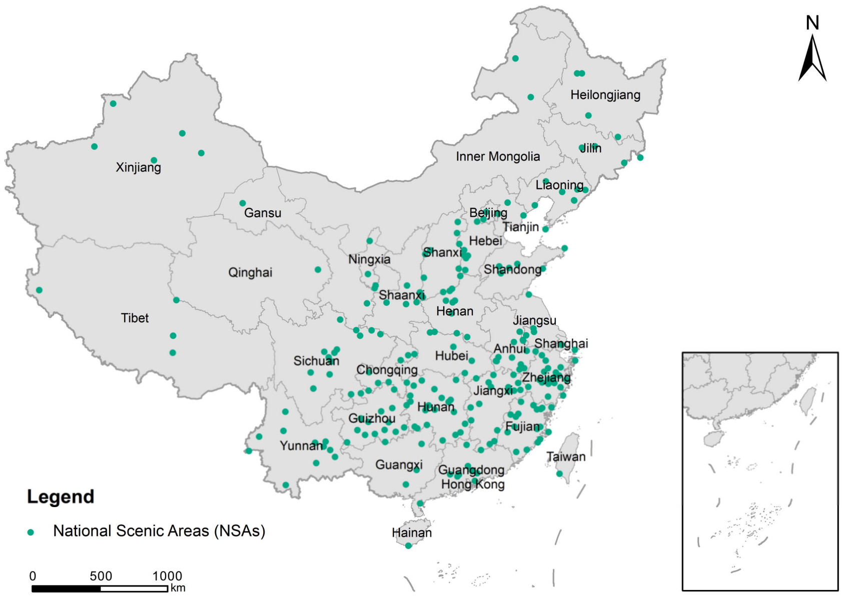

Figure 2. The map of National Scenic Areas' distribution in China.

Based on emphasizing nature protection, NSA follows the market-oriented characteristics and gradually changes its product orientation from the initial resource-based to market-oriented development demand, promoting the rapid development of scenic tourism. This paper selects NSAs as samples to reflect the overall development status of China's mass tourism destinations.

3.2. Models

3.2.1. DEA Model

Data envelopment analysis (DEA) is the most popular and practical method in the field of production frontier analysis [62] and has been widely used in the measurement of tourism industry efficiency. DEA can be regarded as a tool for multiple-criteria evaluation problems where DMUs are alternatives [63]. DEA analysis results are objective and do not need to be based on the subjective opinions of researchers [50]. An additional strength of DEA is that assigning scores to each destination does not require the pre-definition of weights because weights are obtained through linear programming [59]. In addition, DEA can process multiple input and output variables, and each variable can be measured in different units [64].

The efficiency calculated by the DEA method can be decomposed into technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). To be more specific, TE is calculated by the CCR model, which measures the relative distance between the actual input and the minimum input under constant returns to scale [65].

$$Min_{\theta}$$

$$St.$$

$$\begin{aligned} &\textstyle\sum_{j=1}^{n} \lambda_j\, x_{ij} \leq\ \theta_p\ , && i = 1,\ \ldots\ldots, m \\ &\textstyle\sum_{j=1}^{n} \lambda_j\, y_{rj} \leq\ y_{rp}, && r = 1,\ \ldots\ldots, s \\ &\lambda_j \geq 0, && j = 1, \ldots, n \end{aligned}$$

where θ_p specifies the technical efficiency score of the unit DMU, λ_j denotes the dual variables that classify the inefficient benchmarks. If θ_p is equal to one, the DMU denotes a technically efficient unit.

The BCC model changed the Constant Return to Scale (CRS) impression to Variable Return to Scale (VRS). BCC model can calculate PTE and SE. PTE refers to the efficiency brought by advanced or backward technology compared with other DMU (decision-making units), while SE represents the efficiency brought by scale compared with other DMU. The relationship between the three is TE = PTE $\times$ SE. The BCC model is defined as follows:

$$Min_{\theta}$$

$$St.$$

$$\begin{aligned} &\textstyle\sum_{j=1}^{n} \lambda_j\, x_{ij} \leq\ \theta_p, && i = 1,\ \ldots\ldots, m \\ &\textstyle\sum_{j=1}^{n} \lambda_j\, y_{rj} \geq\ y_{rp}, && r = 1,\ \ldots\ldots, s \\ &\lambda_j \geq 0, && j = 1, \ldots, n \end{aligned}$$

This study applies the BBC and CCR models to the national scale analysis, because further decomposition of TE is needed to determine the main factors affecting the variation in inefficiency.

3.2.2. Super-SBM Model

The DEA model can only identify efficient and inefficient DMUs but does not allow a ranking among the efficient DMUs. To solve this problem, Tone (2001) proposed the non-radial slack-based measurement (SBM), which eliminated the deviation and influence caused by the difference in the radial selection and could reflect the slack variable of input surplus and output insufficiency [66]. The Super—SBM model is the evolution of the SBM model [67]. This new mathematical programming approach can further evaluate the DMUs whose efficiency value is more significant than one and fill a gap that the traditional DEA model cannot rank and distinguish the effective DMUs. This study used the Super-SBM model in regional-scale and NSA-scale analyses to realize a more logical ranking of DMUs.

$$\begin{cases} min_\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{ik}}{1+\frac{1}{q}\sum_{r=1}^{q} S_i^+/y_{ik}} \\ subject\ to \quad X_k = X\lambda + s^- \\ \qquad\qquad\quad Y_k = Y\lambda + s^+ \\ \lambda \geq 0,\ s^- \geq 0, s^+ \geq 0 \end{cases}$$

where represents efficiency evaluation index. X_k and Y_k are input and output vectors of DMU, respectively, x_{ik} and y_{ik} are elements of input and output vectors. s^- and s^+ represent the relaxation variables of input-output, and λ is a column vector when $\rho \geq 1$, the decision unit is effective. If $0 \leq \rho < 1$, the input-output ratio should be further increased to obtain the optimum efficiency.

3.3. Data Sources and Index System Construction

In the current research, proxy variables of Capital, Labor, and Intermediate Consumption are the most used inputs in tourism modeling with DEA techniques [50]. Most studies have used the physical and monetary measures of production (i.e., tourists arrivals, revenue, and benefits) to approximate the output [46,68,69]. Considering the rationality of indicators and data accessibility, this paper refers to Cao et al. (2016) input-output indicators to construct an indicator system (Table 1) for NSA efficiency measurement [70]. The input variables are tourism-only area, operational expenditure, and completed investment in fixed assets, and the output variables are the number of visitors per year and operating income. The choice of outputs can reflect the objectives and set of services of the DMU, and the inputs are traceable to these outputs.

Table 1. Input and output indexes of NSA's tourism efficiency.

Division	Variable	Definition
Input	Area	Tourism-Only area (km^2)
	Expenditure	Operational expenditure (10,000 RMB)
	Investment	Completed investment in fixed assets (10,000 RMB)
Output	Visitors	Number of visitors (10,000 person-times)
	Income	Operational income (10,000 RMB)

The data are from the China Urban Construction Statistical Yearbook (2003–2017) and The National Bureau of Statistics of China (http://www.stats.gov.cn/(accessed on 21 December 2021)). The observable period ends in 2017 as there are no more official partial statistics related to NSA after 2017. Some of the NSA data were missing from the datasheet. If only one year of data is missing, the linear interpolation method is used to complete it. In the case of missing multi-year data, the NSA was directly excluded. The DMUs selected in this study differed for various scales of analysis to enhance the accuracy: the set of all NSAs in each province was regarded as the DMU in the national-scale and provincial-scale analyses, and individual NSA was used as DMU in the NSA-scale analyses. What is noticeable is that Inner Mongolia, Hainan, and Tibet, which have very few NSAs and lack multi-year data, were excluded. Ultimately, a total of 27 provinces were finally selected.

