Spatial spillover and determinants of tourism efficiency: a low carbon emission perspective

Abstract

This paper measures tourism carbon efficiency (TCE) in China by incorporating energy consumption and carbon dioxide (CO_2) emissions into an efficiency assessment framework, and to further investigate the determinants of TCE by considering the spatial spillover effects. To do this, a bootstrap slacks-based measure (SBM) model was applied to assess the TCE in 30 provincial-level administrative regions of China from 2008 to 2019. Next, the Moran's index and spatial Durbin model (SDM) were adopted to explore the spatial distribution and determinants of TCE. The results indicate that regional differences affect the level of China's TCE, as do spatial spillover effects. In addition, technology innovation, urbanization rate and government support positively affect TCE. In contrast, economic growth negatively affects TCE. Educational attainment, green infrastructure and government support have a negative spatial spillover effect on TCE. Transportation infrastructure has a negative total effect on TCE.

Keywords

Carbon emission, Tourism carbon efficiency, Bootstrap SBM model, Spatial spillover effect, Spatial Durbin model (SDM)

Introduction

Tourism makes vital contributions to the national economies of many countries, including China (Wang & Ap, 2013) and greatly contributes to global economic growth. In 2019, there were 145 million inbound tourists to China, and China received CNY 0.90 trillion (≈USD 131.25 billion) in foreign exchange income from international tourism, accounting for 9.9% of total global tourists and 8.9% of total tourism income. Meanwhile, domestic tourists in China completed 6.006 billion visits, more than four times the number from total international tourists (NBS, 2019; UNWTO, 2020). These facts show the important role of tourism in the growth of China's national economy, which is also provided in many previous studies (e.g., Liu et al., 2021; Tu and Zhang, 2020; Zhang and Zhang, 2021).

Tourism directly creates economic benefits and reduces unemployment; however, tourism development poses a threat to the environment (Ehigiamusoe, 2020). Most tourism-driven consumption-related activities, such as transportation and accommodation, consume large amounts of fossil fuels, negatively impacting the environment (Liu et al., 2022). As such, a key problem for the tourism sector is determining how to separate projected growth from resource consumption and greenhouse gas (GHG) emissions (WTOITF, 2019). According to Zha et al. (2020), GHG emission reduction and energy conservation can contribute to solving this problem. In 2020, the Chinese government committed to achieving peak carbon dioxide (CO_2) emissions by 2030 and set a target to achieve carbon neutrality by 2060.

Sustainable tourism development requires encompassing both economic and ecological benefits (Lozano-Ramírez et al., 2022). Focusing on assessing energy usage, carbon emissions, and economic factors is essential when balancing economic benefits and environmental protection (Liu et al., 2022; Sun and Pratt, 2014). Furthermore, tourism is affected by different complex factors (Chaabouni, 2019; Divisekera and Nguyen, 2018; Zhou et al., 2020), all of which impact on the sustainable development of tourism. Therefore, in addition to economic factors, external determinants and the detrimental impact on the environment should also be considered in evaluation of tourism industry (Song and Li, 2019). Nevertheless, when analyzing the environmental and economic factors in tourism, previous studies (e.g., Aratuo and Etienne, 2019; Chaabouni, 2019; Eyuboglu and Uzar, 2020) have typically separated the tourism ecological impact from the tourism economic development. However, comprehensive studies on the interaction between tourism efficiency and its external factors such as socio-economic development and environmental capacity considering CO_2 emissions from tourism have been ignored, which is a topic that must be further addressed by current and future studies on sustainable development of tourism. Thus, this study centers on solving these unresolved issues related to sustainable tourism development.

Moreover, tourism development is associated with spatial externalities, manifested through spatial spillover effects due to factors such as geography (Majewska, 2015). This means that tourism development in one region may impact neighboring regions (Ma et al., 2015). In other words, tourism stakeholders in neighboring regions are unlikely to be independent (Jiao et al., 2019). Previous tourism efficiency study has not addressed the spatial spillover effect, particularly with respect to the sustainable tourism development.

To study the ecological and economic benefits generated by tourism development, this study identified the following objectives: (1) Based on energy consumption and CO_2 emissions generated by tourism, to assess tourism carbon efficiency (TCE) by setting up input and output indexes; (2) To investigate the temporal evolution and spatial distribution of TCE; (3) Considering the interaction of spatial factors on tourism in different regions, to identify key determinants affecting TCE.

To achieve these goals, considering the close linkage between tourism and CO_2 emissions (Koçak et al., 2020), energy consumption and CO_2 emissions are included in an index evaluation system to measure TCE in this study. The ultimate goal is to achieve economic benefits while minimizing the impact on GHG. Next, the bootstrap slacks-based measure (SBM) model is applied to evaluate TCE in China. This approach improves upon the conventional data envelopment analysis (DEA) model, which relies heavily on input and output data, making it impossible to observe the true efficiency (Song and Li, 2019). Further, given that tourism development is influenced by inter-regional interactions, socio-economic development and environmental capabilities, the Moran's index and spatial Durbin model (SDM) were adopted to explore the spatial distribution and determinants of TCE. This study's findings enrich the literature on tourism efficiency considering its environmental impact, and provide a useful reference for the tourism industry for improving TCE and contributing to the sustainable tourism development.

The rest of the study is structured as follows. The next section covers the literature review, followed by the methodology, variables and data, and empirical results. The implications and conclusions are showed in the last section.

Literature review

Assessing efficiency in the tourism industry

When considering tourist destinations, improved tourism efficiency usually refers to better connectivity among tourism-related industries, such as transportation and accommodations. This helps attract tourists, promotes tourism competitiveness, and drives regional economic advancement (Li *et al.*, 2018). Therefore, studying tourism efficiency is a significant part of tourism research. To assess tourism efficiency, researchers commonly apply DEA, a non-parametric technique without the need for assuming a production function (Wen et al., 2021) (e.g., Alberca & Parte, 2018; Lozano-Ramírez *et al.*, 2022; Yin *et al.*, 2020). This method can estimate the relative efficiency of decision making units (DMUs) (Charnes et al., 1978) against the best practice DMUs, to help identify any performance gaps (Assaf and Josiassen, 2016).

Several scholars have applied DEA to research tourism efficiency (Chaabouni, 2019; Corne, 2015; Niavis and Tsiotas, 2019; Yi and Liang, 2015); however, they have focused on expected production outputs, and have not considered unexpected outputs or those that could produce a negative environmental byproduct, such as CO_2 emissions (Li et al., 2022; Xia et al., 2022; Zha, Yuan, et al., 2020; Zhang et al., 2021). Given that people are increasingly concerned about environmental issues, Gössling *et al.* (2005) proposed the idea of eco-efficiency, which is a ratio method of tourism eco-efficiency that divides CO_2 emissions by tourism revenue. Other comparable methods have also been derived to assess the eco-efficiency of tourism (Qiu et al., 2017; Sun and Pratt, 2014). Nevertheless, focusing on CO_2 emissions and economic benefits, and not considering input factors such as manpower and capital, leads to an incomplete evaluation of efficiency (Peng et al., 2017).

To overcome these limitations, some researches have introduced environmental variables to estimate tourism eco-efficiency more systematically, using the input and output index evaluation framework of DEA. For example, in China's coastal cities, Liu *et al.* (2017) evaluated tourism efficiency by setting tourism-related environmental pollutants such as sewage and exhaust gas and energy consumption as inputs, and revenue and the number of tourists as outputs. Peng *et al.* (2017) considered labor, capital, energy, and natural resources as inputs, and revenue and tourism waste as outputs, to evaluate the tourism efficiency of Huangshan National Park in China. Sun *et al.* (2020) calculated the tourism efficiency of 63 cities in China by integrating capital, labor, energy consumption, revenue, and CO_2 into the efficiency assessment framework.

Previous studies have considered adverse environmental factors when evaluating tourism efficiency; however, studies of tourism efficiency that have used DEA to consider multi-input and output indicators have mainly focused on the urban level and rarely consider CO_2 emissions. Further, tourism industry relies heavily on travel agencies and star-rated hotels, and the scale and number of these establishments somewhat reflect the development scale of the tourism industry (Yi and Liang, 2015), which was rarely considered in previous studies. This highlights the need to consider energy consumption and CO_2 emissions to establish a more complete DEA index evaluation system to measure TCE in China's provincial administrative regions.

Determinants of tourism efficiency

Previous studies have applied a regression model to further evaluate the determinants impacting tourism efficiency (Corne and Peypoch, 2020). Tobit regression or bootstrap regression are commonly used methods to examine determinants of tourism efficiency. For example, Song & Li (2019) utilized Tobit regression to research the determinants of tourism efficiency in 31 Chinese provinces. They found that urbanization and openness had positive impacts on tourism efficiency. Liu *et al.* (2017) also applied Tobit regression to examine the factors that influence tourism efficiency in 53 cities in China. The findings indicated that tourism efficiency benefits from GDP and tourism industry structure. In contrast, the number of tourists had the opposite impact. Chaabouni (2019) applied double bootstrap regression to study tourism efficiency in 31 Chinese provinces. That study found that trade openness, temperature, and the number of hotels all positively contributed to tourism efficiency, but geographic localization had a negative impact. Barros *et al.* (2011) applied bootstrapped truncated regression to explore determinants of tourism efficiency in France, finding that attractions such as monuments and museums may increase tourism efficiency.

Previous studies analyzed many factors that influence tourism efficiency, which are beneficial for policy making to improve the economic benefits of tourism. However, there is still the gap in the exploration of factors affecting TCE considering the ecological benefits of tourism. Furthermore, few studies assessing environmental impact of tourism development have considered the spatial spillover effect (Li & Lv, 2021). A positive spatial spillover effect occurs when tourism regions benefit each other through complementary activities, support, and resource-sharing to attract tourists (Zhou *et al.*, 2020). In contrast, a negative spatial spillover effect occurs when the similarity of tourism products and supplies attracts similar tourists, generating fierce competition (Yang & Wong, 2012).

