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Railway Expansion and Tourism Transport Ecological Efficiency: Spatial Evidence from China

Yuxiang Yan , ***Chayanon Phucharoen*** *

Faculty of Hospitality and Tourism, Prince of Songkla University, Phuket 83120, Thailand

ABSTRACT

Tourism's link to the Sustainable Development Goals has been a continuing emphasis, adding momentum to long-standing efforts to ensure tourism's sustainability. Tourism transport is one of the largest sources of anthropogenic carbon emissions, driving global ecological change with profound consequences for ecosystem functioning and biodiversity. Large-scale infrastructure projects such as railway expansion are increasingly promoted for their potential to reduce tourism-related carbon dioxide emissions, yet their spatial ecological impacts on regional carbon cycles and ecosystem services remain poorly understood. This study introduces the concept of Tourism Transport Ecological Efficiency (TTEE) to assess the relationship between human infrastructure, carbon emissions, and ecological sustainability. Using panel data from China's railway expansion between 2011 and 2018, the study provides spatially explicit evidence of how transport infrastructure shapes tourism's ecological footprint. Results show that non-Eastern regions experienced a greater increase in TTEE (8.7%) compared to Eastern regions (5.5%), highlighting regional disparities in tourism transport ecological sustainability. Railway density had a significant positive direct effect on TTEE, particularly pronounced in non-Eastern regions. Additionally, a significant indirect effect of railway density in nearby regions was identified. These findings reveal the interconnected ecological impacts of transport systems and underscore the importance of regionally targeted railway investment strategies. By bridging infrastructure development with ecological processes, this study advances understanding of how tourism transport can be aligned with global carbon reduction goals and ecosystem protection.

Keywords: Ecological Efficiency; Carbon Footprint; Ecological Sustainability; Ecosystem Protection

*CORRESPONDING AUTHOR:

Chayanon Phucharoen, Faculty of Hospitality and Tourism, Prince of Songkla University, Phuket 83120, Thailand;
Email: chayanon.p@phuket.psu.ac.th

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1. Introduction

Transport systems are widely recognized as one of the primary sources of anthropogenic carbon emissions, driving global ecological change and accelerating the destabilization of climate and ecosystem processes [1]. These emissions disrupt the carbon cycle, alter the capacity of ecosystems to regulate greenhouse gases, and place unprecedented pressure on biodiversity and ecological functioning. As the demand for mobility rises with globalization and urbanization, the ecological consequences of expanding transport infrastructure have emerged as a central concern in both ecological science and policy. Beyond their immediate role in enabling economic activity, transport systems imprint long-term structural effects on regional ecological dynamics, redistributing flows of people and resources while reshaping energy consumption and emission trajectories [2].

Tourism represents a critical sector where the ecological costs of transport are highly visible. Nearly half of the total carbon footprint of tourism can be attributed to transport-related activities [3]. Yet, in ecological research, the environmental burden of tourism transport has received limited scrutiny compared with the more frequently studied domains of land use change, agriculture, or industrial emissions. Within tourism studies themselves, attention has often been directed toward accommodation, catering, and hospitality services, while the dominant role of transport in generating emissions remains underexplored [4]. This asymmetry in research focus has created a narrow perspective, one that overlooks the deeper ecological implications of transport systems and their capacity to alter regional carbon balances and ecosystem services.

Large-scale infrastructure projects such as railway expansion exemplify this dynamic. Railways are often celebrated for their relatively low emissions per passenger-kilometer compared with air and road transport [5]. From an ecological standpoint, however, their impacts extend beyond substitution effects. Railways reshape spatial patterns of movement, generate new accessibility corridors, and influence how tourism activities are distributed across regions. These processes, in turn, can modify the intensity and geography of carbon emissions, with implications for regional ecological efficiency and the provision of ecosystem services [6]. At the same time, railway projects may carry unintended ecological consequences. They can accelerate flows of people and capital into large urban centers, potentially intensifying ecological pressures in already stressed environments, while leaving peripheral regions vulnerable to ecological and economic marginalization [7].

Existing research has engaged with aspects of the railway-tourism nexus, particularly from economic and developmental perspectives. Scholars highlight that enhanced connectivity fosters tourism growth, reduces travel costs, and facilitates inter-city linkages [8]. Others note that benefits are unevenly distributed, with metropolitan hubs capturing the majority of gains [9]. Yet, these analyses remain limited in two important respects. First, they do not systematically account for the ecological implications of railway expansion, focusing instead on economic outcomes. Second, they largely neglect the spatial interdependencies that characterize transport systems. Tourism activities are inherently spatial, generating externalities that extend beyond administrative boundaries. Development in one region can spill over to influence the ecological performance of neighboring areas, altering their carbon emissions and ecological efficiency [10]. Ignoring these dynamics risks underestimating the broader ecological footprint of infrastructure projects.

To advance ecological understanding of these processes, this study introduces the concept of Tourism Transport Ecological Efficiency (TTEE). TTEE extends the eco-efficiency framework by explicitly linking transport infrastructure, carbon emissions, and ecological outcomes. Building on data envelopment analysis (DEA) models, TTEE evaluates desirable outputs—such as tourist arrivals and associated revenue—in relation to undesirable outputs, notably carbon emissions. By integrating these factors, TTEE allows for a more nuanced assessment of how efficiently tourism transport systems convert resources into economic value while minimizing ecological costs.

