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Original Research

Threshold Effects of Digital Economy on Tourism Carbon Emissions: Empirical Evidence from the Yangtze River Economic Belt in China

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Abstract

The digitization process plays a crucial role in eliminating tourism's "low efficiency" developmental pitfall and addressing the conflict between high-caliber tourism development and the reduction of carbon emissions. The study quantified carbon emissions from tourism in the Yangtze River Economic Belt of China using both the carbon footprint and the "bottom-up" approach and developed a panel threshold model to empirically evaluate the nonlinear effect of the digital economy on tourism carbon emissions. The results show that the effect of the digital economy on carbon emissions in tourism will vary in structure depending on the degree of tourist concentration and the concentration of residents in tourist areas. Particularly, considering varying levels of tourism concentration and the resident population density, the overall impact of the digital economy on carbon emissions from tourism exhibits a reversed "V" type single threshold characteristic. If the concentration of the tourism sector falls below 1.08 or its resident population density is under 389.9, digital tourism growth exacerbates carbon emissions, resulting in incremental impacts of 3.3 and 2.38, respectively. If the concentration of the tourism sector exceeds 1.08 or its resident population density surpasses 389.90, the collective impact of digital tourism growth will be maximized, and advancing the digital economy will aid in lowering carbon emissions in the tourism sector, yielding incremental impacts of -3.94 and -2.17, respectively. The impact of the digital economy on diminishing carbon emissions within the tourism sector primarily focuses on transportation and tourism-related activities. Achieving a harmonious interplay between tourism's digital evolution and the reduction of carbon emissions requires not only the focused growth of the digital economy, but also the strategic direction of tourism businesses and the concentration of populations, thereby disrupting the inflexible trend of tourism carbon emissions clustering.

Keywords: digital economy, tourism carbon emissions, threshold effect, tourism agglomeration, resident population density

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Introduction

Lately, the global concern over climate change due to greenhouse gas emissions has garnered significant international focus. Escalating CO_2 emissions have resulted in regular climatic irregularities and severe global climate catastrophes, making tackling worldwide climate change a widespread human challenge [1]. A variety of initiatives to counteract worldwide greenhouse gas emissions have been initiated by the global community, with the Kyoto Protocol, Copenhagen Conference, and Paris Agreement, among other accords and symposiums, actively working on reducing greenhouse gas emissions. China has unveiled its goals for a "carbon peak" and a "carbon neutral" approach to future worldwide climate management, highlighting its significant role in enhancing global efforts against climate change [2].

Tourism, being among the globe's most robust and extensive sectors, is frequently referred to as a "smoke-free industry". Recent research indicates that worldwide tourism contributes to 8% of the world's total carbon emissions, with its energy use and carbon emissions playing a major role in global climate change [3]. Furthermore, projections indicate that by 2025, the worldwide tourism sector will see a carbon footprint increase of over 40% annually, with CO2 emissions surpassing 6.5 billion tons. The World Tourism Organization's latest study indicates a projected rise in worldwide carbon emissions from tourism transport, projected to climb from 1,597 million tons in 2016 to 1,998 million tons by 2030, representing 5.3% of all human-made CO2 emissions[1]. Clearly, the tourism industry is expected to exceed the majority of economic sectors in contributing significantly to upcoming global carbon emissions. The significant impact of carbon emissions from tourism cannot be overlooked, especially considering its deep integration within the industry and its interconnectedness [4].

China, the world's most populous country, is rich in tourism resources, has become an important international tourist destination and source of visitors, and has the world's largest domestic tourism market. According to the office of the National Bureau of Statistics in China, the annual number of trips per capita has steadily increased, from 1.6 in 2010 to 4.3 in 2019. While the 2020 COVID-19 pandemic has had a huge impact on the tourism industry, the post-pandemic era has also seen a resurgence in tourism. In the first quarter of 2023, China's domestic tourism revenue recovered to 97.7% of the same period in 2019. Tourism revenue reached 1.3 trillion yuan, an increase of 69.5% year-on-year. With tourism becoming a new growth point of our country's economic and social development, large-scale development and tourism activities will inevitably bring a large amount of energy consumption and CO_2 emissions. China's tourism industry will face the dilemma of high-quality development and carbon emission reduction.