Spatial econometric models can address spatial interactions between different geographical regions; as such, some empirical studies have considered spillover effects and have applied these models to analyze the determinants of tourism development from different perspectives. For example, when studying the tourism economy, Tian *et al.* (2020) used the SDM to research whether different types of transportation have affected tourism growth in nearby regions. The results show that high-speed rail transport promotes the growth of domestic and inbound tourism in surrounding regions, while air transport only promotes inbound tourism revenue in surrounding regions.

From the perspective of tourism flow, Yang and Wong (2012) applied a spatial econometric model to examine tourism flows for 341 Chinese cities. They found that both inbound and domestic tourism flows have spatial spillover effects, with total tourist attractions, flight number and density of roads serving as the important factors influencing tourism flow. To study the tourism ecological environment, Xu *et al.* (2020) applied the SDM to discuss the spillover effects of haze on China's inbound tourism; the findings indicated that the number of inbound tourists in neighboring regions is expected to fall by 0.189% for every one percent increase in local haze pollution.

To sum up, despite this important research work, few research has utilized spatial econometric models and analyzed the determinants of tourism efficiency while also considering environmental impacts, in particular, CO_2 emissions.

Methodology

Energy consumption and CO_2 emissions estimation

Data about CO_2 emissions resulting from tourism are critical for tourism stakeholders working to reduce emissions, however, these data have not been published nor made readily available. As such, scholars have proposed different methods of quantifying CO_2 from tourism to directly demonstrate the effect on climate change. One such method is a bottom-up approach that calculates CO_2 emissions based on the classification of products and services consumed by travelers while traveling (Sun & Drakeman, 2020). This approach offers detailed information on the end-use of energy and the major drivers of CO_2 emissions. However, it requires large amounts of raw data (Becken and Patterson, 2006).

Another method is the top-down approach, which assesses tourism as a sector of the wider economy based on environmental accounting and the Tourism Satellite Account (TSA) (Tang & Ge, 2018). This approach treats tourism as an independent sector in the economy, allowing it to be compared with other sectors. However, this approach is based on input-output tables, satellite accounts, and other data, which are difficult to obtain if the government does not publish them (Sun, 2014).

This study adopts the bottom-up method to assess the CO_2 emissions resulting from tourism, as an input-output data table is not available, and China does not have a standard TSA. The bottom-up method used to estimate energy consumption and CO_2 emissions starts with tourists arriving at a destination. It divides tourism-associated energy consumption and CO_2 emissions into three sources: transportation, accommodation, and activities (Becken and Patterson, 2006). First, the energy consumed and CO_2 emissions of the three sources are calculated, respectively, based on the activity data. Then the sum is derived. The formulas are as follows:

$$E_t = E_{Tt} + E_{Ht} + E_{At} \tag{1}$$

$$C_t = C_{Tt} + C_{Ht} + C_{At} \tag{2}$$

where E_t and C_t represent the total energy consumption and CO_2 emissions, respectively, from the tourism industry. Parameters E_{Tt}, E_{Ht}, and E_{At} represent the tourist-related energy consumption from transportation, accommodation, and activities, respectively; and C_{Tt}, C_{Ht} and C_{At} represent the CO_2 emissions from these three same sources, respectively. The method used to calculate energy consumption and CO_2 emissions for transportation and tourism activities was adopted from Chen *et al.* (2018) and Ma *et al.* (2021). Energy consumption and CO_2 emission for tourism accommodation were calculated based on Lu *et al.* (2019).

Bootstrap SBM model with undesirable outputs

In the conventional radial DEA models, the proportion of the decrease (increase) of all inputs (outputs) is used to quantify the inefficiency of DMUs, ignoring the slack improvement. The SBM-DEA model with undesirable outputs can solve the problem that slack variables used to measure inefficiency in the radial model are absent (Tone, 2004). The result generates efficiency values that avoid the deviation and improve the probability of distinguishing DMUs (Lee et al., 2020). The SBM-DEA model with undesirable outputs showed in formula (3) and (4).

$$\min \rho_k = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{\zeta_i^-}{x_{ik}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\zeta_r^+}{y_{rk}^g}+\sum_{q=1}^{s_2}\frac{\zeta_q^-}{y_{qk}^b}\right)} \tag{3}$$

$$\begin{aligned} s.t.\ \ x_{ik} &= \sum_{f=1}^{n} x_{if}\lambda_f + \zeta_i^- \\ g_{rk} &= \sum_{f=1}^{n} y_{rf}^g\lambda_f - \zeta_r^+ \\ y_{qk}^b &= \sum_{f=1}^{n} y_{qf}^b\lambda_f + \zeta_q^+ \\ &\lambda_f,\ \zeta_i^-,\ \zeta_r^+,\ \zeta_q^+ \geq 0 \\ &i = 1,2,\cdots,m;\ f = 1,2,\cdots,n \end{aligned} \tag{4}$$

$$r = 1,2,\cdots,s_1;\ q = 1,2,\cdots,s_2$$

In this model, we assume that there are n DMUs, denoted as DMU_f, and each DMU is composed of m input variables, s_1 desirable outputs, and s_2 undesirable outputs. The matrix of input x, desired output y^g, and undesirable output variables y^b are expressed as $x\epsilon\left(x_{1f}, x_{2f}, \dots, x_{if}\right)_{m\times n}$, $y^g\epsilon\left(y^g_{1f}, y^g_{2f}, \dots, y^g_{rf}\right)_{s_1\times n}$, $y^b\epsilon\left(y^b_{1f}, y^b_{2f}, \dots, y^b_{qf}\right)_{s_2\times n}$, respectively. ρ is the TCE value; the index k identifies the DMU being evaluated; λ is a linear combination coefficient. i, r, and q represent the ith input, rth desired output, and qth undesired output, respectively. ζ_i^-, ζ_r^+, ζ_q^+ are the slack variable of input, desired output, and undesirable output variables, respectively. A DMU is considered relatively efficient when its efficiency value equals one (Adler et al., 2002).

When carrying out production activities, DMUs may be impacted by external factors in addition to inputs and outputs (Bădin et al., 2012, 2019). However, the second-stage regression of DEA efficiency scores has been criticized for its serious separability problem (Bădin et al., 2010, 2014; Daraio et al., 2018). Bootstrap-DEA method can overcome this problem. On the basis of original sample data, this method simulates the generation process of original data by repeated sampling (Simar and Wilson, 2011). By enlarging the sample size, the method corrects the bias of efficiency evaluation value in the case of small sample. Therefore, in efficiency measurement with DEA method, bootstrap technology is used to correct the efficiency value to avoid the bias of efficiency results and improve the reliability of the second stage regression results (Huang et al., 2021). In this study, the bootstrap SBM method is applied, and the steps were as follows (Huang et al., 2021; Song and Li, 2019):

(1) For each DMU ($x_f,\ y_f$), $f = 1,\ldots,$n, x_f and y_f is the input and output of the f[th] DMU, respectively. Using the SBM-DEA model with undesirable outputs for each DMU, we obtain the relative efficiency $\hat{\rho}_f, f = 1, \ldots,$ n;

(2) For the efficiency value $\hat{\rho}_f, f = 1, \ldots,$ n, the bootstrap method is applied to simulate the random efficiency value $\rho^*_{1\gamma}, \rho^*_{2\gamma}, \ldots, \rho^*_{n\gamma}$ with scale Ω ($\gamma = 1, \ldots, \Omega, \Omega = 2000$). $\rho^*_{f\gamma}$ is the random efficiency value γ^{th} iteration among $\hat{\rho}_1, \hat{\rho}_2, \ldots, \hat{\rho}_n$, and $f = 1, \ldots,$ n;

(3) The simulation sample ($x^*_{f\gamma},\ y_f$) are calculated by $x^*_{f\gamma} = \left(\frac{\hat{\rho}_f}{\rho^*_{f\gamma}}\right) * x_f$;

(4) Using SBM-DEA method, the efficiency value $\hat{\rho}_{f\gamma}$ for each simulation sample is evaluated;

(5) By repeating steps (2) to (3) Ω times, a collection of estimated values $\hat{\rho}_{f\gamma}$ is obtained;

(6) The corrected efficiency value for each DMU is calculated by $\tilde{\rho}_f = 2\hat{\rho}_f - (\frac{1}{\Omega}) \sum_{\gamma=1}^{\Omega} \hat{\rho}_{f\gamma}$.

Moran's index

Spatial autocorrelation refers to the dependence of a variable's value in a certain region on the same variable's value in a neighboring region (Getis, 2007). Spatial autocorrelation can expose spatial dependencies and the spatial heterogeneity of geographic data (Wang *et al.*, 2016). Moran's index is one of the most widely used approaches to assess spatial autocorrelation. The global Moran's index is applied to investigate the spatial autocorrelation of observations across a study region; it is formulated as follows:

$$I = \frac{\sum_{h=1}^{z}\sum_{l=1}^{z} w_{hl}(\rho_h-\bar{\rho})(\rho_l-\bar{\rho})}{S^2\sum_{h=1}^{z}\sum_{l=1}^{z} w_{hl}} \tag{5}$$

$$S^2 = \frac{1}{n}\sum_{h=1}^{z}(\rho_h - \bar{\rho})^2 \tag{6}$$

$$\bar{\rho} = \frac{1}{n}\sum_{h=1}^{z}\rho_h \tag{7}$$

$$w_{hl} = \begin{cases} 1, & if\ h\ and\ l\ are\ neighbors \\ 0, & if\ h\ and\ l\ are\ not\ neighbors \end{cases} \tag{8}$$

Here, S^2 is the variance; and ρ_h and ρ_l are the TCE of h and l regions, respectively; $\bar{\rho}$ is the average of all TCE; w_{hl} is the element of spatial weight matrix W; and z is the number of regions. The value of I ranges between negative one and positive one; the closer the value of I is to being positive one, the more geographically concentrated the observed regions possessing similar attributes are. In contrast, the closer the value of I is to being negative one, the more concentrated the observed regions possessing different attributes are. The closer the value of I is to zero, the more randomly scattered the attributes of the observed regions are (Diniz-Filho et al., 2003).