This paper applies the TTEE framework to the case of China, which provides a unique empirical context due to its rapid and extensive railway expansion. Over the period 2011–2018, China developed one of the largest high-speed railway networks in the world, fundamentally altering patterns of regional mobility [11]. Using panel data for 30 provincial-level administrative units, we calculate TTEE values with a super-efficiency DEA model incorporating undesirable outputs. We then employ spatial econometric techniques to capture the direct and indirect (spillover) effects of railway expansion on ecological efficiency. This approach allows us to move beyond localized assessments, revealing how infrastructure investment in one region can reverberate through spatially connected systems, reshaping ecological outcomes at multiple scales.

The contributions of this study are threefold. First, it reframes the ecological debate on transport by foregrounding tourism mobility as a major source of anthropogenic emissions and situating railway expansion within the broader carbon cycle. Second, it fills a critical research gap by assessing the spatial ecological impacts of transport infrastructure, extending beyond conventional tourism-focused approaches. Third, it offers a novel, spatially explicit account of the human infrastructure–carbon cycle–ecosystem service nexus, providing insights that are essential for ecological protection and restoration. Ultimately, this research emphasizes that the ecological consequences of transport infrastructure cannot be reduced to simple calculations of emissions per passenger-kilometer. Instead, they must be understood in terms of their broader spatial dynamics, systemic interactions, and implications for ecosystem functioning. By quantifying how railway expansion shapes TTEE in China, this study contributes to a deeper ecological understanding of how human mobility infrastructure influences the balance between development, carbon emissions, and ecosystem sustainability.

The structure of this paper is organized as follows: Section 2 presents a review of relevant literature. Section 3 details the methodology, along with a description of the data. Section 4 discusses the results and key findings. Finally, Section 5 concludes the paper, summarizing the main insights.

2. Literature Review

Tourism and transport are closely related [12]. Transport infrastructure upgrades have a significant impact on the growth of the tourism industry. In contrast, the growth of the tourism industry inevitably raises demand for transport services. Furthermore, the rise in tourism transport activities is expected to have a wide range of impacts on the environment and society [13].

Although transport is a significant aspect of tourism, tourism literature has not addressed certain aspects of it yet, such as the ecological sustainability of transport-related tourism. Unlike other activities of tourism, transport-related tourism is directly associated with carbon emissions and contributes significantly to their rise [14]. By performing intensive research on transport-related tourism, we can identify strategies to mitigate its carbon footprint. Against this background, it is necessary for us to develop an useful tool to measure the ecological sustainability of transport-related tourism. This specialized approach allows for a more detailed evaluation of the ecological sustainability issues connected with transport-related tourism, as well as the essential initiatives required to reduce its environmental impacts.

Assessing the ecological sustainability of tourism has been a hot topic in recent academic studies [15,16]. There are various methods available to asses the ecological sustainability of tourism, which can be broadly categorized into qualitative and quantitative approaches. In terms of qualitative research, Absalon et al. applied the fuzzy Delphi method to build a system of sustainable tourism indicators to assess the ecological sustainability of tourism sites [17]. Kieżel et al. conducted a theoretical study that critically analyzed existing literature from diverse sources and presented exploratory qualitative research results based on a case study methodology [18]. On the quantitative side, Javdan et al. proposed a new Social Life Cycle Assessment (S-LCA) framework to assist in ensuring the ecological sustainability of tourism destinations [19]. Wang et al. applied the ecological footprint model to quantify the ecological sustainability of tourism [20].

However, these methods sometimes oversimplify or fail to account for dynamic changes in tourism environments. A prominent alternative approach in assessing the ecological sustainability of tourism is Data Envelopment Analysis (DEA). DEA is a non-parametric technique to assess the relative efficiency of decision-making units (DMUs) by evaluating multiple input-output variables [21]. This method is highly suitable for assessing the ecological sustainability of tourism because it provides a multidimensional evaluation that considers both environmental and economic aspects, such as energy consumption, carbon emissions and tourism revenue [22]. In our study, we will adopt DEA as a fundamental tool for measuring the ecological sustainability of transport-related tourism, enabling us to integrate multiple environmental and economic indicators into a unified model.

To measure the ecological sustainability of transport-related tourism, it is crucial to select appropriate environmental indicators. Previous studies have introduced a variety of indicators such as energy consumption and carbon emissions[23,24]. These indicators help capture the environmental cost of tourism activities. However, as noted by Zhang and Tian, water footprint of tourism is also significant, underscoring the need for further research on incorporating water usage into ecological sustainability assessment[25]. Therefore, in our research, we extend traditional metrics by integrating water usage as a key indicator.

Railway expansion has also gained attention in tourism studies. For example, Shu et al. used difference-in-differences (DID) model to assess the impact of railway expansion on tourism efficiency by comparing regions before and after the construction of railway lines[9]. Zhuang et al. used the coupling coordination analysis to examine the interaction between railway transport accessibility and tourism economic connection[26]. However, the methods in these studies usually fail to build a econometric model considering spatial dependence. As noted by Liu et al., the spatial dependence can not be ignored[10]. Spatial econometric models also have been widely applied in many other fields. For example, Zhou et al. studied the spatial spillover effect of tourism agglomeration on carbon emissions[27]. Wang et al. adopted spatial econometric models to study tourism eco-efficiency network centrality[28]. However, the application of spatial econometric models remains unexplored in the context of our study. Thus, our study will adopt spatial econometric models to account for both direct and indirect effects of railway expansion on TTEE. It could allow us to examine the spillover effects in neighboring regions, providing a more comprehensive understanding of the spatial dynamics involved in TTEE.

3. Materials and Methods

3.1. Efficiency Measurement

To obtain the efficiency value that accurately reflects the ecological sustainability of transport-related tourism, we adopted an improved DEA model called the MinDW model with undesirable output, because it can be more appropriate and proved to be effective in previous studies[29]. According to the relevant work of previous researchers[30,31], the specific methods are presented as follows.