4. Results

4.1. National Scale Analysis

DEA-SOLVER Pro software was used to calculate the tourism efficiency of NSAs in China from 2003 to 2017 and further decomposed it into PTE and SE (Table A1). From the overall perspective of China, by observing the trend in Figure 3, the TE of NSAs is in the state of "fluctuation—stationary—fluctuation". Comprehensive efficiency experienced a sharp rise and declined from 2004 to 2006 and leveled off from 2007 to 2013, remaining at about 0.63. There was a noticeable decline process from 2013 to 2015, the degree of reduction was more than 20%, but it recovered rapidly from 0.4486 to 0.5843 in 2016. TE reached the average level in the stable period in 2017, although not at the highest level. The ECR falls below 0 three times during the whole process, the second time (2011) is only a fluctuating decline with minimal values, and the third time (2013–2015) is a very significant continuous decline process with stronger intensity than the first time (2005–2006). The average annual growth rate of TE was 3.26%, which was in an overall upward trend, but the growth rate was relatively low. However, the annual tourism efficiency is below 0.7, far from the effective production frontier. This indicated that tourism destinations in China generally had input redundancy or output insufficiency, which need to be adjusted to form effective allocation.

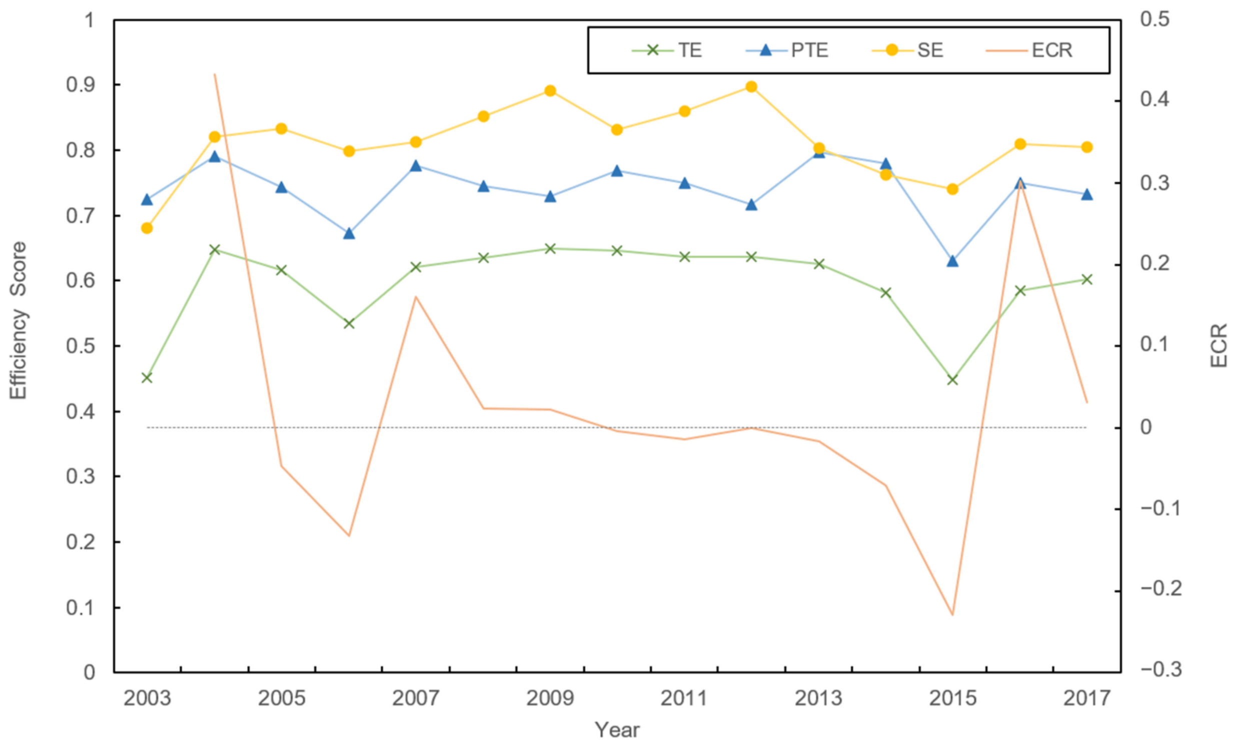

Figure 3. Evolution trend of NSAs' tourism efficiency in China from 2003 to 2017.

The interactions and constraints between TE and each decomposition efficiency were further analyzed for the decomposition efficiency of PTE and SE. PTE indicates the rational degree of resource allocation and utilization of mass tourism destinations. As seen in Figure 3, the two significant decreases in tourism efficiency in 2006 and 2015 are closely related to PTE. Overall, PTE was consistently higher than TE, with scores ranging from 0.6306–0.7804 with a mean of 0.7405, while the mean TE did not exceed 0.6. SE indicates the scale aggregation level of mass tourism destinations, and the highest mean value of SE is 0.8131. In 2003, PTE > SE > TE indicated that PTE representing resource element allocation was higher than SE representing element accumulation, and the input scale of resource element needed to be optimized. SE exceeded PTE in 2004, indicating that factors' scale and aggregation efficiency are larger than the allocation efficiency of resource factors.

The scale of tourism activities has exceeded the optimal scale under the constraint of the technological level. In 2015, PTE > SE > TE showed the characteristics again, reflecting that PTE of resource element allocation led to the improvement of TE.

From the trajectories of the three types of efficiency curves, it can be seen that the change in TE from 2003 to 2007 is mainly driven by SE. The period of 2008–2013 was jointly promoted by PTE and SE. From 2014 to 2017, the driving effect of PTE was more significant, indicating that the efficient evolution of China's mass tourism destination during the study period is characterized by a shift from technology-driven to dual scale-technology-driven and then to technology-driven.

4.2. Provincial Scale Analysis

Table 2 shows an overview of provincial efficiency analysis results. Tourism efficiency was highest in the eastern region and lowest in the central region in 2003, 2008, and 2013. The central region surpassed the west region in 2017, in line with China's economic development. Beijing, Shaanxi, Guangxi, and Jilin consistently maintain high levels of tourism efficiency. The travel efficiency of some provinces showed an upward trend, such as Tianjin (0.1989 in 2003 to 4.7058 in 2017) and Jiangxi (0.1501 in 2003 to 1.4226 in 2017). In the table, Yunnan, Shanxi, and Xinjiang ranked among the top five in China's efficiency rankings in 2003 but even fell into the low-efficiency zones by 2017. The areas mentioned above are rich in tourism resources, with high-quality natural scenery and human landscape, and have relative advantages in the early stage of the tourism resource-oriented model. However, the economic level, governance level, investment environment, technological innovation, and other disadvantages restricted the further development of those mass tourism destinations. A closer inspection of the table shows that the tourism efficiency of Guangzhou and Jiangsu has gone through a process of decreasing and then increasing, in which there is a high probability of a rejuvenation process.

Table 2. Provincial efficiency analysis results of the Super-SBM model.