This study applied the local Moran's index to reflect the spatial dependence of a particular location in the studied regions (Anselin, 1995). The formula is as follows:

$$I_h = \frac{\rho_h-\bar{\rho}}{\sigma}\sum_{l=1(h\neq l)}^{z} w_{hl}\frac{\rho_l-\bar{\rho}}{\sigma} \tag{9}$$

the other parameters have the same meanings as those of the global Moran's index except that σ is the standard deviation of ρ.

The results of the local Moran index are reflected in a Moran scatter plot. The horizontal axis of the scatter plot corresponds to the value of the observed region after data standardization; the vertical axis corresponds to the spatial lag values of the observations. There are four quadrants in the Moran scatter plot. Table 1 shows the corresponding classes of regional differences in each quadrant (Wang *et al.*, 2016). The HH cluster contains regions with high TCE values that are surrounded by high-TCE regions; an analogous scheme is used to describe LH, LL, and HL clusters.

Insert the Table 1

Spatial econometric model

Frequently applied spatial econometric techniques to assess spatial correlation include the spatial autoregressive (SAR) model, spatial error model (SEM), and SDM. The SAR model considers the spatial dependence between observations of adjacent observed regions, or their endogenous interactive effects (Halleck Vega and Elhorst, 2017). The SEM includes the spatial effects between the error terms. SDM is an integrated approach that incorporates SEM and SAR models and it also considers the exogenous interactive effects of the explanatory variables of other units on the explained variables of specific units (Elhorst, 2014). The SDM is a general and popular model, and is formulated as follows:

$$Y = \alpha WY + \tau U_N + X\beta + WX\theta + \varepsilon \qquad (10)$$

Here, Y is an $N \times 1$ vector of the explained variable; X is an $N \times K$ matrix of the explanatory variables; U_N is an $N \times 1$ vector of ones; α, τ, β, and θ are the parameters to be estimated; ε is the random disturbance terms; and w is the spatial weight matrix (the spatial weight matrix in the Moran's index as described above). When θ is zero, the SDM is the SAR model; when θ is $-\alpha\beta$, the SDM is the SEM (Elhorst, 2014).

Variables and Data

The efficiency evaluation depends on input and output indexes (Tsaur, 2001). Based on Cao *et al.* (2016); Chaabouni (2019); He *et al.* (2020); Yi and Liang (2015) and Zha *et al.* (2019), the number of employees, energy consumption, the number of travel agency and star hotel were selected as input indexes from the perspectives of labor, investment scale and energy input. Tourism revenue and number of tourists and were selected as output variables from the economic and ecological perspective. Table 2 shows the input and output index system of TCE.

Insert the Table 2

This research focuses on improving tourism efficiency by understanding and influencing economic benefits and CO_2 emissions generated from tourism. To do this, we reviewed the existing literature, leading to the inclusion of the following factors as explanatory variables to assess their influence on TCE.

First, when considering economic growth as a driver of tourism expansion, enhancing the economy improves a region's tourism infrastructure, education, and safety, possibly attracting more visitors (Paramati et al., 2017). Therefore, economic growth may impact improvements in tourism efficiency (Cao et al., 2016). We used the natural logarithm of per capita GDP to measure the economic growth (ln*EG*) (Danish and Wang, 2018). Second, travelers rely on transportation infrastructure to access tourist destinations, accounting for a significant element of tourism development (Tian et al., 2020). This transportation produces a significant volume of CO_2 emissions (Li and Zhang, 2020), also possibly influencing TCE. Transportation accessibility (ln*TA*) was used to represent the service capacity of transportation infrastructure, and was measured using the logarithm of the sum of the density of road and railway networks (Yang & Wong, 2012).

Third, the high urbanization rate creates a better environment for tourism development and enables more people to participate in tourism activities (Song and Li, 2019). Based on Shi and Li (2018), for calculating the urbanization rate (ln*UR*) of a region, we used the logarithm of the proportion of urban population in total population. Fourth, the financial support from government symbolizes the economic impetus for tourism investment (Ruan et al., 2019). We measured government support for tourism (ln*GS*) using the logarithm of the tourism-related fiscal expenditure as a share of total fiscal expenditure.

For the fifth variable, technology innovation and reduced input expenses may reduce CO_2 emissions related to tourism infrastructure and services (Stamboulis and Skayannis, 2003). Technological progress can help increase economic development and resource utilization (Xie et al., 2021). Therefore, technology innovation (ln*TI*) was measured using the logarithm of the number of patent applications (Paramati et al., 2018). For the sixth variable, educational attainment is another possible determinant of tourism efficiency. Paramati *et al.* (2017) noted that educational improvements in a region can help attract more tourists, as more educated residents may be more aware of low carbon-emission concepts, which may reduce CO_2 emissions (Zhou *et al.*, 2019). The logarithm of the proportion of people with higher education as a percentage of the population represented educational attainment (ln*EA*). Finally, green infrastructure can help improve air quality and maintain sustainable environmental development (Badiu et al., 2016; Ruan et al., 2019). If the tourism regions show green function, it can not only reduce the CO_2 emissions generated by tourism activities, but also promote tourism development and contribute to the tourism ecological security (Xiaobin et al., 2021). Green infrastructure (ln*GI*) was represented by the logarithm of the per capita park green area (Badiu et al., 2016).

This study analyzed tourism data from 30 provincial-level administrative regions in China (all regions of mainland China except Xizang) from 2008 to 2019. The study period ended after 2019 due to the availability of data. Linear interpolation was adopted to address missing data, as suggested by Song and Szafir (2019). To reduce heteroscedasticity, the variables in all the spatial models were logarithm-transformed (Eyuboglu and Uzar, 2020). The data were mainly collected from the Yearbook of China Tourism Statistics and its Supplement, provincial and municipal Statistical Yearbooks, provincial and municipal Statistical Bulletins, China City Statistical

Yearbook, China Tourism Sample Survey Data, China Statistical Yearbook during 2009-2020.

Results and analysis

TCE values

Figure 1 shows the TCE values of 30 provincial administrative regions in China from 2008 to 2019 through applying bootstrap SBM model, along with SBM-DEA efficiency results for comparison purposes.

Insert the Figure 1

Specifically, the average TCE value of China's tourism industry after correction by bootstrap method is lower than the SBM-DEA efficiency value every year. In view of the small number of samples for measurement, DEA model is highly dependent on the original data, and the estimation neglects the problem of statistical properties, leading to certain deviations in the evaluation value of production efficiency (Huang et al., 2021). Obviously, from Figure 1, the deviations of average TCE values are positive in the study. Therefore, the results of bootstrap SBM model are more reliable and real. Furthermore, the TCE values by bootstrap SBM model and SBM-DEA model showed the same trend over time, with a trend of increasing first, followed by decreasing, increasing, and then decreasing. After the global economic crisis of 2008, tourism gradually recovered. In December 2011, China National Tourism Administration published the outline of the 12th Five-Year Plan, which promoted the demand and development of tourism. Therefore, TCE value showed an overall growth trend from 2008 to 2016 and reached a peak in 2016. On the whole, China's TCE value showed an upward trend from 2008 to 2019.

Figure 2 shows the spatial distributions of average TCE values using bootstrap SBM model in 2008-2019.

Insert the Figure 2

In figure 2, the average TCE value after correction ranged from 0.128 to 0.896, with an average value of 0.529. The TCE varied significantly across China's administrative regions during the study period. At the national level, the east-central China, southwest China and northeastern China had the high TCE values, while the northwest China and southeast coastal China had TCE value less than 0.5, accounting for 43% of the 30 regions. Specifically, the four regions with the highest average TCE levels (all above 0.8) were Guizhou (0.896), Tianjin (0.858), Jiangsu (0.843), and Henan (0,817), which belonged to the first echelon. Chongqing, Anhui, Liaoning, Sichuan and Jilin were the second echelon, which had an average TCE values between 0.7 and 0.8.

Spatial spillover effect

The Moran's index method was applied to assess the overall geographic correlation of TCE values and the result is disputed in Table 3.

Insert the Table 3

Table 3 shows that during the study period, in nine out of 12 years, the Moran's index values were positive and significant. This indicates there was a significant spatial autocorrelation of TCE in China; administrative regions with similar TCE values have a spatial aggregation effect. In other words, TCE values of regions are not independent of the others, and TCEs are not distributed randomly; they are spatially dependent. The geographical proximity allows the administrative regions to interact with each other, and that relationship is positive.

Figure 3 displays the Moran scatter distribution of average TCE values in 2008-2019, spatially and geographically illustrating the local spatial correlations of average TCE value. The quadrant distribution of average TCE value is shown on the right, and the spatial pattern of average TCE value is shown on the left. The TCE in China shows significant local spatial agglomeration, with two main classifications: HH and LL agglomeration. The HH-cluster was present mostly in central China, southwest China, and eastern China; the LL-cluster was present mostly in northwestern and southeastern China. Each cluster region's quantity and spatial distribution revealed regional dynamic characteristics. In 2008-2019, the HH cluster contained 18 regions and the LL cluster contained eight, accounting for 87% of the 30 regions.