There are n DMUs which have m inputs, s desirable outputs and u undesirable outputs. Let X stand for the input data matrix, Y^g for the desirable output and Y^b for the undesirable output. Suppose DMU_o is an alternative decision-making unit where o ranges over 1, 2, ..., n. Let x_o be the input data for DMU_o, y_o^g be the desirable output data for DMUo and y_o^b be the undesirable output data for DMUo, which are defined below.

$$x_o = [x_{1o}, x_{2o}, \ldots, x_{mo}]^T \tag{1}$$

$$y_o^g = \left[y_{1o}^g, y_{2o}^g, \ldots, y_{so}^g\right]^T \tag{2}$$

$$y_o^b = \left[y_{1o}^b, y_{2o}^b, \ldots, y_{uo}^b\right]^T \tag{3}$$

In order to evaluate the efficiency value ρ* of DMUo, the formulas are given below.

$$\rho^* = \max\left\{\theta_z^*\right\}; \quad z = 1, \ldots, m+s+u \tag{4}$$

$$\theta_z^* = \frac{1 - \frac{1}{m}\sum_{i_1=1}^{m} \frac{\beta_z^* e_{i_1}}{x_{i_1 o}}}{1 + \frac{1}{s+u}\left(\sum_{i_2=1}^{s} \frac{\beta_z^* e_{i_2}}{y_{i_2 o}^g} + \sum_{i_3=1}^{u} \frac{\beta_z^* e_{i_3}}{y_{i_3 o}^b}\right)} \tag{5}$$

where βz* is the optimal estimate of βz, which could be defined as follows.

$$\max\ \beta_z; \quad z = 1, 2, \ldots, m+s+u \tag{6}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{i_1 j} + \beta_z e_{i_1} \le x_{i_1 o}; \quad i_1 = 1, 2, \ldots, m \tag{7}$$

$$\sum_{j=1}^{n} \lambda_j y_{i_2 j}^g - \beta_z e_{i_2} \ge y_{i_2 o}^g; \quad i_2 = 1, 2, \ldots, s \tag{8}$$

$$\sum_{j=1}^{n} \lambda_j y_{i_3 j}^b + \beta_z e_{i_3} \le y_{i_3 o}^b; \quad i_3 = 1, 2, \ldots, u \tag{9}$$

$$\lambda_j \ge 0 \tag{10}$$

where e_1, e_2, e_3 are defined as:

$$e_{i_1} = \begin{cases} 1, & \text{if } i_1 = z \\ 0, & \text{if } i_1 \ne z \end{cases} \tag{11}$$

$$e_{i_2} = \begin{cases} 1, & \text{if } i_2 = z - m \\ 0, & \text{if } i_2 \ne z - m \end{cases} \tag{12}$$

$$e_{i_3} = \begin{cases} 1, & \text{if } i_3 = z - m - s \\ 0, & \text{if } i_3 \neq z - m - s \end{cases} \tag{13}$$

If the efficiency scores from these models above are obtained by eliminating the data on the DMUo to be evaluated from the solution set [32], then this model is called the super-efficiency model. In this model, the efficiency value can be higher than 1. Besides, for panel data, window analysis is often regarded as a more appropriate method [33]. Therefore, our DEA framework will integrate window analysis, super-efficiency and the minDW model with undesirable outputs to assess TTEE.

Inspired by the Cobb-Douglas production function, many researchers have modeled tourism efficiency by considering capital, labor, energy and water as input variables, with Gross Domestic Product (GRP) as the desirable output and carbon dioxide (CO_2) emissions as the undesirable output [34,35]. In line with previous studies, we also adopt these input and output variables to calculate Tourism Transport Ecological Efficiency (TTEE). Definitions of these variables are summarized in **Table 1**.

Table 1. Definitions of input and output variables.

Type	Variable Name	Definition	Unit
Input	Capital	Fixed assets investment in transport sector	100 million CNY
Input	Labor	Number of employees in transport sector	10^4 persons
Input	Energy	Energy consumption in tourism transport-related sector	10^4 tons CE
Input	Water	Water usage in tourism transport-related sector	10^4 L
Desirable output	GRP	Gross Regional Product in tourism transport-related sector	100 million CNY
Desirable output	Tourists	Tourist arrivals	10^4 visitors
Undesirable output	CO_2	CO_2 emissions from tourism transport-related sector	10^4 tons

Notes: CNY denotes Chinese Yuan; CE denotes coal equivalent.

Specifically, the tourism transport-related CO_2 emissions (C) and tourism transport-related energy consumption (E) are calculated according to our previous work [36]. Follow the suggestion of literature [25], the tourism transport-related water consumption (Water) is calculated using the following formula:

$$\text{Water} = 130 \times N \times T \tag{14}$$

where N represents the number of tourists; T represents the stay days of tourists; 130 is per capita daily water consumption measured in liters [37].

3.2. Spatial Econometric Model

To examines the impact of railway expansion on the Tourism Transport Ecological Efficiency (TTEE)., railway density (R) is set as the core explanatory variable in this study. Meanwhile, other control variables, namely Origin (O), Urbanization (U) and Price Gradient (PG), are incorporated, according to previous studies [10,38]. Definitions of these factors are summarized in **Table 2**.

Table 2. Definitions of factors.