DMU	2003		2008		2013		2017	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Beijing	3.4610	1	2.5808	1	1.1999	5	1.0922	7
Tianjin	**0.1989**	**19**	**0.2884**	**14**	**1.5445**	**2**	**4.7058**	**1**
Hebei	0.3263	10	0.1852	16	0.1869	20	0.1270	21
Shanxi	**1.7850**	**2**	**0.5206**	**10**	**1.1328**	**7**	**0.1159**	**22**
Liaoning	0.2237	15	1.0838	9	0.3305	13	0.6554	10
Jilin	0.2565	13	1.2340	7	1.0986	8	1.1130	6
Heilongjiang	0.3235	11	0.1138	25	0.0733	27	0.0565	26
Jiangsu	**0.4231**	**7**	**1.3601**	**5**	**1.3269**	**4**	**0.8461**	**9**
Zhejiang	0.4494	6	0.4254	11	0.2626	17	0.3979	13
Anhui	0.1337	25	0.1390	22	0.0804	26	0.1839	18
Fujian	0.4225	8	0.2581	15	0.3867	11	0.6410	11
Jiangxi	**0.1501**	**24**	**0.1467**	**20**	**0.1976**	**19**	**1.4226**	**3**
Shandong	0.3404	9	0.3943	13	0.5535	9	0.6103	12
Henan	0.1266	26	1.1273	8	0.1564	23	0.2801	16
Hubei	0.1847	20	0.1850	17	0.1867	21	0.3227	15
Hunan	0.2145	17	0.1728	19	0.3559	12	0.9264	8
Guangdong	**1.7411**	**3**	**1.3255**	**6**	**0.5167**	**10**	**1.2313**	**4**
Guangxi	**0.2356**	**14**	**1.4722**	**4**	**1.3521**	**3**	**1.2286**	**5**
Chongqing	0.1803	21	0.1315	23	0.1156	24	0.0899	23
Sichuan	0.2683	12	0.1807	18	0.1771	22	0.1812	19
Guizhou	0.1770	22	0.1273	24	0.2729	16	0.1425	20

Table 2. *Cont.*

DMU	2003		2008		2013		2017	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Yunnan	**1.3356**	**5**	**0.4041**	**12**	**0.2785**	**15**	**0.2568**	**17**
Shaanxi	**0.2020**	**18**	**1.6588**	**2**	**2.0143**	**1**	**2.1641**	**2**
Gansu	0.1547	23	0.1397	21	0.2272	18	0.3633	14
Qinghai	0.0518	27	0.0573	27	0.0931	25	0.0352	27
Ningxia	0.2221	16	0.1095	26	0.3034	14	0.0821	25
Xinjiang	**1.6401**	**4**	**1.5349**	**3**	**1.1803**	**6**	**0.0886**	**24**
Mean	0.5640	/	0.6428	/	0.5779	/	0.7171	/
East part	0.8429	/	0.8780	/	0.7009	/	0.8865	/
Middle part	0.3968	/	0.4549	/	0.4102	/	0.5526	/
West part	0.4764	/	0.6316	/	0.6554	/	0.5047	/

Together these results provide important insights into the overall development of China's mass tourism destinations. During the past 14 years, China's mass tourism destinations have undergone great variation at the provincial scale, especially the decline. It can be more comprehensible in Appendix B.

4.3. NSA-Scale Analysis

4.3.1. Spatial Characteristic

The kernel density maps of NSA's tourism efficiency in 2003, 2008, 2013, and 2017 were calculated and plotted by ArcGIS 10.8. Figure 4 shows that from 2003 to 2007, NSA's tourism efficiency evolved from single-center to multi-center, and the high-efficiency area was also constantly shifting. In 2003, Hengshan Mountain was formed as the center, covering Hunan, Guangxi, and Jiangxi. In addition, Circum-Bohai Sea Region turned into a high-value zone. In 2008, the agglomeration center shifted to the Yangtze River Delta region, and the efficiency concentration dropped significantly. One or two high-value zones have been formed in the eastern, central, and western regions, namely, the Sichuan-Chongqing region represented by Mount Emei and Mount Jinyun, the Hunan region represented by Mount Heng-Yuelu, the Central Plains region represented by Hukou Waterfall of the Yellow River and Longmen of Luoyang, and Beijing-Tianjin-Hebei region defined by Badaling and the Ming Tombs.

In 2013, the polarization trend of the high-value region became more prominent, showing the characteristics of multi-center. Compared with 2008, Guangdong, represented by Baiyun Mountain and West Lake in Huizhou, became a new high-value zone. Due to the efficiency of the bamboo sea, the concentration center in the Sichuan-Chongqing area began to move down to the junction of Yunnan, Guizhou, Sichuan, Jiuzhaigou in southern Sichuan was at the forefront of the country. In 2017, the trend towards multi-polarity was even more pronounced. NSA's tourism efficiency presents a "dual core, agglomeration" pattern and obvious development polarization, with significant core-edge structure characteristics.

4.3.2. Characteristics of NSA's Categories

Combined with the classification standard of NSA in China and considering the balance of the number of different types of NSA, this section divided NSA into seven categories, including Mountain, Cave, River & Waterfall, Coast, Wetland & Lake, Special landform, and Human landscape. A horizontal comparison of different types of NSAs shows that Coast has the highest overall tourism efficiency, with an average value of 0.5078 and a maximum value of 0.6903. The overall efficiency of the special landform is second only to the Coast, with an average of 0.3169. Mountain, Human landscape, Rivers & Waterfall have similar tourism efficiency, with an efficiency value between 0.2 and 0.3, which can be regarded as the third tier. Wetland & Lake had the lowest efficiency at 0.2 or less.