Insert the Figure 3

Analysis of spatial regression results

The Lagrange Multiplier (LM), Wald, and Likelihood Ratio (LR) tests were used to determine an appropriate spatial econometric model. In Table 4, LM-error, Robust LM-error, and Robust LM-lag were all significant, while the LM-lag results were not significant, indicating that the error terms have spatial effects. Furthermore, the results of Wald and LR test are both statistically significant, showing that influencing factors have spatial effects. Because the SDM has the advantage of including the spatial dependence of dependent variables and independent variables and the spatial effect between error terms (Elhorst, 2014), the SDM was adopted. Next, a Hausman test yielded a result of -68.53, based on Schreiber (2008), we used the fixed-effect SDM model to analyze the factors influencing the TCE.

Insert the Table 4

Table 5 shows the results using the SAR, SEM, and SDM models. Comparing the Akaike Info Criterion (AIC) and log-likelihood values of the three models revealed that the SDM model has the lowest AIC value and highest log-likelihood value. This identified SDM as the optimal choice. This result is also consistent with the test results discussed above, thus verifying that the SDM regression results should be used. Given this, only the SDM results were used for further analysis.

Table 5 indicates that the ln*TI* (0.175) and ln*UR* (2.845) coefficients all exceeded zero. This shows that improving technology innovation and urbanization rate helped promote improvements in TCE at a statistically significant level. Specifically, for each 1% increase in technology innovation and urbanization rate, the TCE increased by 0.1756% and 2.845%, respectively. However, the coefficients of ln*EG* (-0.594) was less than zero (statistically significant at 1% levels), showing a decrease in the TCE by 0.594 % for every one percent increase in economic growth.

A positive coefficient of the lag term indicates an agglomeration effect; a negative coefficient indicates a spatial competition effect (Yang & Fik, 2014). The coefficients of W*ln*EA*, W*ln*TR*, W*ln*GI*, W*ln*GS* were both negative and significant, showing that educational attainment, transportation, green infrastructure, and government support in surrounding regions had a negative impact on TCE in focal region. That is, there was a tourism competition effect between a focal region and its neighbors. Improvements in educational attainment, transportation, green infrastructure, and government support of a surrounding region may negatively affect the TCE of the focal region. The coefficient of W*ln*UR* was greater than zero and was statistically significant, showing that improvements in urbanization rate in the neighboring regions promoted TCE in the focal region. This result indicates that urbanization rate complementarity between neighboring regions contributed to TCE. However, the spatial lag coefficients of ln*EG* and ln*TI* were not significant, meaning that economic growth and technology innovation in nearby regions did not clearly impact the region's TCE.

Insert the Table 5

The marginal effects of explanatory variable on explained variable, which is not directly reflected by the coefficients of SDM (Kim et al., 2021). As such, the process may generate incorrect results concerning the impact of different factors on the TCE (LeSage and Pace, 2009). Given this, the influence was further divided into direct, indirect, and total effects. The influence of a change of a factor in a region on its regional TCE is called the direct effect; and the influence of a change of a factor in one region on the TCE in other regions is called the indirect effect. The indirect effect reflects the spatial spillover effect (Elhorst, 2014), and the direct effect plus the indirect effect equals the total effect. The findings of the spatial dependence effect decomposition are showed inTable 6.

Insert the Table 6

The coefficient of the direct effect coefficient of ln*EG* was -0.648 (p<0.01), showing that improving the economic growth in a region directly impede improvement in its TCE. Economic expansion boosts the tourism sector in China, however, it inevitably leads to increased energy consumption and CO_2 emission (Zhang and Zhang, 2021), which may not be conducive to the development of TCE. The results remind tourism-related companies that long-term sustainable development needs to focus on economic and ecological benefits.

The direct and indirect effects of ln*TA* were not statistically significant, and the coefficient of total effect was -1.174 (p<0.05). This indicates that every 1% increase in transportation accessibility in a region reduced TCE by 1.174%. Regions with high transportation accessibility attract more tourists, but also reduce the number of overnight stays (Fan et al., 2022). Most of the CO_2 emissions of tourism come from transportation (Li & Zhang, 2020), which may adversely impact TCE. The direct impact of ln*UR* exceeded zero and were significant, which shows that developing urbanization level increases TCE. This result is consistent with Li and Liu (2021). The increase of urbanization rate means convenient infrastructure, reasonable economic structure and cleaner production technology, which can increase the efficiency of sectors associated to tourism and encourage more people to travel and visit (Luo et al., 2016; Sun and Huang, 2020).

The spatial spillover effect of ln*TI* on TCE were not significant, but ln*TI* had a significant positive direct and total effects on TCE. Liu et al. (2021) suggested that technological innovation was conducive to economic growth. Paramati et al. (2018) found that technological growth has helped reduce CO_2 emissions from tourism, thus negative environmental effects of tourism. Therefore, technology innovation can improve TCE by acting on the economy and CO_2 of tourism. However, when considering the indirect effect of ln*EA* on TCE, a one percent increase in educational attainment was associated with a 0.333% decrease in TCE of surrounding region, which was statistically significant at a 0.05 level. This may be due to the talent competition between neighboring regions, which drives up labor costs and has a detrimental effect on TCE (Chaabouni, 2019).

The coefficients for direct and indirect effects of ln*GS* were 0.181 and -0.307, respectively, which were statistically significant values. These results indicate that if government support increases by 1% in a region, the region's TCE is expected to increase by 0.181%, and the TCE of the neighboring region may decrease by 0.307%. The effective development of economic activities is inseparable from government intervention (Liu et al., 2021). As a major stakeholder in tourism governance, the support from government is essential for the sustainable tourism development (Shone et al., 2016). The tourism sector is driven by government backing, which promotes the development of tourism by supporting the material and social impact of tourism activities (Ruhanen, 2013). Thus, government support has a direct positive influence on focal TCE. However, there may be a phenomenon of convergence of government intervention in the tourism industry of adjacent regions, such as investment in the same type of tourism products or development of similar tourist attractions, which will cause inter-regional competition and not conducive to the improvement of TCE.

Finally, for green infrastructure, the spatial spillover effect of ln*GI* was significantly negative. Every 1% increase in per capita park green area in a region reduced TCE by 0.447 % in the neighboring region. Park green space is not only the place of recreation for residents but also the tourist destination (Terkenli et al., 2020). In adjacent regions, the park green space may have the same resource endowment, resulting in competition effect and hinder the growth of tourism efficiency.

Implications

Theoretical implications

The theoretical implications of this study are as follows. First, compared with previous studies (Aratuo and Etienne, 2019; Cao et al., 2016; Chaabouni, 2019; Eyuboglu and Uzar, 2020) that separate the economic benefits and ecological benefits of tourism, this study considered the comprehensive effect from tourism economic activities and ecological environment. The study supports that energy consumption is a crucial factor and material inputs and CO_2 are significant products in the course of tourism production. In addition, previous studies on efficiency evaluation using DEA model has certain limitations, such as sample sensitivity (Chang et al., 2021) and deviation from the real efficiency value (Simar and Wilson, 2011). Therefore, this study combines bootstrap technology with SBM-DEA method considering undesired output, to measure the real tourism efficiency value of China, enriching the tourism efficiency literature of sustainable tourism development.

Second, some previous studies (Chaabouni, 2019; Xue et al., 2022) applied Tobit regression or bootstrap regression to explore the determinants of tourism efficiency, which neglected the spatial spillover effect between data based on geographical location, leading to bias in the regression results. Further, tourism development has inter-regional interactions and is affected by different complex factors including environmental factors. As such, another contribution of this paper is that it considered geographic spatial relationships and sustainable development factors when determining TCE using Moran's index and the spatial econometric model. This explores the spatial distribution of TCE and reduces deviations and inefficient parameter estimation caused by the absence of spatial interactions, providing a new perspective for the study of tourism efficiency.

Practical implications

In practice, the results of this study can support policy making by Chinese tourism authorities. First, the study found that TCE is at a low level in China, with an average efficiency value of roughly 0.529. This leaves significant room to improve China's TCE. According to UNWTO (2017), the CO_2 emissions from tourism account for approximately 5% of overall carbon emissions. Climate affects tourism seasonality, and climate change may affect the popularity of tourist destinations and people's travel experience (Hoogendoorn and Fitchett, 2018). Therefore, while creating economic value is important, another top priority for tourism authorities is to devise policies and monitor measures that reduce CO_2 emissions, to minimize the negative effect of tourism on climate change.

In addition, the study found positive spatial spillover effects of TCE among the different regions of China. Tourism in different regions does not occur independently; the knowledge, economy, and climate impacted by tourism in one region is likely to spill over and affect neighboring regions (Kim *et al.*, 2021; Li & Lv, 2021). Studies have shown that the TCE of a region positively relates to the TCE of its neighboring region. This highlights the need for decision-makers in all regions to strengthen inter-regional cooperation in tourism (Jiao et al., 2019).

Regional tourism sectors should collectively focus on improving TCE; and knowing the determinants of TCE can be of great significance for tourism development (Ruan et al., 2019). The findings of our study were as follows. First, the technology innovation, urbanization rate and government support can help improve China's TCE, while further improving economic growth and transportation infrastructure may hinder China's TCE. Second, educational attainment, green infrastructure and government support have a negative spillover effect on TCE. These findings can help the government work on improving tourism efficiency from both socio-economic and ecological standpoints.

Given the implications above, we provide the following policy recommendations for tourism related-sectors. First, the negative impact of economic growth on TCE should also be capitalized on. Economic expansion results in increased energy use and CO_2 emissions. Although economic growth can promote the development of tourism, in the long run, the sustainable development of energy saving and emission reduction is more suitable. The government should formulate CO_2 emission reduction targets and measures for tourism-related enterprises, with the goal of ensuring high-quality and sustainable economic development to achieve sustainable economic development. This could include assigning carbon reduction tasks to each region or different type of hotel; increasing investments in ecological protection; promoting employment in resource recovery and pollutant treatment fields; adopting green trade policies (Destek and Sinha, 2020).