Emerging from recent technological and industrial shifts, the digital economy represents a novel economic model and is currently a key catalyst for worldwide economic and social progress. The emergence of the digital economy has significantly contributed to the growth of the tourism sector, ensuring its high quality. As an illustration, on both macro and meso scales, the digital economy enhances the availability of tourism goods and services and fosters the evolution and enhancement of the tourism sector from various angles and throughout the entire chain. On a smaller scale, the digital economy aids tourism businesses in elevating the quality of services and products, attaining precise marketing strategies, advancing smart analytical skills, and boosting operational management effectiveness. With the ongoing evolution of the digital economy, global researchers and governmental bodies are examining the potential of digital technology as a means for the tourism sector to fulfill its carbon reduction objectives and foster superior tourism growth. Consequently, accurately determining how the digital economy affects carbon emissions in tourism aids government agencies in pinpointing crucial aspects of reducing carbon emissions in this sector. This can be achieved by scientifically modifying strategies for the digital economy, aiming to meet the dual objectives of superior tourism growth and lowering carbon emissions, and to break free from the 'inefficiency' pitfall of tourism development.

The organization of this research is as follows: Section 2 encapsulates the current research advancements and theoretical propositions; Section 3 offers an overview of the case site, methods for identifying tourism carbon emissions, and the model of the digital economy's threshold effect on tourism carbon emissions; Section 4 conducts an empirical analysis of the digital economy's threshold impact on tourism carbon emissions; and Section 5 encapsulates the research outcomes and their implications for policies. The logical framework for identifying threshold effects is shown in Fig. 1.

Literature Review and Theoretical Hypothesis

Since the emergence of the digital economy, academics from both domestic and foreign countries have extensively discussed how the digital economy may reduce emissions. From a research standpoint, the majority of studies examine how the digital economy affects carbon emissions in a nation or region directly and through spatial spillover effects [5-7]. A few studies specifically look at how the digital economy affects carbon emissions in manufacturing, agriculture,

1 Please refer to the Climate Change and Environment section of United Nations News on December 4, 2019. https://news.un.org/zh/story/2019/12/1046761

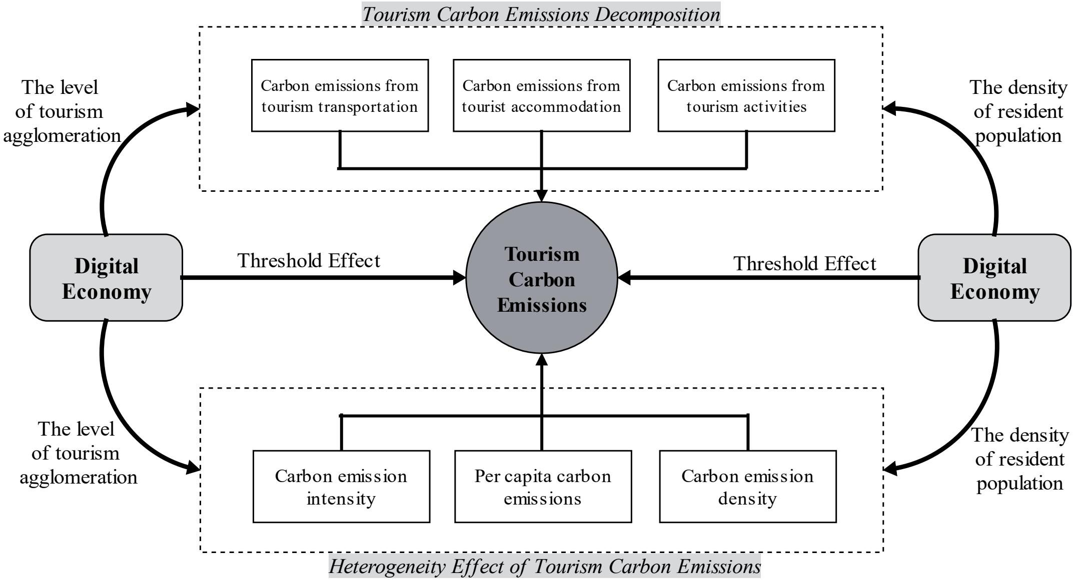

Fig. 1. Logical framework for threshold effects identification.