Symbol	Variable	Indicator	Unit
R	Railway density	Railway mileage divided by the provincial area	km/100 km^2
O	Trade Openness	Import and export volume as percentage to Gross Regional Product	%
U	Urbanization	Proportion of urban residents in total population	%
PG	Economic growth	Per capita Gross Regional Product	10^4 CNY

Notes: CNY denotes Chinese Yuan.

When considering individual fixed effect, a typical non-spatial ordinary least squares (OLS) model can be written as:

$$\text{OLS}: \quad TTCE_{it} = \alpha + \beta_1 R_{it} + \beta_2 O_{it} + \beta_3 U_{it} + \beta_4 \ln PG_{it} + \mu_i + \varepsilon_{it} \tag{15}$$

If we extend the OLS model with spatial interaction effects, we can establish the following 3 econometric models:

$$\text{SAC}: \quad \begin{cases} TTEE_{it} = \delta \sum_{j=1}^{n} w_{ij} TTEE_{jt} + \alpha + \beta_1 R_{it} + \beta_2 O_{it} + \beta_3 U_{it} + \beta_4 \ln PG_{it} + \mu_i + u_{it} \\ u_{it} = \lambda \sum_{j=1}^{n} w_{ij} u_{jt} + \varepsilon_{it} \end{cases} \tag{16}$$

$$\text{SLM}: \quad \text{TTEE}_{it} = \delta \sum_{j=1}^{n} w_{ij}\text{TTEE}_{jt} + \alpha + \beta_1 R_{it} + \beta_2 O_{it} + \beta_3 U_{it} + \beta_4 \ln \text{PG}_{it} + \mu_i + \varepsilon_{it} \tag{17}$$

$$\text{SEM}: \quad \begin{cases} \text{TTEE}_{it} = \alpha + \beta_1 R_{it} + \beta_2 O_{it} + \beta_3 U_{it} + \beta_4 \ln \text{PG}_{it} + \mu_i + u_{it} \\ u_{it} = \lambda \sum_{j=1}^{n} w_{ij} u_{jt} + \varepsilon_{it} \end{cases} \tag{18}$$

where

SAC stands for the spatial autoregressive combined model[39];

SLM stands for the spatial lag model[40];

SEM stands for the spatial error model[41];

i or j represents the data for the i^{th} or j^{th} region and t for the t^{th} year;

α represents the constant term;

$\beta_1 \sim \beta_5$ represent unknown parameters;

w represents the spatial weights matrix, which is set to a row-normalized contiguity weights matrix here;

μ represents the individual fixed effect;

u and ε represent the error terms.

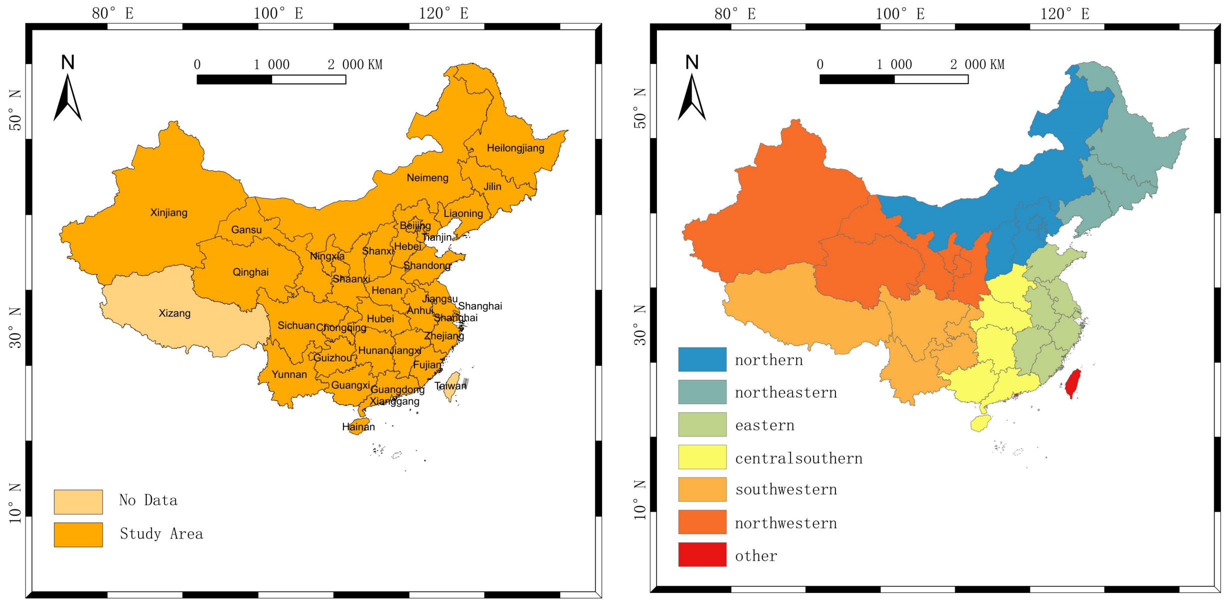
This study employs a likelihood ratio (LR) test to evaluate whether the spatial autoregressive combined (SAC) model can be simplified to the spatial lag model (SLM) or spatial error model (SEM). The SAC model, which integrates both spatial lag and spatial error dependence, serves as the unrestricted model. In contrast, the SLM (which assumes $\lambda = 0$) and SEM (which assumes $\delta = 0$) act as restricted models. The LR test compares the log-likelihood values of the SAC model against these restricted specifications. If the null hypothesis is rejected, it indicates that spatial lag or spatial error dependencies are statistically significant, necessitating the use of the SAC framework. This approach ensures that the model does not oversimplify spatial dependence structures, particularly when cross-regional interactions manifest through both endogenous variable spillovers (captured by SLM) and unobserved spatially correlated shocks (captured by SEM).