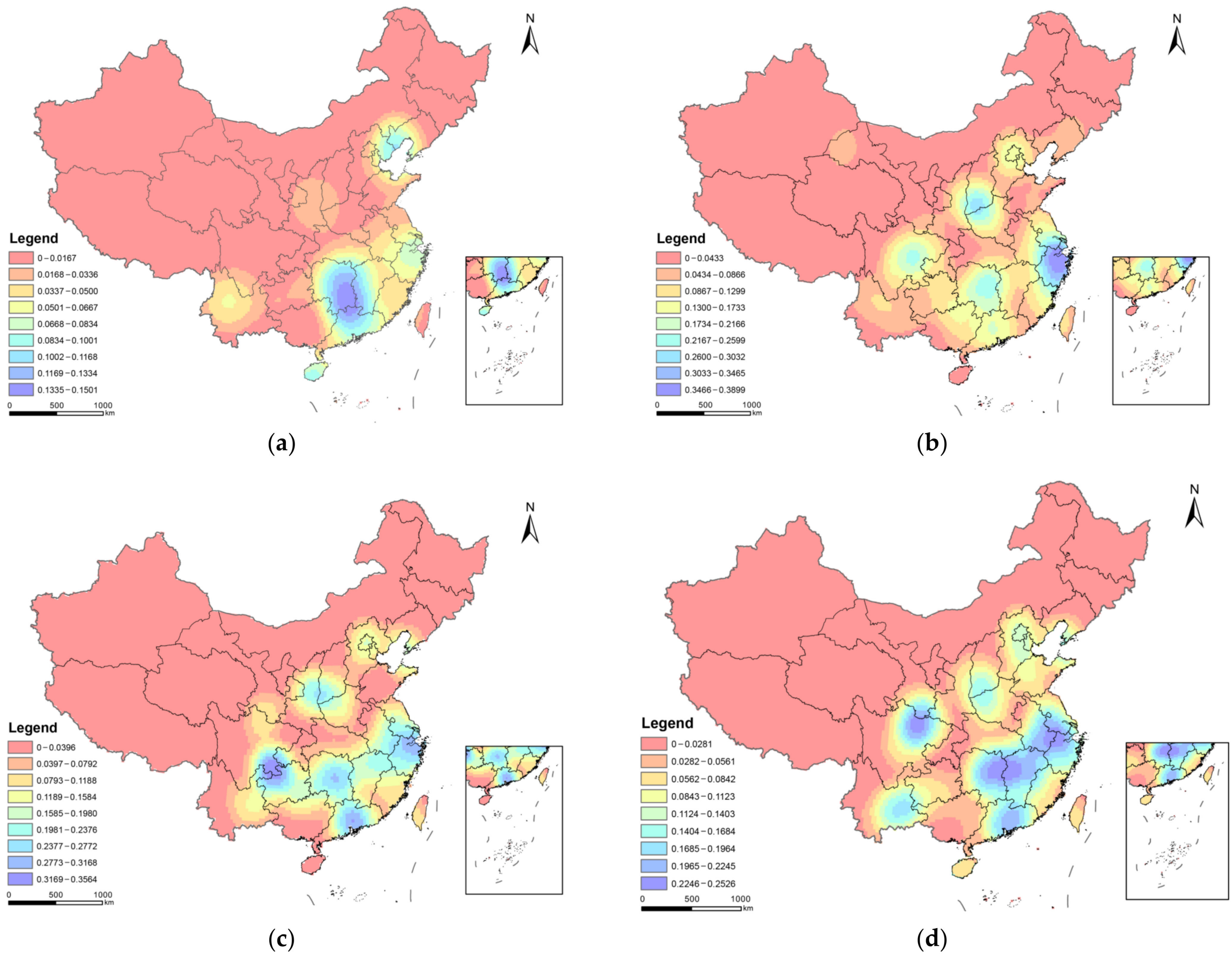

Figure 4. Efficiency of NSAs kernel density analysis results. (**a**) 2003; (**b**) 2008; (**c**) 2013; (**d**) 2017.

TE values and ECR of each type in NSA from 2003 to 2017 were drawn as a line chart (Figure 5). The overall trend is consistent for most types of NSAs, but there are also exceptions. For instance, all types of efficiency gains were positive except for the continuous decline of Special Landform from 2016 to 2017. Furthermore, from 2003 to 2004, the efficiency of most types of NSA showed a downward trend, and the efficiency of Wetlands and Lakes even decreased from 0.2685 to 0.1415. However, the efficiency of the Human landscape and Coast increased slightly. The above results indicate that different tourism destinations face diverse development opportunities even in the same environment.

In general, each type has a different trajectory, and the steady or fluctuating development is the main tone with the underlying decline and rejuvenation process. First, Mountains, Rivers & Waterfalls and Wetland & Lake experienced a significant drop in tourism efficiency from 2003 to 2004, with the largest fall even approaching 50%. This is probably because the SARS outbreak in China in 2003 dealt a huge blow to tourism development. As a result of SARS, inbound and domestic tourism in China fell for the first time in more than a decade. After the SARS epidemic was successfully controlled in 2004, the efficiency values of River & Waterfall, Wetland & Lake, and Special landforms rebounded rapidly in the same year with fast feedback. On the other hand, Mountain and Cave were hit by the SARS epidemic in 2004 and 2005, when development briefly stalled and only gradually entered the renewal phase in 2006.

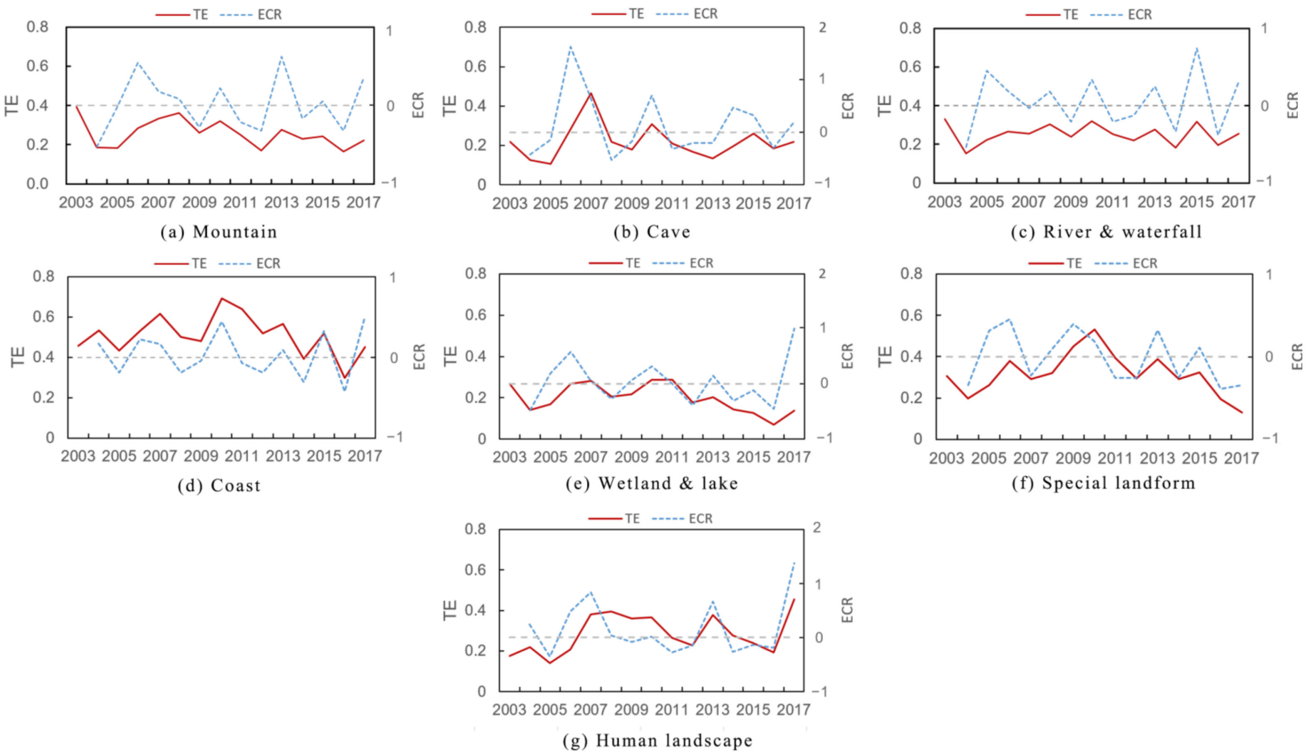

Figure 5. Line charts of tourism efficiency values for different types of NSA from 2003 to 2017.

Secondly, the development curves of Wetland & Lake and the Human landscape have similar phases of decline and rejuvenation. After four consecutive years of persistent decline from 2013 to 2016, Wetland & Lake and the Human landscape experienced a substantial increase in tourism efficiency. The difference is that the Human landscape has a higher efficiency gain (from 0.1912 to 0.4540). In addition, unlike Wetland & Lake cyclical fluctuations between 2006 and 2013, human geography is in a stagnant phase of development. In addition, the peak efficiency varies among the types of mass tourism destinations. Most of the types peaked around 2010, such as Coast, River & Waterfall, and Special landform 2010. The peak efficiency of Caves appeared earliest, in 2007, while the efficiency peak of the Human landscape appeared the latest, in 2017.

Finally, it can be found that the tourism efficiency of Mountain, Rivers & Waterfall, Wetland & Lake, and Special landforms in 2017 is lower than that of 2003, and the tourism efficiency of Cave and Coast in both years is the same by comparing the efficiency values of 2003 and 2017. The human landscape is the only NSA type with an increased efficiency value and a growth rate of 61.96%. This implies a shift from nature-based to humanistic tourism in China, creating the "cultural and tourism integration" premise in 2018.

5. Discussion

5.1. Identifying the Three Stages of Mass Tourism Destinations in China

According to the evolution time sequence of tourism efficiency, combined with the tourism policy proposed by the government and the actual situation of the tourism destination, the development process of mass tourism destinations in China can be divided into three stages (see Figure 6).