and other industries by using the industry as the object of study [8, 9]. The impact of tourism on reducing carbon emissions has not been extensively studied. The research findings do not yet support a consistent conclusion about whether the digital economy has successfully encouraged the reduction of carbon emissions in specific geographic areas or industrial sectors. The primary cause is because the digital economy is a "double-edged sword," meaning that there may be a coexistence of the effects of rising emissions and falling carbon [10, 11]. According to some scholars, the growth of the digital economy industry necessitates a significant quantity of carbon-intensive intermediate inputs from industries other than information and communication technology, and these inputs will generate a significant amount of carbon emissions [12]. However, the majority of research indicates that the new sectors, new formats, and new models brought forth by the digital economy effectively integrate digital technology with conventional industrial sectors, quicken the process of industrial green development transformation, and result in reduced use of fossil fuels and carbon dioxide emissions [13, 14].

Considering the simultaneous existence of the digital economy's gradual and carbon-lowering impacts, what is the theoretical influence of the digital economy on carbon emissions in tourism? Research indicates that the digital evolution of tourism contributes to gradual carbon emissions [15, 16], yet it also aids in curtailing carbon emissions in tourism through three distinct routes [17]. Initially, the advent of the digital economy has transformed consumer preferences, incorporating cutting-edge technologies like artificial intelligence, big data, cloud computing, 5G, AR, and VR into the tourism sector. This integration has led to the enhancement of tourism products and services [18] and a notable decrease in energy use and carbon emissions within the tourism industry [19]. Furthermore, the advancement of technology in the tourism sector and businesses has been propelled by the digital economy, enhancing the refinement of production and management methods as well as the efficiency of resource distribution and energy use in the tourism field via digital means, effectively realizing objectives related to reducing costs and carbon emissions [20]. Thirdly, the advent of the digital economy introduces innovative methods, technologies, and approaches for environmental oversight by environmental protection agencies and public environmental engagement, aiding the tourism sector in lowering carbon emissions [21-23]. Specifically, the extensive use of digital tools like big data and AI has significantly improved the capacity of environmental protection agencies and citizens to actively gather emission data, precisely monitor pollution origins, and adeptly alert and oversee the carbon emissions patterns of tourism sectors and businesses [24, 25]. The complexity of the digital economy is evident, and its overall effect on carbon emissions within the tourism sector varies, hinging on the balance between its gradual and gradual impacts. Should the digital economy's impact on diminishing carbon in tourism surpass its gradual effect, then its growth will lead to a decrease in carbon emissions in tourism, and the reverse is also true. Consequently, in certain areas, the impact of reducing carbon might surpass that of incremental changes; conversely, in other areas, the effect of reducing carbon could be less significant than the incremental one. Consequently, the digital economy's effect on tourism-related carbon emissions varies across regions. Therefore, this document presents the first proposition.

Proposition 1. The overall impact of the digital economy on tourism-related carbon emissions could display non-linear traits.

Economic models suggest that the impact of the digital economy on diminishing carbon emissions in tourism hinges on external factors, such as the density of tourism products and services on the local supply side or the density of tourism demand [26, 27]. Should the density of tourism products and services on the local supply side be minimal or on the demand side, it hinders the complete utilization of the tourism agglomeration phenomenon [28]. Currently, the gradual increase in CO2 emissions due to the digital evolution of the tourism sector is immeasurable, making it challenging to fully leverage the carbon reduction impact [29]. Consequently, the decrease in carbon emissions due to the growth of the digital economy on tourism is expected to be less significant than the rise in emissions, meaning the overall impact of the digital economy on tourism carbon emissions will be beneficial. Conversely, when the demand for tourism products and services on the local supply side is substantial or there's a high concentration of tourism demand, the collective impact of digital tourism growth will be maximized, leading to a notably greater reduction in carbon emissions than the gradual effect [30]. Currently, advancing the digital economy is advantageous for lowering carbon emissions in the tourism sector. Consequently, this paper introduces the second theoretical proposition.