3.3. Data

This study focuses on the tourism situation across 30 provinces in mainland China, excluding the regions of Xianggang, Aomen, Taiwan and Xizang, due to incomplete or unavailable data for these areas. The selected 30 provinces are depicted in **Figure 1**, which illustrates their geographical distribution. This study divides the study area into two main parts: the Eastern Region and the Non-Eastern Region. Among them, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Jiangxi and Anhui are classified as part of the Eastern Region, while the remaining provinces belong to the Non-Eastern Region. The study spans the years from 2011 to 2018, a period that precedes the disruptive impact of the COVID-19 pandemic, capturing a phase of rapid expansion in China's tourism sector. Based on information from National Bureau of Statistics of China, domestic tourism in these 30 regions saw a significant rise, with the number of domestic travelers increasing nearly by 159%. Inbound tourism followed a similar upward trend, growing nearly by 87%.

In addition to tourism, the expansion of railway networks, played a key role in facilitating this growth. Based on information from the National Railway Administration of China, the total length of the railway network in these 30 regions increased by nearly 41% over the period. China's extensive railway system, which includes high-speed rail networks linking major cities and tourist destinations, has significantly improved accessibility across the country, further stimulating domestic and international tourism flows.

Data for this study were sourced from several authoritative publications, including the China Statistical Yearbook, the Yearbook of China Tourism Statistics, the China Transport Statistical Yearbook, the Yearbook of China Transportation, and the Statistical Yearbook of each province. In addition, relevant official reports were consulted to supplement the data. To analyze and process the data, statistical software such as MATLAB R2019b and STATA 18 were employed. These tools were used for data cleaning, statistical analysis, and the creation of spatial econometric models. This paper partially draws from our previously published work[36].



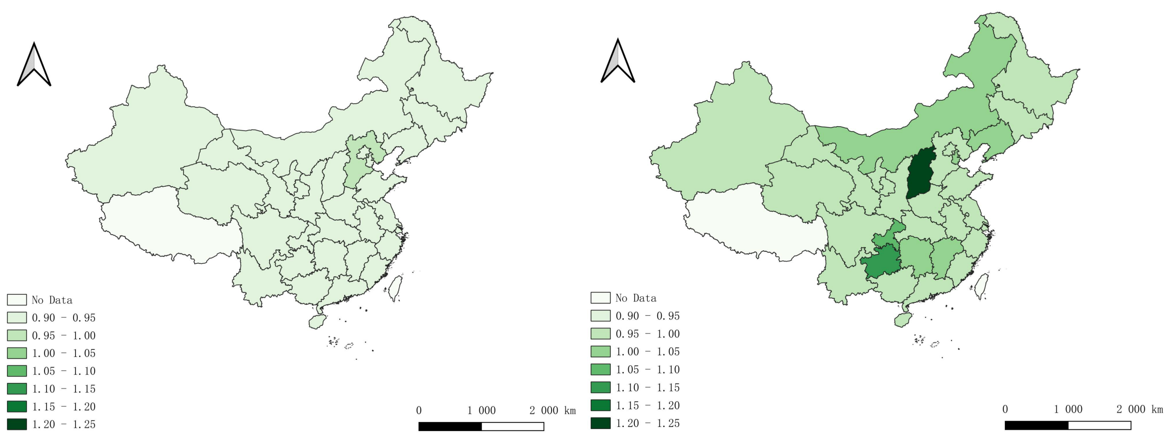
(**a**) (**b**)

Figure 1. Map of China. (**a**) study area; (**b**) administrative division. (source National Geomatics Center of China).

4. Results and Discussions

4.1. Efficiency

According to the methods and raw data described in Section 3, the Tourism Transport Ecological Efficiency (TTEE) was calculated and then presented in **Figure 2**, which depicts the spatial distribution of TTEE in 2011 and 2018. As the efficiency is evaluated through super DEA model [32], the calculated efficiency value can be higher than 1. As shown in **Figure 2**, the TTEE increased apparently between 2011 and 2018 throughout the country, particularly in central and western part of China. This non-eastern region experienced an 8.7% average increase in transport-related tourism carbon efficiency, compared to 5.5% in the eastern region, summarized value is shown in **Table 3**.



2011 2018

Figure 2. Tourism Transport Ecological Efficiency.

It should be noted that the provinces in central and western part of China including Chongqing, Guizhou and Hunan had significant progress in TTEE. There are over 20 5A-rated tourist attractions across these there provinces, including UNESCO World Heritage sites like Wulong Karst, Mount Fanjing as well as Zhangjiajie National Forest Park which famously featured as the “Avatar” filming inspiration.

Table 3. Basic descriptive result of TTEE.

Year	Eastern Regions			Non-Eastern Regions		
	Min	Max	Average	Min	Max	Average
2011	0.924	0.982	0.933	0.924	0.946	0.928
2018	0.972	1.039	0.984	0.971	1.214	1.009
Change (%)	-	-	5.5%	-	-	8.7%

Notes: In super-efficiency model, the efficiency can be higher than 1 [32].

To further illustrate the temporal evolution of the distribution of Tourism Transport Ecological Efficiency (TTEE) across provinces in China, kernel density estimation was applied to two representative years, 2011 and 2018 (**Figure 3**). The horizontal axis represents TTEE values, and the vertical axis indicates the estimated density. By examining changes in the location, shape, and tail behavior of the kernel density curves, we can gain intuitive insights into the dynamic distributional patterns of provincial TTEE over time. Overall, between 2011 and 2018, the kernel density curves exhibit a clear rightward shift of the main peak, accompanied by a moderate widening of the peak and a lengthening of the right tail. This pattern indicates a general improvement in TTTE across provinces, coupled with some increase in inter-provincial differences. Importantly, the distributions remain unimodal across both years, with no evidence of polarization or multiple clusters, implying a converging trend with localized divergence at the upper tail.