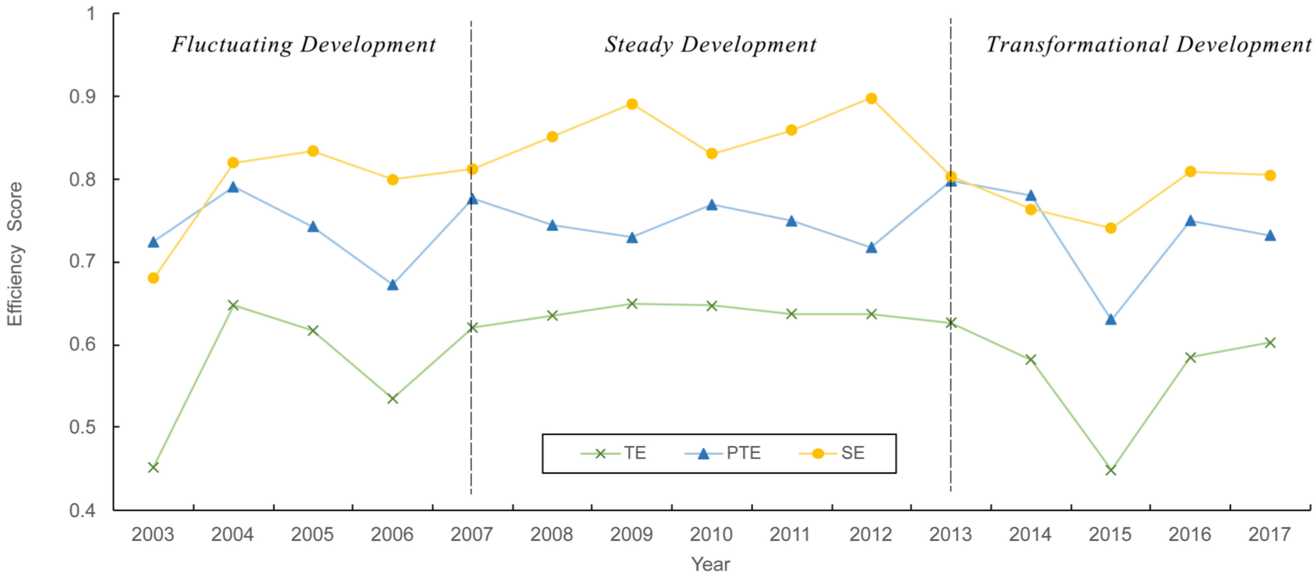

Figure 6. Three stages of mass tourism destinations in China.

The first phase is a period of fluctuating development from 2003 to 2007. Due to the severe impact of the SARS epidemic on China's tourism development in 2003, the efficiency of mass tourism destinations was at the lowest point within the observable range. In 2004, with the end of SARS, the rapid growth of SE led to the significant improvement of TE. However, the inability of technology and resource allocation levels to grow rapidly in the short term firmly limited this strong growth momentum, leading to inevitable declines in 2005 and 2006. The advancement of technology and the improvement of destination operations in 2007 brought about the first rejuvenation in China's development of mass tourism destinations. The NSAs with high-efficiency values are mainly located in the Yangtze River Delta, the most economically developed region.

Mass tourism destinations in China moved into the second phase—a period of steady development (2008–2013). During this phase, NSA's tourism efficiency remained stable, while the number of tourists and operating revenue grew steadily. Some high-profile tourism destinations did not have famous mountains and rivers or cultural heritage of great antiquity, such as the rise of Shenzhen theme park, the prosperity of Chengdu agritainment, and the prosperity of homestay in Zhejiang Mogan Mountain [41]. The efficiency of NSAs in the Pearl River Delta and Chengdu-Chongqing regions also increased during this phase and clustered into high-value areas. The mass tourism market gradually spread to the west and south.

The third phase is the transformational development stage (from 2014 to the present). Since 2014, the efficiency of NSAs has declined for two consecutive years, with a decline of more than 0.1. In terms of changes in input-output indicators, the increase in fixed asset inputs and operating expenditures in some of China's mass tourism destinations does not match the changes in the number of tourists and tourism economic income. Traditional mass tourism destinations are becoming less attractive to tourists. The demand of China's tourism consumption market is gradually changing to "experience consumption", and the monotonous tourism products of NSAs can no longer meet the demand of tourists for diversified tourism experiences [71]. However, the need to protect the original and cultural heritage limits the creative elements in tourism development, so there is a need to find more flexible creative paths under the premise of conservation, such as cultural and creative products, forest SPA, etc. On the other hand, the long-term reliance on ticket revenue is a significant reason for the plight of mass tourism destinations. The tourism industrial chain has not yet been completed, and the development of hotels, restaurants, performing arts and other industries is lagging behind. After realizing this, NSAs had taken revival measures, such as conducting tourism festivals, launching special cultural and creative products, and carrying out market-oriented reforms. China's mass tourism destinations had a gradual transformation from "scenic spots tourism" to "high-quality tourism". It can be seen from the above analysis that, in China, government involvement cast in an essential role of tourism destinations. This can be corroborated by Javed and Tučková's (2020) study [72].

5.2. The Distinguishing Characteristic in Different Types of Destinations

Different types of tourism resources are suitable for developing diverse tourism products, thus various characteristics of decline or renewal curves. A possible explanation for these results may be the differences in input-output characteristics of different resource types. To be more specific, Mountains, Human landscape, Rivers & Waterfall require more investment in infrastructure construction, operation, and maintenance. Their tourism products were mostly sightseeing tours until 2010, making it difficult to bring in multi-source income such as accommodation and amusement. Thus, their overall efficiency values are low. At the same time, with the transformation of tourism market demand, their development is more dependent on purely technical efficiency aspects such as tourism industry upgrading and product renewal. By contrast, coastal tourism destinations require less infrastructure investment and operating costs to develop, and their resort attributes dictate that tourists generally stay for multiple days, which leads to the highest efficiency. However, with the rise of other resorts (e.g., mountain resorts, desert resorts), a downward trend of coastal tourism destinations has been observed.

Focusing on the decline and rejuvenation of tourism destinations and comparing it with existing studies, the following features can be identified. NSAs can be classified into wave-shaped, stable, and growing types based on the changes in efficiency curves. Coast, Special landform and Cave are crest types, with their highest efficiency values occurring in the middle range. Coast and Special landform peaked around 2010 and Cave earlier (in 2007). Mountain, River & Waterfall are stable types, with flat changes in efficiency values over the observed period. Wetland & Lake and Human landscape is the only growing type, with a substantial increase in efficiency from 2016 to 2017. The wave-shaped tourism destination has gone through a nearly complete maturity phase, with the difference that Special landform is gradually going into decline, Cave is in a stagnant phase, and Coast is in a fluctuating decline. With regard to the stable types, Mountain and River & Waterfall are the representative resource of Chinese landscape culture, as the earliest developed and most representative type of mass tourism destinations has entered a stagnant period of development. The Human landscape and Wetland & Lake have similar persistent decline stages, but the path to rejuvenation is different. The implementation of China's cultural tourism integration policy has promoted the rejuvenation of the Human landscape. The enhancement of the cultural content of mass tourism destinations, and the cooperation between cultural tourism and other industries have been emphasized. Wetland & Lake continues to explore the transformation of tourism products into healthy tourism, leisure and holiday-making. The above results may also be closely related to the tourism supply chain and tourism activities of various mass tourism destinations.