Proposition 2. The digital economy exerts a critical influence on tourism-related carbon emissions, with the overall impact being beneficial during the lower threshold period and detrimental in the higher threshold phase.

Materials and Methods

Case

Spanning east, middle, and west China from Shanghai in the east to Yunnan in the west, the Yangtze River Economic Belt is a globally influential inland economic zone and a trailblazing example of ecological civilization development (Fig. 2). Spanning roughly 2,052,300 square kilometers, the Yangtze River Economic Belt encompasses 11 cities such as Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Guizhou, Chongqing, Sichuan, and Yunnan, making up 21.4% of the nation's total area, yet it encompasses over 40% of its population and GDP. Boasting a substantial tourism sector and a robust tourism economy, the Yangtze River Economic Belt holds a significant role in the country's tourism economic framework. Data from the China Tourism Development Report reveals that, by 2017, this area had 3,602 A-grade tourist spots, making up 40.23% of the nation's total A-grade tourist attractions. Moreover, its top-tier tourist attractions, particularly those of superior quality, hold a significant role within the nation. Furthermore, the Yangtze River Economic Belt attracts 4.929 billion tourists, constituting almost 50% of the nation's total tourist population. This area's overall tourism income constitutes 44.21% of the nation's total tourism income, placing five provinces and cities in the top 10 for both international and domestic tourism revenues. Research by the China Tourism Research Institute reveals that

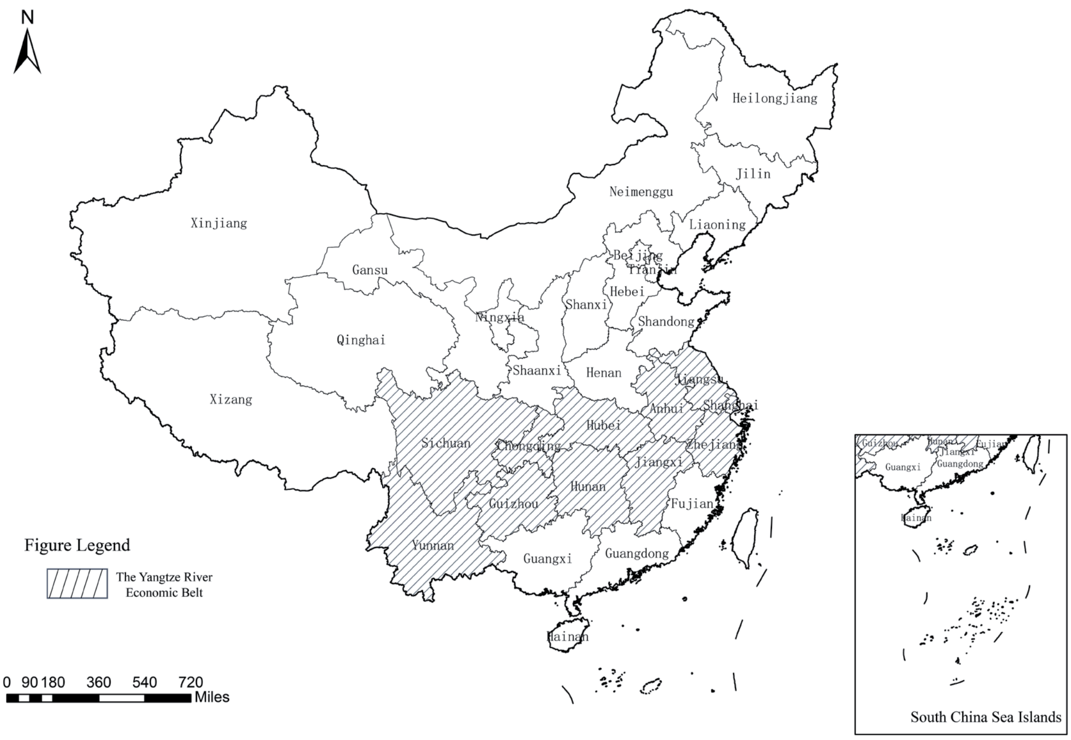

Fig. 2. The location and scope of Yangtze River Economic Belt in China.