However, urbanization is directly related to TCE, which may be attributed to the improvement of urbanization level driving the tourism development and the progress of environmentally friendly production technology, thus reducing energy usage and CO_2 emission intensity (Han et al., 2019). As such, the government should advocate the development of a new type of energy-saving and low-carbon urbanization and encourage investment in green production and cleaner production technologies. In terms of tourism infrastructure construction, the construction of green buildings with low energy usage and low carbon emission should be encouraged (Sun and Huang, 2020), for example, the construction of green hotels should be funded (Olya et al., 2019).

Next, the study found that technology innovation had a direct positive impact on TCE, increasing its level. Therefore, tourism related sectors could pursue ecological innovation and actively cooperate with surrounding regions to conduct tourism innovation research and development (Divisekera and Nguyen, 2018). Environmental technology and innovation inputs, for example, can be applied to hotels and the transportation system to foster green and low-carbon-emission tourism development (Sun *et al.*, 2021). For the negative spatial spillover effect of educational attainment and green infrastructure, the government can consider expanding educational efforts and green infrastructure construction, and reduce talent competition and green space competition between regions through inter-regional cooperation. Furthermore, tourists and residents should be instilled with the concept and awareness of the need to lower carbon emissions (Zhou et al., 2019).

Special attention should be paid to the negative impact of transportation on TCE. Transportation is the basis of tourism development; however, it is also the source of most tourism-related CO_2 emissions (Cadarso et al., 2015; Tsai et al., 2018). Therefore, stakeholders should adopt measures such as clean energy use, develop public transportation infrastructure (Yang *et al.*, 2019), fund new energy vehicle development, and remind tourists of the carbon footprint incurred by air travel, and publicize possible alternatives, such as high speed rail. These approaches may help reduce energy usage and CO_2 emissions in tourism-related transportation.

Finally, for government investment, it is necessary for local governments to participate in or coordinate tourism strategic planning (Ruhanen, 2013). Although proper government intervention can improve China's TCE, the government should avoid investing in the same tourism products as the surrounding regions, such as creating similar tourist attraction, which my form competition with the surrounding areas. Seeking common ground and win-win cooperation should be considered for government intervention in tourism (Xiaobin et al., 2021).

Conclusions

This study found that the TCE varied significantly between regions in China, and there were many regions with low efficiency levels needing improvement. Guizhou, Tianjin, Jiangsu, and Henan outperformed other regions in terms of average TCE in 2008-2019. More than 43% of the administrative regions had a TCE below 0.529; those with the low efficiencies were mainly located in northwest and southeast coastal China. The results of Moran's index showed that the TCE has spatial spillover effects and local spatial differences; regions with high-TCE surrounded by high-TCE regions and regions with low TCE surrounded by low-TCE regions formed the principal types of clustering. Finally, technology innovation, urbanization rate and government support have direct impacts on improving TCE in China, while economic growth has a negative effect on TCE. Educational attainment, green infrastructure and government support have a negative spatial effect. Transportation infrastructure hinder China's TCE in total effect on TCE.

Like all studies, this one has some limitations. First, the study focused on measuring and improving TCE, but did not address how much CO_2 should be reduced in each region to achieve energy-saving and emission reduction goals in tourism. Therefore, future research should consider the allocation of carbon emission reductions for tourism, without lowering or increasing TCE. Second, this study analyzed 30 provincial-level administrative regions in China. Further research should be expanded to include more regions and other countries. Finally, we focused on seven influencing factors for the spatial regression; future studies should explore the other factors on the TCE in China.

References

Adler N, Friedman L and Sinuany-Stern Z (2002) Review of ranking methods in the data envelopment analysis context. *European Journal of Operational Research* 140(2): 249–265. DOI: 10.1016/S0377-2217(02)00068-1.

Alberca P and Parte L (2018) Operational efficiency evaluation of restaurant firms. *International Journal of Contemporary Hospitality Management* 30(3). input-oriented DEA model. Emerald Publishing Limited: 1959–1977. DOI: 10.1108/IJCHM-09-2016-0547.

Anselin L (1995) Local indicators of spatial association—LISA. *Geographical Analysis* 27(2): 93–115. DOI: 10.1111/j.1538-4632.1995.tb00338.x.

Aratuo DN and Etienne XL (2019) Industry level analysis of tourism-economic growth in the United States. *Tourism Management* 70: 333–340. DOI: 10.1016/j.tourman.2018.09.004.

Assaf AG and Josiassen A (2016) Frontier analysis: A state-of-the-art review and meta-analysis. *Journal of Travel Research* 55(5): 612–627. DOI: 10.1177/0047287515569776.

Bădin L, Daraio C and Simar L (2010) Optimal bandwidth selection for conditional efficiency measures: A data-driven approach. *European Journal of Operational Research* 201(2): 633–640. DOI: 10.1016/j.ejor.2009.03.038.

Bădin L, Daraio C and Simar L (2012) How to measure the impact of environmental factors in a nonparametric production model. *European Journal of Operational Research* 223(3): 818–833. DOI: 10.1016/j.ejor.2012.06.028.

Bădin L, Daraio C and Simar L (2014) Explaining inefficiency in nonparametric production models: the state of the art. *Annals of Operations Research* 214(1): 5–30. DOI: 10.1007/s10479-012-1173-7.

Bădin L, Daraio C and Simar L (2019) A bootstrap approach for bandwidth selection in estimating conditional efficiency measures. *European Journal of Operational Research* 277(2): 784–797. DOI: 10.1016/j.ejor.2019.02.054.

Badiu DL, Iojă CI, Pătroescu M, et al. (2016) Is urban green space per capita a valuable target to achieve cities' sustainability goals? Romania as a case study. *Ecological Indicators* 70. Navigating Urban Complexity: Advancing Understanding of Urban Social – Ecological Systems for Transformation and Resilience: 53–66. DOI: 10.1016/j.ecolind.2016.05.044.

Barros CP, Botti L, Peypoch N, et al. (2011) Performance of French destinations: Tourism attraction perspectives. *Tourism Management* 32(1): 141–146. DOI: 10.1016/j.tourman.2010.01.015.

Becken S and Patterson M (2006) Measuring national carbon dioxide emissions from tourism as a key step towards achieving sustainable tourism. *Journal of Sustainable Tourism* 14(4): 323–338. DOI: 10.2167/jost547.0.

Cadarso M-Á, Gómez N, López L-A, et al. (2015) Quantifying Spanish tourism's carbon footprint: the contributions of residents and visitors: a longitudinal study. *Journal of Sustainable Tourism* 23(6): 922–946. DOI: 10.1080/09669582.2015.1008497.

Cao F, Huang Z, Jin C, et al. (2016) Influence of Chinese economic fluctuations on tourism efficiency in national scenic areas. *Tourism Economics* 22(5): 884–907. DOI: 10.5367/te.2015.0463.

Chaabouni S (2019) China's regional tourism efficiency: A two-stage double bootstrap data envelopment analysis. *Journal of Destination Marketing & Management* 11: 183–191. DOI: 10.1016/j.jdmm.2017.09.002.

Chang Y-T, Jo A, Choi K-S, et al. (2021) Port efficiency and international trade in China. *Transportmetrica A: Transport Science* 17(4). Taylor & Francis: 801–823. DOI: 10.1080/23249935.2020.1817169.

Charnes A, Cooper WW and Rhodes E (1978) Measuring the efficiency of decision making units. *European Journal of Operational Research* 2(6): 429–444. DOI: 10.1016/0377-2217(78)90138-8.

Chen L, Thapa B and Yan W (2018) The relationship between tourism, carbon dioxide emissions, and economic growth in the Yangtze River Delta, China. *Sustainability* 10(7): 2118. DOI: 10.3390/su10072118.

Corne A (2015) Benchmarking and tourism efficiency in France. *Tourism Management* 51: 91–95. DOI: 10.1016/j.tourman.2015.05.006.

Corne A and Peypoch N (2020) On the determinants of tourism performance. *Annals of Tourism Research* 85: 103057. DOI: 10.1016/j.annals.2020.103057.

Danish and Wang Z (2018) Dynamic relationship between tourism, economic growth, and environmental quality. *Journal of Sustainable Tourism* 26(11). Routledge: 1928–1943. DOI: 10.1080/09669582.2018.1526293.

Daraio C, Simar L and Wilson PW (2018) Central limit theorems for conditional efficiency measures and tests of the 'separability' condition in non-parametric, two-stage models of production. *The Econometrics Journal* 21(2): 170–191. DOI: 10.1111/ectj.12103.

Destek MA and Sinha A (2020) Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic co-operation and development countries. *Journal of Cleaner Production* 242: 118537. DOI: 10.1016/j.jclepro.2019.118537.

Diniz-Filho J, Bini LM and Hawkins B (2003) Spatial autocorrelation and red herrings in geographical ecology. *Global Ecology and Biogeography* 12(1): 53–64.

Divisekera S and Nguyen VK (2018) Drivers of innovation in tourism: An econometric study. *Tourism Economics* 24(8). SAGE Publications Ltd: 998–1014. DOI: 10.1177/1354816618794708.

Ehigiamusoe KU (2020) Tourism, growth and environment: analysis of non-linear and moderating effects. *Journal of Sustainable Tourism* 28(8): 1174–1192. DOI: 10.1080/09669582.2020.1729164.

Elhorst JP (2014) *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. SpringerBriefs in Regional Science. Berlin, Heidelberg: Heidelberg: Springer. DOI: 10.1007/978-3-642-40340-8.