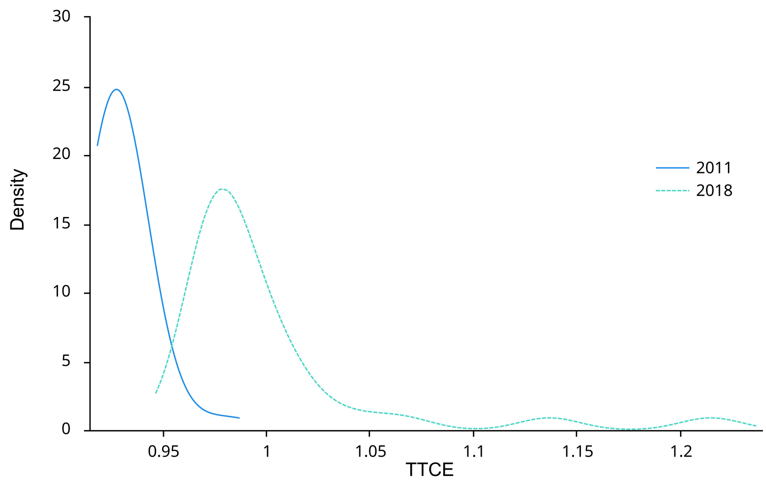


Figure 3. Kernel density estimation.

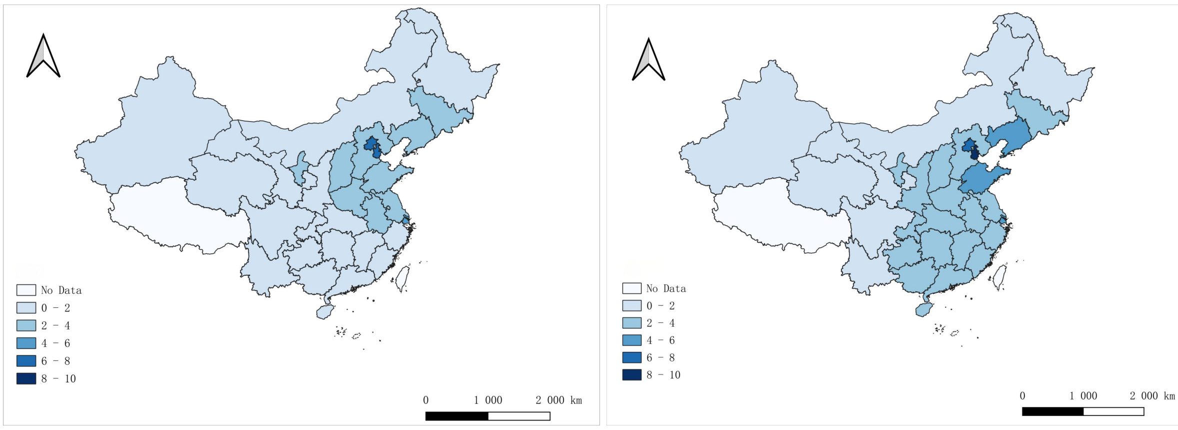
4.2. Railway Density

Figure 4 depicts the spatial distribution of railway density in year 2011 and 2018. It is evident that there was a significant rise in railway density during this period.

Table 4 presents the statistics on railway density for both the Eastern and Non-Eastern regions. This table indicates that the expansion rate of railway density in both the Eastern and Non-Eastern regions is nearly the same, with no great difference between them. Specifically, the Eastern region experienced an expansion rate of 33.4%, while the Non-Eastern region saw a slightly higher expansion rate of 33.7%.

Table 4. Basic descriptive result of railway density.

Year	Eastern Regions			Non-Eastern Regions		
	Min	Max	Average	Min	Max	Average
2011	1.686	5.515	2.528	0.265	7.485	2.075
2018	2.563	5.576	3.373	0.337	9.679	2.775
Change (%)	-	-	33.4%	-	-	33.7%



2011 2018

Figure 4. Railway density [km/100 km^2].

4.3. Bivariate Spatial Correlation

The bivariate spatial correlation between TTEE and railway density was tested using Geoda software. As shown in **Table 5**, the bivariate Moran's I value between TTEE and railway density are positive and the *p*-values are mostly less than 10% except for 2012 and 2018, indicating a significant positive spatial autocorrelation. Apparently, these findings reveal the necessity of considering spatial interaction in econometric analysis. This is confirmative result for the previous finding which found the spatial interplay across Chinese province[10], even we had scoped then analysis toward the carbon emissions from tourism transport-related activities.

Table 5. Bivariate Moran's I.

Year	Moran's I	z-Value	*p*-Value
2011	0.161	1.735	*
2012	0.058	0.636	> 0.1
2013	0.125	1.347	*
2014	0.117	1.342	*
2015	0.174	1.955	**
2016	0.163	1.847	**
2017	0.272	3.885	***
2018	0.006	0.122	> 0.1

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.4. Spatial Econometric Model

In this paper, the STATA software was used to estimate the spatial panel models. **Table 6** reports the estimation results. As shown in **Table 6**, the log-likelihood (Log-L) value of SAC model is greater than others, and the AIC value is less. Hence, the SAC model seems more suitable to describe the relationship.

Table 6. Estimation results.