in 2022, the Yangtze River Economic Belt was home to six out of the nation's top 10 inter-provincial tourist spots, and it also accommodates four of the leading 10 provinces in the country for intra-provincial tourism. Eleven provinces and cities in the Yangtze River Economic Belt collaboratively agreed on a tourism industry partnership declaration in 2015. Committing to the creation of a comprehensive regional tourism public service system, this initiative aims to foster a thriving, cohesive, and systematic tourism market along the Yangtze River. It seeks to shape an exemplary model of tourism amalgamation and growth within the Yangtze River Economic Belt, thereby fulfilling the strategic objective of amalgamating tourism resources, enhancing tourism services, elevating the quality of tourism, and collaboratively establishing a premier tourism region. Consequently, this study chooses the Yangtze River Economic Belt in China as a representative example for research.

Identification of Tourism Carbon Emissions

Method

The carbon emissions of the tourism industry mainly refer to various direct or indirect carbon emissions generated by tourism products throughout the entire production process. Globally, in numerous nations and areas, there's a lack of a system to monitor and statistically assess energy usage in tourism, indicating that the magnitude of carbon emissions cannot be directly discounted by tourism energy consumption. Current research indicates that the primary focus of carbon emissions from tourism lies in three sectors: transportation, lodging, and tourism-related activities. Consequently, this study utilizes a "bottom-up" decomposition approach, followed by a summation process, to determine the carbon emissions resulting from tourism in every area. Initially, we break down the trio of tourism transportation, lodging, and activities, employing the carbon footprint technique to assess each subsystem's carbon emissions; subsequently, we apply the summation approach to calculate the tourism sector's overall carbon emissions.

(1) Carbon emissions from tourism transportation

Given the primary existence of four tourism transport modes - road, railroad, civil aviation, and water transport - this research evaluates each mode's passenger turnover and carbon emission factor to determine the carbon emissions in tourism transportation [31]. To facilitate the calculation, it is assumed that $turnover_i$ is the passenger turnover of traffic mode i, $traveler_i$ is the percentage of tourists in the passenger turnover of traffic mode i, and λ_i is the carbon emission factor of traffic mode i. and, referring to existing research literature, the carbon emission factors of road, railroad, civil aviation, and water transportation are set at 133, 27, 106, and 137 *g/pkm*, $traveler_i$ is set at 13.8%, 31.6%, 64.7%, and 10.6% [30]. The formula for carbon emissions from travel and transportation C_{travel} is as follows:

$$C_{travel} = \sum_{i=1}^{4} \lambda_i \times turnover_i \times traveler_i \tag{1}$$

(2) Carbon emissions from tourist accommodation

Since the carbon emission of tourist accommodation is related to the number of room beds, room occupancy rate, and carbon emission factor of tourist accommodation, this paper assumes that the number of tourist hotel room beds is *bed*, room occupancy rate is *rental*, carbon emission factor of tourist accommodation is θ, and the number of days in a year is *Day*. Meanwhile, θ is taken as 2.456 $g/(bed \cdot day)$. Thus, the formula for carbon emissions from tourist accommodation C_{stay} is as follows:

$$C_{stay} = \sum_{day=1}^{365} \theta \times bed \times rental \tag{2}$$

(3) Carbon emissions from tourism activities

Considering that tourism activities mainly include sightseeing, leisure and vacation, visiting friends and relatives, business meetings, and other activities, this paper sums up the carbon emissions of the above-mentioned five types of activities as the carbon emissions of tourism activities. Among them, assume that $reception_j$ is the number of receptions of various types of tourism activities, and δ_j is the carbon emission factor of various types of tourism activities, and take the values of 417, 1670, 591, 786, and 172 g per person, respectively, with reference to the general practice of existing literature. Therefore, the formula for measuring carbon emissions from tourism activities C_{active} is as follows:

$$C_{active} = \sum_{j=1}^{5} \delta_j \times reception_j \tag{3}$$

(4) Total carbon emissions from tourism

Since tourism transportation, tourism accommodation, and tourism activities are the three main sources of carbon emissions from tourism. In this paper, those three are summed up to use as the total carbon emissions from tourism *C*. The specific calculation formula is as follows:

$$C = C_{travel} + C_{stay} + C_{active} \tag{4}$$

Spatiotemporal Differences in Tourism Carbon Emissions

Utilizing the previously mentioned metrics for tourism carbon emissions, this study calculates the carbon footprint of tourism across different areas of the Chinese Yangtze River Economic Belt between 2000 and 2020. Concurrently, using the years 2000, 2010, and 2020 as reference points, Fig. 3 depicts the geographical spread of carbon emissions within the tourism sector at each of these points. Overall, the Yangtze River Economic Belt's tourism-related carbon emissions exhibited a reverse "U" pattern, initially rising and subsequently falling, reaching a pivotal moment in 2011. This aligns with the perspective that initial tourism views the industry as one free of smoke. Over the coming years, swift economic and social progress has led to a significant surge in tourism needs, causing a swift rise in energy use and carbon emissions. Subsequently, as global warming due to greenhouse gas emissions alarmed every country, the focus shifted to reducing carbon emissions in the tourism sector.

In particular, back in 2000, Yunnan, situated in the higher segments of the Yangtze River Economic Belt, held the record for the most tourism-related carbon emissions, surpassing 4,000 tons. Conversely, the carbon emissions from tourism in the central areas were under 2,000 tons, while those in Jiangsu, Shanghai, and Zhejiang in the lower regions ranged from 2,000 to 4,000 tons. As of 2010, the carbon footprint from tourist activities in Guizhou's upper segments and Jiangxi's middle segments stayed under 2,000 tons. Tourism-related carbon emissions in Anhui's lower regions rose, while those in other locales escalated to over 4,000 tons. By 2020, with the worldwide agreement on reducing carbon emissions, there has been a decrease in carbon emissions across the majority of regions in the Yangtze River Economic Belt. Nonetheless, the carbon footprint from tourism in Hubei's central areas and Zhejiang's lower regions continues to exceed 4,000 tons.

Threshold Panel Model Specification

The fundamental concept of the nonlinear threshold model revolves around investigating if there's a structural shift in the relationship between explanatory variables and the explanatory variable following the alteration of the threshold variable. In essence, the impact of explanatory factors on the variables being explained can undergo substantial alterations once the threshold variable's value surpasses a specific critical threshold. Earlier theoretical studies indicate that the overall impact of the digital economy on tourism's carbon emissions is likely to vary structurally due to shifts in the local tourism market's size and the clustering of tourism industries, suggesting a potential