Eyuboglu K and Uzar U (2020) The impact of tourism on CO_2 emission in Turkey. *Current Issues in Tourism* 23(13): 1631–1645. DOI: 10.1080/13683500.2019.1636006.

Fan DXF, Hsu CHC and Liu AX (2022) Transforming brand identity to hotel performance: the moderating effect of social capital. *Journal of Hospitality & Tourism Research*. SAGE Publications Inc: 10963480221074278. DOI: 10.1177/10963480221074278.

Getis A (2007) Reflections on spatial autocorrelation. *Regional Science and Urban Economics* 37(4): 491–496. DOI: 10.1016/j.regsciurbeco.2007.04.005.

Gössling S, Peeters P, Ceron J-P, et al. (2005) The eco-efficiency of tourism. *Ecological Economics* 54(4): 417–434. DOI: 10.1016/j.ecolecon.2004.10.006.

Hadad S, Hadad Y, Malul M, et al. (2012) The economic efficiency of the tourism industry: a global comparison. *Tourism Economics* 18(5): 931–940. DOI: 10.5367/te.2012.0165.

Halleck Vega S and Elhorst JP (2017) Regional labour force participation across the European Union: a time–space recursive modelling approach with endogenous regressors. *Spatial Economic Analysis* 12(2–3): 138–160. DOI: 10.1080/17421772.2016.1224374.

Han X, Cao T and Sun T (2019) Analysis on the variation rule and influencing factors of energy consumption carbon emission intensity in China's urbanization construction. *Journal of Cleaner Production* 238: 117958. DOI: 10.1016/j.jclepro.2019.117958.

He L, Zha J and Loo HA (2020) How to improve tourism energy efficiency to achieve sustainable tourism: evidence from China. *Current Issues in Tourism* 23(1): 1–16. DOI: 10.1080/13683500.2018.1564737.

Hoogendoorn G and Fitchett JM (2018) Tourism and climate change: a review of threats and adaptation strategies for Africa. *Current Issues in Tourism* 21(7). Routledge: 742–759. DOI: 10.1080/13683500.2016.1188893.

Huang J-B, Zou H and Song Y (2021) Biased technical change and its influencing factors of iron and steel industry: Evidence from provincial panel data in China. *Journal of Cleaner Production* 283. bootstrapSBM: 124558. DOI: 10.1016/j.jclepro.2020.124558.

Jiao S, Gong W, Zheng Y, et al. (2019) Spatial spillover effects and tourism-led growth: an analysis of prefecture-level cities in China. *Asia Pacific Journal of Tourism Research* 24(7): 725–734. DOI: 10.1080/10941665.2019.1630454.

Kim YR, Williams AM, Park S, et al. (2021) Spatial spillovers of agglomeration economies and productivity in the tourism industry: The case of the UK. *Tourism Management* 82: 104201. DOI: 10.1016/j.tourman.2020.104201.

Koçak E, Ulucak R and Ulucak ZŞ (2020) The impact of tourism developments on CO2 emissions: an advanced panel data estimation. *Tourism Management Perspectives* 33: 100611. DOI: 10.1016/j.tmp.2019.100611.

Lee H, Choi Y and Seo H (2020) Comparative analysis of the R&D investment performance of Korean local governments. *Technological Forecasting and Social Change* 157: 120073. DOI: 10.1016/j.techfore.2020.120073.

LeSage J and Pace RK (2009) *Introduction to Spatial Econometrics*. New York: Chapman and Hall/CRC. DOI: 10.1201/9781420064254.

Li KX, Jin M and Shi W (2018) Tourism as an important impetus to promoting economic growth: A critical review. *Tourism Management Perspectives* 26: 135–142. DOI: 10.1016/j.tmp.2017.10.002.

Li S and Lv Z (2021) Do spatial spillovers matter? Estimating the impact of tourism development on CO_2 emissions. *Environmental Science and Pollution Research* 28(25): 32777–32794. DOI: 10.1007/s11356-021-12988-6.

Li Y and Zhang L (2020) Ecological efficiency management of tourism scenic spots based on carbon footprint analysis. *International Journal of Low-Carbon Technologies* 15(4): 550–554. DOI: 10.1093/ijlct/ctaa023.

Li Y, Liu A-C, Yu Y-Y, et al. (2022) Bootstrapped DEA and clustering analysis of eco-efficiency in China's hotel industry. *Sustainability* 14(5). 5. Multidisciplinary Digital Publishing Institute: 2925. DOI: 10.3390/su14052925.

Li Z and Liu H (2021) How tourism industry agglomeration improves tourism economic efficiency? *Tourism Economics*. SAGE Publications Ltd: 13548166211009116. DOI: 10.1177/13548166211009116.

Liu H, Xiao Y, Wang B, et al. (2021) Effects of tourism development on economic growth: An empirical study of China based on both static and dynamic spatial Durbin models. *Tourism Economics*: 13548166211021176. DOI: 10.1177/13548166211021175.

Liu J, Zhang J and Fu Z (2017) Tourism eco-efficiency of Chinese coastal cities–Analysis based on the DEA-Tobit model. *Ocean & Coastal Management* 148. DEA: 164–170. DOI: 10.1016/j.ocecoaman.2017.08.003.

Liu Z, Lan J, Chien F, et al. (2022) Role of tourism development in environmental degradation: A step towards emission reduction. *Journal of Environmental Management* 303: 114078. DOI: 10.1016/j.jenvman.2021.114078.

Lozano-Ramírez J, Arana-Jiménez M and Lozano S (2022) A pre-pandemic Data Envelopment Analysis of the sustainability efficiency of tourism in EU-27 countries. *Current Issues in Tourism*. Routledge: 1–19. DOI: 10.1080/13683500.2022.2062309.

Lu X, Shi P, Deng Z, et al. (2019) Calculation of green production efficiency of tourism in the Yangtze River Economic Belt and analysis of its spatial and temporal evolution. *China Population, Resources and Environment* 29(7): 19–30.

Luo JM, Qiu H and Lam CF (2016) Urbanization impacts on regional tourism development: a case study in China. *Current Issues in Tourism* 19(3). Routledge: 282–295. DOI: 10.1080/13683500.2015.1033385.

Ma T, Hong T and Zhang H (2015) Tourism spatial spillover effects and urban economic growth. *Journal of Business Research* 68(1): 74–80. DOI: 10.1016/j.jbusres.2014.05.005.

Ma X, Han M, Luo J, et al. (2021) The empirical decomposition and peak path of China's tourism carbon emissions. *Environmental Science and Pollution Research* 28(46): 66448–66463. DOI: 10.1007/s11356-021-14956-6.

Majewska J (2015) Inter-regional agglomeration effects in tourism in Poland. *Tourism Geographies* 17(3): 408–436. DOI: 10.1080/14616688.2014.997279.

National Bureau of Statistics of China (NBS) (2019) Development of Tourism 2019. Available at: https://data.stats.gov.cn/english/easyquery.htm?cn=C01 (accessed 19 January 2022).

Niavis S and Tsiotas D (2019) Assessing the tourism performance of the Mediterranean coastal destinations: A combined efficiency and effectiveness approach. *Journal of Destination Marketing & Management* 14: 100379. DOI: 10.1016/j.jdmm.2019.100379.

Olya HGT, Bagheri P and Tümer M (2019) Decoding behavioural responses of green hotel guests: A deeper insight into the application of the theory of planned behaviour. *International Journal of Contemporary Hospitality Management* 31(6): 2509–2525. DOI: 10.1108/IJCHM-05-2018-0374.

Paramati SR, Alam MdS and Chen C-F (2017) The effects of tourism on economic growth and CO_2 emissions: a comparison between developed and developing economies. *Journal of Travel Research* 56(6): 712–724. DOI: 10.1177/0047287516667848.

Paramati SR, Alam MdS and Lau CKM (2018) The effect of tourism investment on tourism development and CO_2 emissions: empirical evidence from the EU nations. *Journal of Sustainable Tourism* 26(9): 1587–1607. DOI: 10.1080/09669582.2018.1489398.

Peng H, Zhang J, Lu L, et al. (2017) Eco-efficiency and its determinants at a tourism destination: A case study of Huangshan National Park, China. *Tourism Management* 60. DEA: 201–211. DOI: 10.1016/j.tourman.2016.12.005.

Qiu X, Fang Y, Yang X, et al. (2017) Tourism eco-efficiency measurement, characteristics, and its influence factors in China. *Sustainability* 9(9). Multidisciplinary Digital Publishing Institute: 1634. DOI: 10.3390/su9091634.

Ruan W, Li Y, Zhang S, et al. (2019) Evaluation and drive mechanism of tourism ecological security based on the DPSIR-DEA model. *Tourism Management* 75: 609–625. DOI: 10.1016/j.tourman.2019.06.021.

Ruhanen L (2013) Local government: Facilitator or inhibitor of sustainable tourism development? *Journal of Sustainable Tourism* 21(1). Routledge: 80–98. DOI: 10.1080/09669582.2012.680463.

Schreiber S (2008) The Hausman test statistic can be negative even asymptotically. *Jahrbücher für Nationalökonomie und Statistik* 228(4): 394–405. DOI: 10.1515/jbnst-2008-0407.

Shi X and Li X (2018) Research on three-stage dynamic relationship between carbon emission and urbanization rate in different city groups. *Ecological Indicators* 91: 195–202. DOI: 10.1016/j.ecolind.2018.03.056.

Shone MC, Simmons DG and Dalziel P (2016) Evolving roles for local government in tourism development: a political economy perspective. *Journal of Sustainable Tourism* 24(12). Routledge: 1674–1690. DOI: 10.1080/09669582.2016.1184672.

Simar L and Wilson PW (2011) Two-stage DEA: caveat emptor. *Journal of Productivity Analysis* 36(2): 205–218. DOI: 10.1007/s11123-011-0230-6.