6. Conclusions

This paper explored and presented an operational evaluation model to estimate whether a mass tourism destination is in a decline or rejuvenation stage, using tourism efficiency as a predictor. Using this model, a stage-by-stage review of the efficient development of China's mass tourism destinations is conducted. It takes the NSAs as samples, and on this basis, differentiation by region and type is discussed. The results revealed the following: (i) The development of China's mass tourism destinations can be divided into three phases, in which there is a clear process of persistent decline and rejuvenation. (ii) NSA's tourism efficiency presents a "dual core, agglomeration" pattern and obvious development polarization, with significant core-edge structure characteristics. (iii) Different types of NSAs vary in terms of efficiency level and change trends. Human landscape, Cave, and

Wetland & Lakes all have distinct phases of persistent decline, but humanistic landscapes show a significant rejuvenation trend. This study attempts to make an extension based on the initial TALC and a re-interpretation by efficiency. The post-stagnation stage is further divided into fluctuating decline, fluctuating rise, persistent decline, and rejuvenation. In such a way, potential risks can be more accurately identified and volatility changes do not affect the overall stage judgment.

There are still some limitations in this study. Firstly, as the data of NSAs are officially counted only from 2003 to 2017, this study cannot measure the efficiency of mass tourism destinations in 2018 and after. Due to the impact of COVID-19, the efficiency of NSAs is likely to decline. Thus, in the future, other measurement methods could be used to verify it. Secondly, the efficiency evaluation model proposed in this paper must be verified in other countries' tourism destinations due to the different development stages and external environments. This study would be well complemented by empirical studies examining the effectiveness and influence factor of the efficiency evaluation model. Finally, carrying capacity shows a pivotal part in Butler's TALC model, although it is not mentioned in this paper [73]. Future studies may explore the influence mechanism with efficiency and carrying capacity interaction.

Author Contributions: L.X.: Conceptualization, methodology, writing—original draft, project administration, writing—review & editing. H.Y.: supervision, funding acquisition, writing—review & editing. B.Z.: methodology, supervision, writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the 2nd Comprehensive Scientific Investigation and Research Project of the Qinghai-Tibet Plateau (2019QZKK0401), The National Natural Science Foundation of China (41701164) and The Special Project for Type-A Strategic and Leading Technologies under the CAS (XDA20020301).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study can be found in http://www.stats.gov.cn/ (accessed on 21 December 2021).

Acknowledgments: We would like to thank the National Bureau of Statistics of China for providing the data of NSAs. We are also very grateful to Pengfei Zhang for his ideas on the research framework.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. National efficiency analysis results from 2003 to 2017.

Year	Technical Efficiency (TE)	Pure Technical Efficiency (PTE)	Scale Effect (SE)
2003	0.4519	0.7242	0.6805
2004	0.6477	0.7908	0.8200
2005	0.6170	0.7430	0.8339
2006	0.5350	0.6724	0.7992
2007	0.6207	0.7762	0.8122
2008	0.6352	0.7445	0.8514
2009	0.6495	0.7296	0.8907
2010	0.6469	0.7693	0.8310
2011	0.6374	0.7494	0.8592
2012	0.6370	0.7176	0.8977
2013	0.6265	0.7977	0.8029
2014	0.5822	0.7804	0.7632
2015	0.4486	0.6306	0.7407
2016	0.5843	0.7501	0.8091
2017	0.6023	0.7321	0.8045
Mean	0.5948	0.7405	0.8131

Appendix B

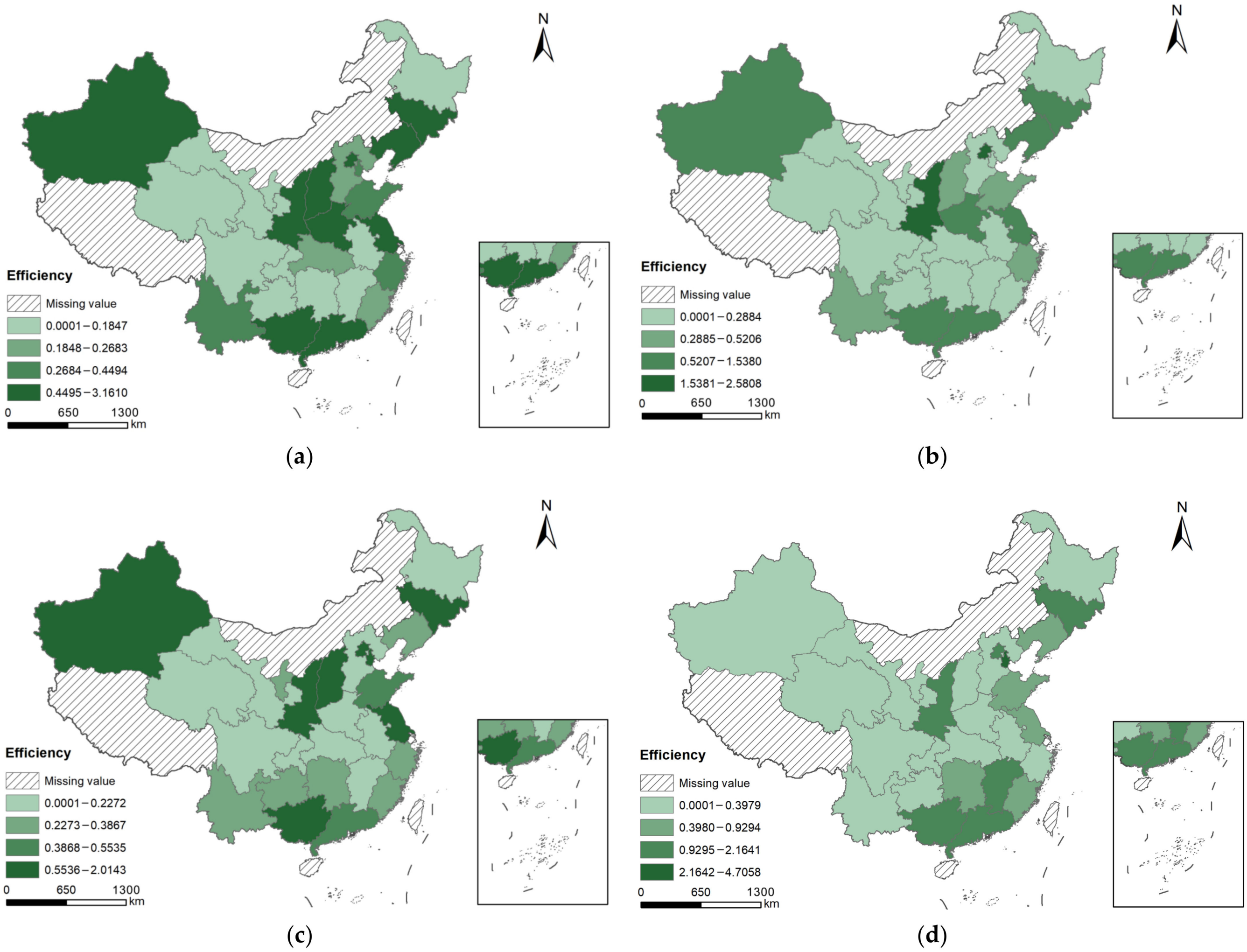

Figure A1. Evolution trend of NSAs' tourism efficiency in China from 2003 to 2017. (**a**) 2003; (**b**) 2008; (**c**) 2013; (**d**) 2017.