Variable	SAC			SLM			SEM		
	Coefficient	z-Value	*p*-Value	Coefficient	z-Value	*p*-Value	Coefficient	z-Value	*p*-Value
R	0.079	8.783	***	0.052	6.630	***	0.064	8.577	***
O	0.001	1.835	*	0.001	2.196	**	0.000	1.044	> 0.1
U	−0.009	−3.869	***	−0.004	−2.857	***	−0.006	−2.952	***
lnPG	0.135	3.253	***	0.059	1.944	*	0.145	4.200	***
W·TTEE	0.788	33.562	***	0.801	38.666	***	-	-	-
W·e	0.794	35.437	***	-	-	-	0.810	42.615	***
Log-L	561.342	-	-	534.976	-	-	543.335	-	-
AIC	−1108.685	-	-	−1057.951	-	-	−1074.670	-	-

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

To further determine whether the SAC model can be simplified, we adopted the LR test. We compare the SAC model with the SLM model and the SEM model respectively. The LR test results are reported in **Table 7**. The first row of **Table 7** shows that the null hypothesis should be rejected. It means that SAC can not be simplified to SLM. In the same way, the second row of **Table 7** shows that the null hypothesis should be rejected. This means that SAC can not be simplified to SEM. Thus, both tests show that the SAC model is more appropriate for describing spatial dependence.

Table 7. LR test.

Model 1	Model 2	χ^2	*p*-Value	Model 1 nested within Model 2?
SLM	SAC	52.73	***	No
SEM	SAC	36.01	***	No

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Unlike traditional econometric models, the spatial panel model's coefficients are unable to reflect the spatial impacts. Following the suggestion of Liu et al.[10], we should disseminate the impacts as direct and indirect effects. The dependent variable is affected by the independent variable in the same location, which we refer to as a direct effect. The dependent variable is affected by the independent variable in surrounding areas, which we refer to as an indirect effect or spillover effect. Therefore, the analysis of spatial panel regression should not focus on individual coefficients, but on the direct and indirect effects. **Table 8** reports the direct and indirect effects of SAC model.

Table 8. The direct and indirect effects of SAC model.

Variable	Value	z-Value	*p*-Value
Direct effect			
R	0.104	8.43	***
O	0.001	1.83	*
U	−0.012	−3.83	***
lnPG	0.176	3.24	***
Indirect effect			
R	0.272	5.36	***
O	0.003	1.76	*
U	−0.030	−3.33	***
lnPG	0.461	2.96	***

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

From **Table 8** we can see that the direct effect of railway density (R) is positive and statistically significant, indicating that a larger railway density tends to raise TTEE in the same region. The indirect effect of railway density (R) is positive and significant, suggesting that a larger railway density in neighboring regions tends to raise the local TTEE.

We extended our analysis to compare the effects of railway expansion on TTEE in eastern versus non-eastern provinces. As shown in **Table 9**—with direct and indirect effects detailed in **Table 10**—the influence of railway density is both more significant and of greater magnitude in non-eastern regions. One plausible explanation draws on "regression to the mean", a concept widely discussed in statistics[42]. Regions starting from lower tourism transport-related efficiency tend to exhibit disproportionately larger improvements over time, converging toward or even surpassing the other provinces. By contrast, areas already endowed with relatively advanced infrastructure and economic size typically experience more modest incremental gains.

Table 9. Estimation results of SAC model for Eastern and Non-Eastern regions.

Variable	Eastern			Non-Eastern		
	Coefficient	z-Value	*p*-Value	Coefficient	z-Value	*p*-Value
R	−0.014	−2.404	**	0.093	8.086	***
O	0.000	0.664	> 0.1	0.001	2.051	**
U	0.002	1.658	*	−0.012	−3.813	***
lnPG	−0.007	−0.411	> 0.1	0.159	2.963	***
W·TTEE	1.083	22.466	***	0.923	36.576	***

Table 9. *Cont.*

Variable	Eastern			Non-Eastern		
	Coefficient	**z-Value**	***p*-Value**	**Coefficient**	**z-Value**	***p*-Value**
W·e	−0.074	−0.858	> 0.1	0.926	38.311	***
Log-L	206.964	-	-	416.492	-	-
AIC	−399.928	-	-	−818.984	-	-

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 10. The direct and indirect effects for Eastern and Non-Eastern regions.

Variable	Eastern			Non-Eastern		
	Value	**z-Value**	***p*-Value**	**Value**	**z-Value**	***p*-Value**
Direct effect						
R	0.012	0.83	> 0.1	0.174	5.55	***
O	0.000	−0.67	> 0.1	0.002	1.98	**
U	−0.001	−0.70	> 0.1	−0.023	−3.40	***
lnPG	0.006	0.37	> 0.1	0.297	2.77	***
Indirect effect						
R	0.159	1.66	*	1.029	2.58	**
O	−0.001	−0.73	> 0.1	0.014	1.64	> 0.1
U	−0.017	−1.16	> 0.1	−0.134	−2.21	**
lnPG	0.075	0.40	> 0.1	1.754	2.02	**

Notes:*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5. Implications

This study found that Tourism Transport Ecological Efficiency (TTEE) grew more rapidly in non-Eastern regions (8.7%) than in Eastern regions (5.5%), revealing spatial disparities in ecological performance. From an ecological perspective, this uneven growth reflects how infrastructure interacts with landscape structure. In less-developed regions, new railways improve connectivity and shift mobility away from carbon-intensive modes, thereby enhancing the ability of ecosystems to regulate carbon fluxes. In contrast, infrastructure-saturated Eastern regions appear to yield diminishing ecological returns, consistent with theories in landscape ecology, where spatial arrangement and connectivity determine the flow of ecological processes—in this case, anthropogenic emissions.