Song H and Szafir DA (2019) Where's my data? evaluating visualizations with missing data. *IEEE Transactions on Visualization and Computer Graphics* 25(1): 914–924. DOI: 10.1109/TVCG.2018.2864914.

Song M and Li H (2019) Estimating the efficiency of a sustainable Chinese tourism industry using bootstrap technology rectification. *Technological Forecasting and Social Change* 143. bootstrap-DEA: 45–54. DOI: 10.1016/j.techfore.2019.03.008.

Stamboulis Y and Skayannis P (2003) Innovation strategies and technology for experience-based tourism. *Tourism Management* 24(1): 35–43. DOI: 10.1016/S0261-5177(02)00047-X.

Sun W and Huang C (2020) How does urbanization affect carbon emission efficiency? Evidence from China. *Journal of Cleaner Production* 272: 122828. DOI: 10.1016/j.jclepro.2020.122828.

Sun Y, Hou G, Huang Z, et al. (2020) Spatial-temporal differences and influencing factors of tourism eco-efficiency in China's three major urban agglomerations based on the Super-EBM model. *Sustainability* 12(10): 4156. DOI: 10.3390/su12104156.

Sun Y, Duru OA, Razzaq A, et al. (2021) The asymmetric effect eco-innovation and tourism towards carbon neutrality target in Turkey. *Journal of Environmental Management* 299: 113653. DOI: 10.1016/j.jenvman.2021.113653.

Sun Y-Y (2014) A framework to account for the tourism carbon footprint at island destinations. *Tourism Management* 45: 16–27. DOI: 10.1016/j.tourman.2014.03.015.

Sun Y-Y and Drakeman D (2020) Measuring the carbon footprint of wine tourism and cellar door sales. *Journal of Cleaner Production* 266: 121937. DOI: 10.1016/j.jclepro.2020.121937.

Sun Y-Y and Pratt S (2014) The economic, carbon emission, and water impacts of hinese visitors to Taiwan: Eco-efficiency and impact evaluation. *Journal of Travel Research* 53(6). SAGE Publications Inc: 733–746. DOI: 10.1177/0047287513517420.

Tang M and Ge S (2018) Accounting for carbon emissions associated with tourism-related consumption. *Tourism Economics* 24(5): 510–525. DOI: 10.1177/1354816618754691.

Terkenli TS, Bell S, Tošković O, et al. (2020) Tourist perceptions and uses of urban green infrastructure: An exploratory cross-cultural investigation. *Urban Forestry & Urban Greening* 49: 126624. DOI: 10.1016/j.ufug.2020.126624.

Tian F, Yang Y and Jiang L (2020) Spatial spillover of transport improvement on tourism growth. *Tourism Economics* 28(5): 1416–1432. DOI: 10.1177/1354816620982787.

Tone K (2004) Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach. In: Toronto, 2004, pp. 44–45. Presentation At NAPW III.

Tsai K-T, Lin T-P, Lin Y-H, et al. (2018) The carbon impact of international tourists to an Island Country. *Sustainability* 10(5): 1386. DOI: 10.3390/su10051386.

Tsaur S (2001) The operating efficiency of international tourist hotels in Taiwan. *Asia Pacific Journal of Tourism Research* 6(1): 73–81. DOI: 10.1080/10941660108722090.

Tu J and Zhang D (2020) Does tourism promote economic growth in Chinese ethnic minority areas? A nonlinear perspective. *Journal of Destination Marketing & Management* 18: 100473. DOI: 10.1016/j.jdmm.2020.100473.

Wang D and Ap J (2013) Factors affecting tourism policy implementation: A conceptual framework and a case study in China. *Tourism Management* 36: 221–233. DOI: 10.1016/j.tourman.2012.11.021.

Wang S, Fang C and Wang Y (2016) Spatiotemporal variations of energy-related CO_2 emissions in China and its influencing factors: An empirical analysis based on provincial panel data. *Renewable and Sustainable Energy Reviews* 55: 505–515. DOI: 10.1016/j.rser.2015.10.140.

Wen Y, An Q, Hu J, et al. (2021) DEA game for internal cooperation between an upper-level process and multiple lower-level processes. *Journal of the Operational Research Society*. Taylor & Francis: 1–12. DOI: 10.1080/01605682.2021.1967212.

World Tourism Organization and International Transport Forum (WTOITF) (2019) *Transport-Related CO_2 Emissions of the Tourism Sector – Modelling Results*. Madrid: UNWTO. Available at: https://www.e-unwto.org/doi/abs/10.18111/9789284416660.

World Tourism Organization (UNWTO) (2017) *World Conference on Tourism and Future Energy – Unlocking Low-Carbon Growth Opportunities*. Madrid: UNWTO. DOI: 10.18111/9789284419425.

World Tourism Organization (UNWTO) (2020) *International Tourism Highlights, 2020*. Madrid: UNWTO. Available at: https://www.e-unwto.org/doi/abs/10.18111/9789284422456.

Xia B, Dong S, Li Z, et al. (2022) Eco-efficiency and its drivers in tourism sectors with respect to carbon emissions from the supply chain: An integrated EEIO and DEA approach. *International Journal of Environmental Research and Public Health* 19(11). Multidisciplinary Digital Publishing Institute: 6951. DOI: 10.3390/ijerph19116951.

Xiaobin M, Biao S, Guolin H, et al. (2021) Evaluation and spatial effects of tourism ecological security in the Yangtze River Delta. *Ecological Indicators* 131: 108190. DOI: 10.1016/j.ecolind.2021.108190.

Xie Z, Wu R and Wang S (2021) How technological progress affects the carbon emission efficiency? Evidence from national panel quantile regression. *Journal of Cleaner Production* 307: 127133. DOI: 10.1016/j.jclepro.2021.127133.

Xu D, Huang Z, Hou G, et al. (2020) The spatial spillover effects of haze pollution on inbound tourism: evidence from mid-eastern China. *Tourism Geographies* 22(1): 83–104. DOI: 10.1080/14616688.2019.1612464.

Xue D, Li X, Ahmad F, et al. (2022) Exploring tourism efficiency and its drivers to understand the backwardness of the tourism industry in Gansu, China. *International Journal of Environmental Research and Public Health* 19(18). 18. Multidisciplinary Digital Publishing Institute: 11574. DOI: 10.3390/ijerph191811574.

Yang G, Li P, Zheng B, et al. (2008) GHG emission-based eco-efficiency study on tourism itinerary products in Shangri-La, Yunnan Province, China. *Current Issues in Tourism* 11(6). Routledge: 604–622. DOI: 10.1080/13683500802475943.

Yang W, Wang W and Ouyang S (2019) The influencing factors and spatial spillover effects of CO2 emissions from transportation in China. *Science of The Total Environment* 696: 133900. DOI: 10.1016/j.scitotenv.2019.133900.

Yang Y and Fik T (2014) Spatial effects in regional tourism growth. *Annals of Tourism Research* 46: 144–162. DOI: 10.1016/j.annals.2014.03.007.

Yang Y and Wong KKF (2012) A spatial econometric approach to model spillover effects in tourism flows. *Journal of Travel Research* 51(6): 768–778. DOI: 10.1177/0047287512437855.

Yi T and Liang M (2015) Evolutional model of tourism efficiency based on the DEA method: A case study of cities in Guangdong Province, China. *Asia Pacific Journal of Tourism Research* 20(7): 789–806. DOI: 10.1080/10941665.2014.932294.

Yin P, Chu J, Wu J, et al. (2020) A DEA-based two-stage network approach for hotel performance analysis: An internal cooperation perspective. *Omega* 93. novel DEAbased bi-objective model: 102035. DOI: 10.1016/j.omega.2019.02.004.

Zha J, He L, Liu Y, et al. (2019) Evaluation on development efficiency of low-carbon tourism economy: A case study of Hubei Province, China. *Socio-Economic Planning Sciences* 66: 47–57. DOI: 10.1016/j.seps.2018.07.003.

Zha J, Tan T, Yuan W, et al. (2020) Decomposition analysis of tourism CO_2 emissions for sustainable development: A case study of China. *Sustainable Development* 28(1): 169–186. DOI: 10.1002/sd.1980.

Zha J, Yuan W, Dai J, et al. (2020) Eco-efficiency, eco-productivity and tourism growth in China: a non-convex metafrontier DEA-based decomposition model. *Journal of Sustainable Tourism* 28(5). Routledge: 663–685. DOI: 10.1080/09669582.2019.1699102.

Zhang J and Zhang Y (2021) Tourism, economic growth, energy consumption, and CO_2 emissions in China. *Tourism Economics* 27(5). SAGE Publications Ltd: 1060–1080. DOI: 10.1177/1354816620918458.

Zhang Xixi, Sun D, Zhang Xiaofan, et al. (2021) Regional ecological efficiency and future sustainable development of marine ranch in China: An empirical research using DEA and system dynamics. *Aquaculture* 534: 736339. DOI: 10.1016/j.aquaculture.2021.736339.

Zhou B, Wen Z, Sutherland I, et al. (2020) The spatial heterogeneity and dynamics of tourism-flow spillover effect: The role of high-speed train in China. *Tourism Economics*: 135481662095830. DOI: 10.1177/1354816620958309.

Zhou C, Wang S and Wang J (2019) Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Science of The Total Environment* 675: 472–482. DOI: 10.1016/j.scitotenv.2019.04.269.

Table 1. Types of different quadrants of Moran scatter plot.

Quadrant	Class	Meaning
First	HH	Regions with high TCE surrounded by high-TCE regions, and the spatial correlation is positive.
Second	LH	Regions with low TCE surrounded by high-TCE regions, and the spatial correlation is negative.
Third	LL	Regions with low TCE surrounded by low-TCE regions, and the spatial correlation is positive.
Fourth	HL	Regions with high TCE surrounded by low-TCE regions, and the spatial correlation is negative.