References

1. Hall, C.M. Tourism and regional competitiveness. In *Developments in Tourism Research*; Routledge: London, UK, 2007; pp. 233–246, ISBN 0-08-055168-8.
2. Singh, S. Time, tourism area 'life-cycle,'evolution and heritage. *J. Herit. Tour.* **2021**, *16*, 218–229. [CrossRef]
3. Oreja Rodríguez, J.R.; Parra-López, E.; Yanes-Estévez, V. The sustainability of island destinations: Tourism area life cycle and teleological perspectives. The case of Tenerife. *Tour. Manag.* **2008**, *29*, 53–65. [CrossRef]
4. Ayikoru, M. Destination competitiveness challenges: A Ugandan perspective. *Tour. Manag.* **2015**, *50*, 142–158. [CrossRef]
5. Agarwal, S.; Brunt, P. Social exclusion and English seaside resorts. *Tour. Manag.* **2006**, *27*, 654–670. [CrossRef]
6. Chapman, A.; Speake, J. Regeneration in a mass-tourism resort: The changing fortunes of Bugibba, Malta. *Tour. Manag.* **2011**, *32*, 482–491. [CrossRef]
7. Weaver, D.; Tang, C.; Zhao, Y. Facilitating sustainable tourism by endogenization: China as exemplar. *Ann. Tour. Res.* **2020**, *81*, 102890. [CrossRef]
8. Leiper, N. Are destinations' the heart of tourism'? The advantages of an alternative description. *Curr. Issues Tour.* **2000**, *3*, 364–368. [CrossRef]
9. Zhong, L.; Wu, B.; Morrison, A.M. Research on China's tourism: A 35-year review and authorship analysis. *Int. J. Tour. Res.* **2015**, *17*, 25–34. [CrossRef]
10. Wang, D.; Ap, J. Factors affecting tourism policy implementation: A conceptual framework and a case study in China. *Tour. Manag.* **2013**, *36*, 221–233. [CrossRef]
11. Butler, R. The concept of a tourist area cycle of evolution: Implications for management of resources. *Can. Geogr. Géographe Can.* **1980**, *24*, 5–12. [CrossRef]

12. Di Benedetto, C.A.; Bojanic, D.C. Tourism area life cycle extensions. *Ann. Tour. Res.* **1993**, *20*, 557–570. [CrossRef]
13. Pryer, M. The traveller as a destination pioneer. *Prog. Tour. Hosp. Res.* **1997**, *3*, 225–237. [CrossRef]
14. Nieves, J.; Diaz-Meneses, G. Knowledge sources and innovation in the hotel industry: Empirical analysis on Gran Canaria Island, a mature mass-tourism destination. *Int. J. Contemp. Hosp. Manag.* **2018**, *30*, 2537–2561. [CrossRef]
15. Conti, G.; Perelli, C. Traditional mass tourism destinations: The decline of Fordist tourism facing the rise of vocational diversification. *Gov. Sustain. New Tour. Trends Planum* **2005**, *11*, 1–20.
16. Kozak, M.; Martin, D. Tourism life cycle and sustainability analysis: Profit-focused strategies for mature destinations. *Tour. Manag.* **2012**, *33*, 188–194. [CrossRef]
17. Wheeller, B. Sustainable mass tourism: More smudge than nudge the canard continues. *Tour. Recreat. Res.* **2007**, *32*, 73–75. [CrossRef]
18. Zhang, T.; Sun, Y. Spatial Characteristics and Functions of National Scenic Spots in China. *Urban Dev. Stud.* **2019**, *26*, 6–12.
19. Haraldsson, H.; Ólafsdóttir, R. Evolution of Tourism in Natural Destinations and Dynamic Sustainable Thresholds over Time. *Sustainability* **2018**, *10*, 4788. [CrossRef]
20. Cracolici, M.F.; Nijkamp, P. The attractiveness and competitiveness of tourist destinations: A study of Southern Italian regions. *Tour. Manag.* **2009**, *30*, 336–344. [CrossRef]
21. Xu, C. Theoretical Thinking on tourism Product Life Cycle Theory. *Tour. Trib.* **1997**, *5*, 43–46, 62.
22. Brouder, P.; Clavé, S.A.; Gill, A.; Ioannides, D. *Tourism Destination Evolution*; Routledge: London, UK, 2017; ISBN 1-4724-5399-9.
23. Sanz-Ibáñez, C.; Anton Clavé, S. The evolution of destinations: Towards an evolutionary and relational economic geography approach. *Tour. Geogr.* **2014**, *16*, 563–579. [CrossRef]
24. Holladay, P.J. Destination Resilience and Sustainable Tourism Development. *Tour. Rev. Int.* **2018**, *22*, 251–261. [CrossRef]
25. Nazneen, S.; Xu, H.; Ud Din, N. Assessment of residents' destination image and their pro-tourism development behaviour: Perspectives on the China–Pakistan economic corridor. *Tour. Rev.* **2020**, *76*, 184–197. [CrossRef]
26. *The Tourism Area Life Cycle, Vol. 1: Applications and Modifications*; Butler, R. (Ed.) Multilingual Matters: Bristol, UK, 2006; ISBN 978-1-84541-027-8.
27. Getz, D. Tourism planning and destination life cycle. *Ann. Tour. Res.* **1992**, *19*, 752–770. [CrossRef]
28. Canavan, B. Sustainable tourism: Development, decline and de-growth. Management issues from the Isle of Man. *J. Sustain. Tour.* **2014**, *22*, 127–147. [CrossRef]
29. Gunter, U.; Smeral, E. The decline of tourism income elasticities in a global context. *Tour. Econ.* **2016**, *22*, 466–483. [CrossRef]
30. Botti, L.; Goncalves, O.; Ratsimbanierana, H. French Destination Efficiency: A Mean–Variance Approach. *J. Travel Res.* **2012**, *51*, 115–129. [CrossRef]
31. Agarwal, S. Restructuring seaside tourism: The resort lifecyle. *Ann. Tour. Res.* **2002**, *29*, 25–55. [CrossRef]
32. Agarwal, S. Global–local interactions in English coastal resorts: Theoretical perspectives. *Tour. Geogr.* **2005**, *7*, 351–372. [CrossRef]
33. Prideaux, B. The Resort Development Spectrum: The Case of The Gold Coast, Australia. *Tour. Geogr.* **2004**, *6*, 26–58. [CrossRef]
34. Bujosa, A.; Riera, A.; Pons, P.J. Sun-and-beach tourism and the importance of intra-destination movements in mature destinations. *Tour. Geogr.* **2015**, *17*, 780–794. [CrossRef]
35. Rebollo, J.F.V.; Castiñeira, C.J.B. Renewal and restructuring of consolidated coastal tourist destinations: Recreational practices in the evolution of tourist space. *Boletín Asoc. Geógrafos Españoles* **2010**, *8*, 419–425.
36. Abujamous, I.M.; Jawabreh, O.A.; Jahmani, A.; Alsarayreh, M.N.; Harazneh, A.A. Developing tourism through sports events to assist in the rejuvenation of the strategic position of the Aqaba Special Economic Zone Authority (ASEZA). *Afr. J. Hosp. Tour. Leis.* **2019**, *8*, 1–14.
37. Kubickova, M.; Martin, D. Exploring the relationship between government and destination competitiveness: The TALC model perspective. *Tour. Manag.* **2020**, *78*, 104040. [CrossRef]
38. Mandić, A.; Mrnjavac, Ž.; Kordić, L. Tourism Infrastructure, Recreational Facilities and Tourism Development. *Tour. Hosp. Manag.* **2018**, *24*, 41–62. [CrossRef]
39. Nolasco-Cirugeda, A.; Martí, P.; Ponce, G. Keeping mass tourism destinations sustainable via urban design: The case of Benidorm. *Sustain. Dev.* **2020**, *28*, 1289–1303. [CrossRef]
40. Rodríguez-Díaz, M.; Rodríguez-Díaz, R. A Decision-Making and Governance Framework for the Renewal of Tourism Destinations: The Case of the Canary Islands. *Sustainability* **2018**, *10*, 310. [CrossRef]
41. Lee, S.; Kim, D.; Park, S.; Lee, W. A Study on the Strategic Decision Making Used in the Revitalization of Fishing Village Tourism: Using A'WOT Analysis. *Sustainability* **2021**, *13*, 7472. [CrossRef]
42. Zhang, C.; Xiao, H. Destination development in China: Towards an effective model of explanation. *J. Sustain. Tour.* **2014**, *22*, 214–233. [CrossRef]
43. Boivin, M.; Tanguay, G.A. Analysis of the determinants of urban tourism attractiveness: The case of Québec City and Bordeaux. *J. Destin. Mark. Manag.* **2019**, *11*, 67–79. [CrossRef]
44. Sendra, M.; Kristianto, Y.; Widyatmaja, G.N.; Nugroho, S. Bali tourism revitalization based on chinatown tourism development. *PalArch's J. Archaeol. Egypt Egyptol.* **2020**, *17*, 15563–15566.
45. Wang, Z.; Liu, Q.; Xu, J.; Fujiki, Y. Evolution characteristics of the spatial network structure of tourism efficiency in China: A province-level analysis. *J. Destin. Mark. Manag.* **2020**, *18*, 100509. [CrossRef]