The significant positive direct effect of railway density on TTEE indicates that rail systems function as ecological interventions by lowering the carbon intensity of tourism transport. Their impact is especially pronounced in non-Eastern regions, where infrastructure expansion alters ecosystem functioning by reshaping regional carbon budgets and reducing pressure on local ecosystems to act as sinks. Railways thus represent not only a mobility solution but also a mechanism for modifying the balance between emission sources and ecological capacity. Equally notable are the positive spillover effects: higher railway density in one province improves ecological efficiency in its neighbors. These indirect benefits mirror the concept of landscape connectivity, where processes transcend boundaries and produce emergent regional outcomes. Just as natural flows of nutrients or species operate across landscapes, transport networks redistribute emissions and ecological efficiency beyond local jurisdictions.

These findings suggest that railway expansion should not be viewed solely through an economic or policy lens. Instead, it constitutes a form of ecological infrastructure that reshapes spatial carbon dynamics. Effective governance therefore requires a cross-regional ecological perspective, recognizing that investments in one area can amplify ecological benefits across the wider landscape.

In summary, the study demonstrates that transport infrastructure plays a pivotal role in the ecological response to global change. By enhancing TTEE, railways contribute to ecological sustainability, reducing anthropogenic pressures and supporting ecosystem resilience. Recognizing transport as part of the human–environment system advances understanding of how infrastructure development influences carbon cycles, ecosystem functioning, and long-term ecological sustainability.

6. Conclusions and Future Study

6.1. Conclusions

The ecological sustainability of transport-related tourism is not only an industry concern but also an ecological one, as mobility systems are tightly linked to carbon emissions and global environmental change. By introducing the Tourism Transport Ecological Efficiency (TTEE) framework, this study provides a tool to evaluate how tourism transport interacts with regional carbon cycles and ecological sustainability.

Two main contributions emerge. First, the assessment of TTEE highlights the extent to which tourism transport contributes to anthropogenic pressures on ecosystems. As transport accounts for nearly half of tourism's carbon footprint, measuring its ecological efficiency allows for a clearer understanding of how infrastructure alters regional carbon budgets and the capacity of ecosystems to function as carbon sinks. Second, the examination of railway expansion demonstrates that transport infrastructure exerts both direct and indirect ecological effects. Non-Eastern regions displayed higher growth in TTEE, suggesting that new railway connectivity can enhance ecological efficiency where baseline emissions are higher. Equally significant are the positive spillover effects, whereby improvements in one region extend to its neighbors. These spatial dynamics resonate with principles of landscape ecology, where connectivity shapes the flow of ecological processes—in this case, the redistribution of emissions and ecological benefits across regions.

Methodologically, by integrating DEA with spatial econometric modeling, this research advances an analytical lens for understanding how infrastructure interacts with ecological systems through local and cross-regional mechanisms. Beyond methodological contribution, the findings offer actionable implications for ecological improvement. The TTEE framework can inform policy design by pinpointing regions where green transport investment yields the highest ecological dividends. Promoting modal shifts toward low-emission railways, restoring ecosystems along transport corridors, and aligning infrastructure expansion with carbon offset and biodiversity goals can further enhance ecological resilience.

6.2. Limitation and Further Study

There are several limitations that need to be acknowledged. Firstly, this research only used data prior to the COVID-19 pandemic. Secondly, this research is based on data from specific regions, with a particular emphasis on Eastern and Non-Eastern China. While this provides valuable regional insights, the generalizability of the findings may be limited to similar contexts. The conclusions drawn here may not necessarily hold true in other countries with different infrastructure, economic structures, or tourism characteristics. Therefore, further studies are needed to replicate this analysis in diverse geographical and cultural settings to explore the broader applicability of the results. Thirdly, while this study addresses the direct and indirect effects of railway density on TTEE, it does not account for the potential influence of external factors such as policy changes, technological advancements, or global economic shifts.

Future research could explore several avenues to build on the findings of this study. First, it would be valuable to extend the analysis to other countries or regions to assess whether the observed spatial effects of railway density on TTEE are universally applicable or specific to the Chinese context. Comparative studies across different countries could yield insights into how varying levels of railway infrastructure development interact with regional tourism dynamics to affect carbon efficiency. Second, the study could be expanded to include a broader range of factors affecting TTEE. For instance, including the impact of tourism-related activities beyond transport—such as accommodation, entertainment, and leisure—could provide a more comprehensive assessment of the overall carbon footprint of the tourism sector. Future work should aim to integrate these dimensions into the analysis of TTEE to propose more effective strategies for reducing the environmental impacts of tourism. Finally, while this research highlights the importance of railway density, it would be valuable to examine the role of other sustainable practices in reducing the carbon footprint of tourism transport. For example, the adoption of green technologies, the promotion of energy-efficient practices, and the development of sustainable tourism policies could all contribute to reducing emissions. Future studies should focus on identifying which specific practices and technologies are most effective in enhancing TTEE, offering practical recommendations for policymakers and industry stakeholders aiming to create a more sustainable tourism transport system.

Author Contributions

Conceptualization, Y.Y.; methodology, Y.Y.; software, Y.Y.; validation, Y.Y. and C.P.; formal analysis, Y.Y.; investigation, Y.Y.; resources, Y.Y.; data curation, Y.Y.; writing—original draft preparation, Y.Y.; writing—review and editing, C.P.; visualization, Y.Y.; supervision, C.P. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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