Table 2. Indexes of inputs, outputs and influencing factor.

Tourism sector	Indices	Unit
Inputs	Employees	Quantity
	Energy consumption	10^8 MJ
	Travel agency	Quantity
	Star hotel	Quantity
Desirable outputs	Tourism revenue	10^8 CNY
	Number of tourists	Quantity
Undesirable output	CO_2	10^4 tons
Influencing factor	Economic growth (ln*EG*)	CNY/person
	transportation accessibility (ln*TA*)	km/km^2
	Urbanization rate (ln*UR*)	%
	Government support (ln*GS*)	%
	Technology innovation (ln*TI*)	Quantity
	Educational attainment (ln*EA*)	%
	Green infrastructure (ln*GI*)	m^2

Table 3. Moran's index of TCE.

Year	Moran's *I*	*Z*-statistic
2008	0.245 **	2.277
2009	0.265 **	2.440
2010	0.375***	3.319
2011	0.295***	0.008
2012	0.298***	2.693
2013	0.310 ***	2.797
2014	0.286***	2.600
2015	0.243**	2.252
2016	0.190 *	1.810
2017	0.079	0.913
2018	0.055	0.723
2019	0.026	0.485

Note: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 4. Test results of the spatial panel model.

Test		Statistic
LM test	LM-error	9.08***
	Robust LM-error	24.89***
	LM-lag	0.72
	Robust LM-lag	16.52***
Wald test	Wald-lag	20.50***
	Wald-error	18.79***
LR test	LR-lag	19.57***
	LR-error	16.37**

Note: *** p<0.01, ** p<0.05.

Table 5. Analysis of factors influencing TCE.

Dependent Variable	SEM	SAR	SDM
ln*EG*	-0.299***	-0.372***	-0.594***
ln*TA*	-0.723***	-0.569**	-0.394
ln*UR*	2.583***	2.881***	2.845***
ln*GS*	0.103	0.141	0.135
ln*TI*	0.194***	0.185***	0.175***
ln*EA*	-0.092	-0.049	0.013
ln*GI*	-0.150	-0.019	0.001
W*ln*EG*			0.209
W*ln*TA*			-1.349*
W*ln*UR*			1.712***
W*ln*GS*			-0.333*
W*ln*TI*			0.097
W*ln*EA*			-0.436***
W*ln*GI*			-0.603*
AIC	-51.508	-48.311	-53.883
Log-likelihood	34.754	33.155	42.941
N	360	360	360

Notes: *** p<0.01, ** p<0.05, and * p<0.1; ln*EG* is the economic growth; ln*TA* is transportation accessibility; ln*UR* is urbanization rate; ln*GS* is government support; ln*TI* is technology innovation; and ln*EA* is educational attainment; ln*GI* is green infrastructure.

Table 6. Decomposition of spatial effect.

	Direct effect	Indirect effect	Total effect
ln*EG*	-0.648***	0.392	-0.257**
ln*TA*	-0.259	-0.915	-1.174**
ln*UR*	2.846***	0.114	2.960***
lnG*S*	0.181*	-0.307**	-0.126
ln*TI*	0.170***	0.015	0.184**
ln*EA*	0.047	-0.333***	-0.286**
ln*GI*	0.069	-0.447*	-0.378

Notes: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$; ln*EG* is the economic growth; ln*TA* is transportation accessibility; ln*UR* is urbanization rate; ln*GS* is government support; ln*TI* is technology innovation; and ln*EA* is educational attainment; ln*GI* is green infrastructure.

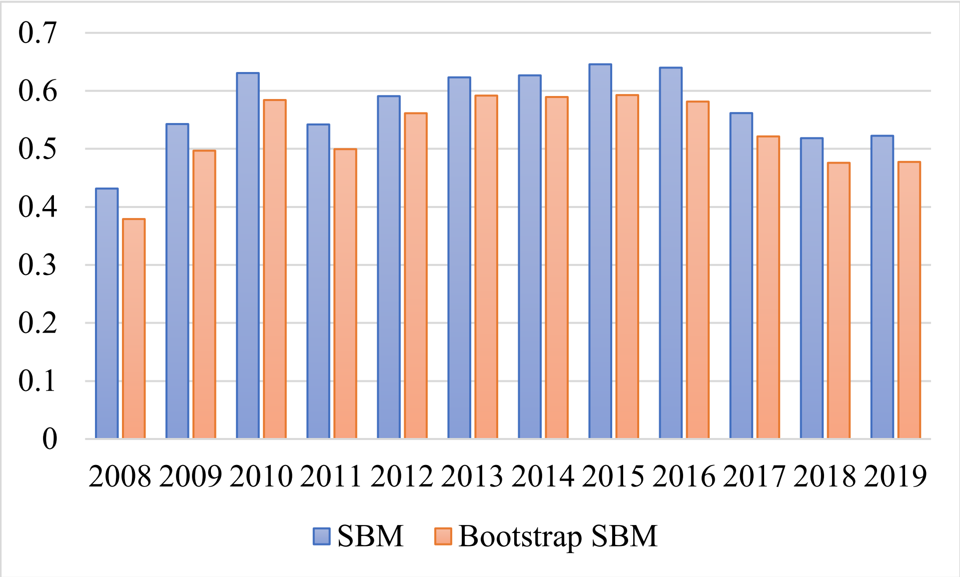

Figure 1. China's TCE trends over time.

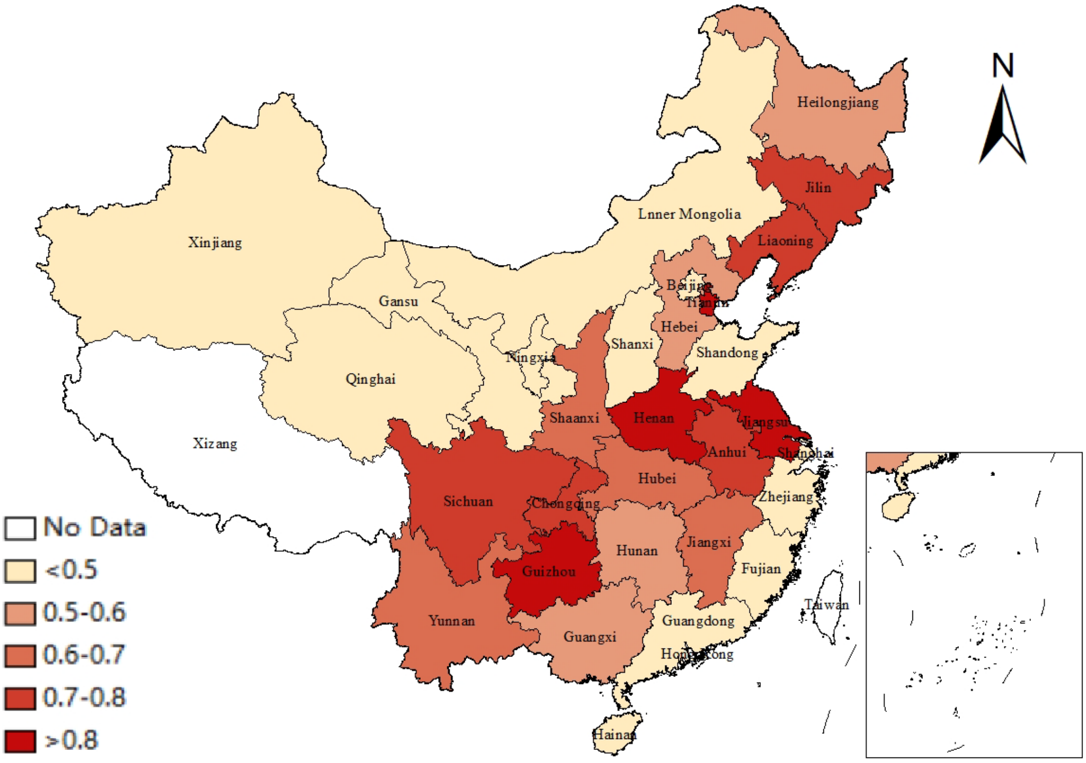

Figure 2. Spatial distribution of average TCE in 2008-2019.

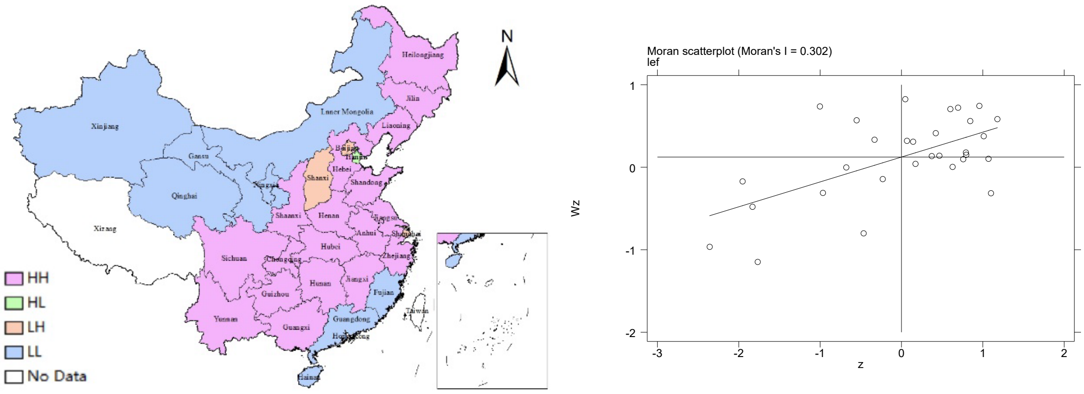

Figure 3. Moran’s scatter plot of average TCE in 2008-2019.

Left: spatial pattern of TCE. Right: quadrant distribution of TCE.