46. Cracolici, M.F.; Nijkamp, P.; Rietveld, P. Assessment of Tourism Competitiveness by Analysing Destination Efficiency. *Tour. Econ.* **2008**, *14*, 325–342. [CrossRef]
47. Radovanov, B.; Dudic, B.; Gregus, M.; Marcikic Horvat, A.; Karovic, V. Using a Two-Stage DEA Model to Measure Tourism Potentials of EU Countries and Western Balkan Countries: An Approach to Sustainable Development. *Sustainability* **2020**, *12*, 4903. [CrossRef]
48. Altin, M.; Koseoglu, M.A.; Yu, X.; Riasi, A. Performance measurement and management research in the hospitality and tourism industry. *Int. J. Contemp. Hosp. Manag.* **2018**, *30*, 1172–1189. [CrossRef]
49. Yi, T.; Liang, M. Evolutional Model of Tourism Efficiency Based on the DEA Method: A Case Study of Cities in Guangdong Province, China. *Asia Pac. J. Tour. Res.* **2015**, *20*, 789–806. [CrossRef]
50. Nurmatov, R.; Fernandez Lopez, X.L.; Coto Millan, P.P. Tourism, hospitality, and DEA: Where do we come from and where do we go? *Int. J. Hosp. Manag.* **2021**, *95*, 102883. [CrossRef]
51. Cao, F.; Huang, Z.; Jin, C.; Xu, M. Chinese National Scenic Areas' Tourism Efficiency: Multi-scale Fluctuation, Prediction and Optimization. *Asia Pac. J. Tour. Res.* **2016**, *21*, 570–595. [CrossRef]
52. Soteriades, M. Tourism destination marketing: Approaches improving effectiveness and efficiency. *J. Hosp. Tour. Technol.* **2012**, *3*, 107–120. [CrossRef]
53. Yin, P.; Tsai, H.; Wu, J. A hotel life cycle model based on bootstrap DEA efficiency: The case of international tourist hotels in Taipei. *Int. J. Contemp. Hosp. Manag.* **2015**, *27*, 918–937. [CrossRef]
54. Koval, V.; Prymush, Y.; Popova, V. *The Influence of the Enterprise Life Cycle on the Efficiency of Investment*; Social Science Research Network: Rochester, NY, USA, 2017.
55. Ingrao, C.; Messineo, A.; Beltramo, R.; Yigitcanlar, T.; Ioppolo, G. How can life cycle thinking support sustainability of buildings? Investigating life cycle assessment applications for energy efficiency and environmental performance. *J. Clean. Prod.* **2018**, *201*, 556–569. [CrossRef]
56. Wang, N.; Shen, R.; Wen, Z.; De Clercq, D. Life cycle energy efficiency evaluation for coal development and utilization. *Energy* **2019**, *179*, 1–11. [CrossRef]
57. Lozano, S.; Iribarren, D.; Moreira, M.T.; Feijoo, G. The link between operational efficiency and environmental impacts: A joint application of Life Cycle Assessment and Data Envelopment Analysis. *Sci. Total Environ.* **2009**, *407*, 1744–1754. [CrossRef]
58. Egilmez, G.; Gumus, S.; Kucukvar, M.; Tatari, O. A fuzzy data envelopment analysis framework for dealing with uncertainty impacts of input–output life cycle assessment models on eco-efficiency assessment. *J. Clean. Prod.* **2016**, *129*, 622–636. [CrossRef]
59. Niavis, S.; Tsiotas, D. Assessing the tourism performance of the Mediterranean coastal destinations: A combined efficiency and effectiveness approach. *J. Destin. Mark. Manag.* **2019**, *14*, 100379. [CrossRef]
60. Shen, H. Separation Effect of Scenic Spots: Connotation, Characteristics and Causes. *Urban. Archit.* **2020**, *17*, 188–191. [CrossRef]
61. Wang, R.; Xia, B.; Dong, S.; Li, Y.; Li, Z.; Ba, D.; Zhang, W. Research on the Spatial Differentiation and Driving Forces of Eco-Efficiency of Regional Tourism in China. *Sustainability* **2021**, *13*, 280. [CrossRef]
62. Emrouznejad, A.; Yang, G. A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Econ. Plan. Sci.* **2018**, *61*, 4–8. [CrossRef]
63. Cook, W.D.; Tone, K.; Zhu, J. Data envelopment analysis: Prior to choosing a model. *Omega* **2014**, *44*, 1–4. [CrossRef]
64. Cooper, W.W.; Seiford, L.M.; Zhu, J. *Handbook on Data Envelopment Analysis*; Springer: Berlin/Heidelberg, Germany, 2011.
65. Cullinane, K.; Wang, T.-F.; Song, D.-W.; Ji, P. The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis. *Transp. Res. Part A Policy Pract.* **2006**, *40*, 354–374. [CrossRef]
66. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
67. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
68. Barros, C.P.; Botti, L.; Peypoch, N.; Robinot, E.; Solonandrasana, B.; George-Assaf, A. Performance of French destinations: Tourism attraction perspectives. *Tour. Manag.* **2011**, *32*, 141–146. [CrossRef]
69. Ben Aissa, S.; Goaied, M. Performance Of Tourism Destinations: Evidence From Tunisia. *J. Hosp. Tour. Res.* **2017**, *41*, 797–822. [CrossRef]
70. Cao, F.; Huang, Z.; Jin, C.; Xu, M. Influence of Chinese economic fluctuations on tourism efficiency in national scenic areas. *Tour. Econ.* **2016**, *22*, 884–907. [CrossRef]
71. Li, H.; Hu, M.; Li, G. Forecasting tourism demand with multisource big data. *Ann. Tour. Res.* **2020**, *83*, 102912. [CrossRef]
72. Javed, M.; Tučková, Z. The role of government in tourism competitiveness and tourism area life cycle model. *Asia Pac. J. Tour. Res.* **2020**, *25*, 997–1011. [CrossRef]
73. Butler, R.W. Tourism Destination Development: Cycles and Forces, Myths and Realities. *Tour. Recreat. Res.* **2009**, *34*, 247–254. [CrossRef]