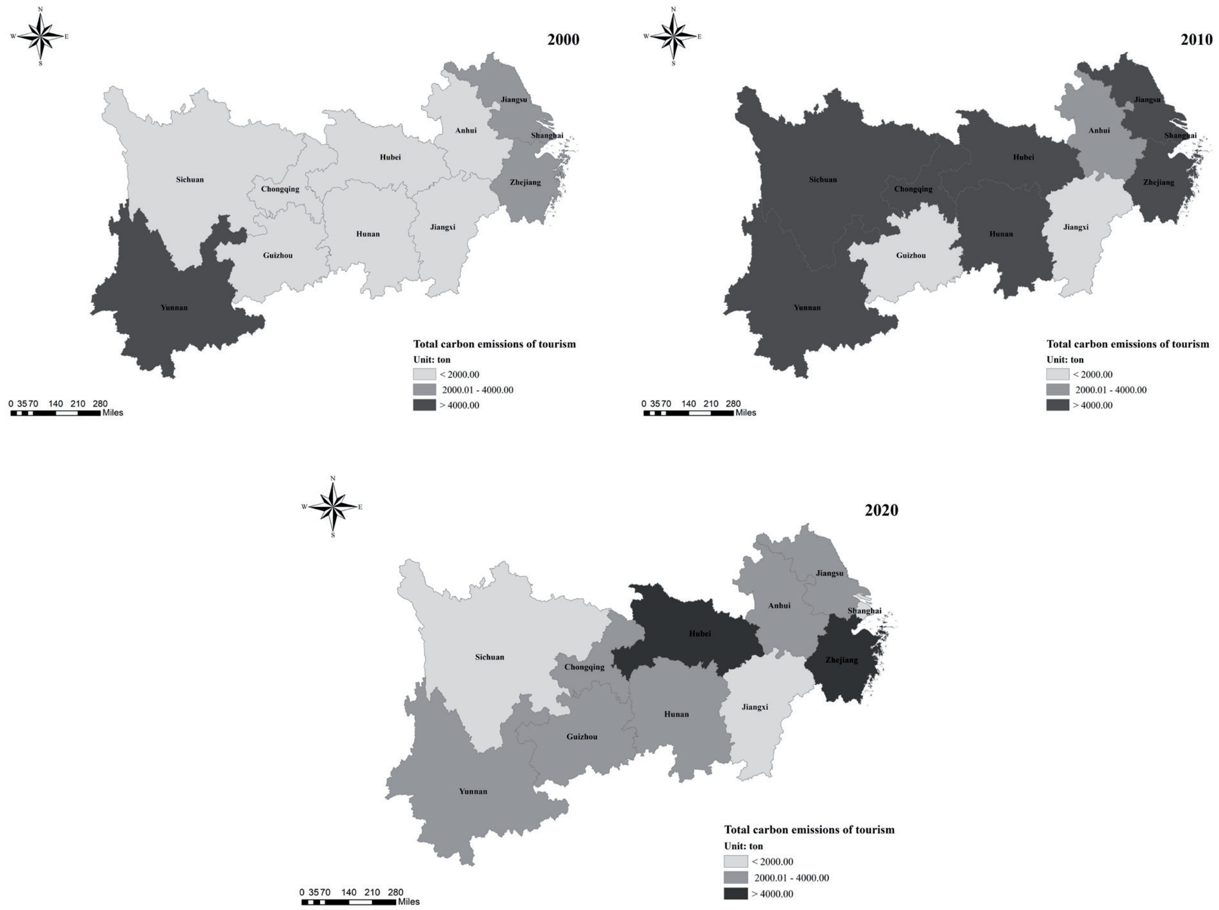

Fig. 3. Spatial-temporal evolution of tourism carbon emissions in 2000, 2010, and 2020.

threshold effect on the digital economy's influence on tourism's carbon emissions. For additional confirmation of this nonlinear correlation, the study employs Hansen's panel threshold model concept to develop a multi-threshold panel data model for the digital economy and tourism carbon emissions[2]:

$$
\begin{aligned}
\ln C_{it} &= \alpha + \beta_1 digital_{it} \times I(M \le \delta_1) + \beta_2 digital_{it} \times I(\delta_1 < M \le \delta_2) \\
&\quad + \cdots + \beta_n digital_{it} \times I(\delta_{n-1} < M \le \delta_n) \\
&\quad + \beta_{n+1} digital_{it} \times I(M > \delta_n) + \gamma_1 \ln(economy)_{it} \qquad ec \\
&\quad + \gamma_2 \ln(economy)^2_{it} + \gamma_3 \ln(efficiency)_{it} \\
&\quad + \gamma_4 \ln(innovation)_{it} + \gamma_5 opening_{it} + \gamma_6 urbanizati \\
&\quad + \gamma_7 ownership_{it} + \varepsilon_{it}
\end{aligned} \tag{5}
$$

Where i is the region, and t is the time. $\ln C_{it}$ is the explanatory variable that represents the natural logarithm of tourism emissions in region i at time t. $dogital_{it}$ is the explanatory variable that represents the level of digital economy in region i at time t. M is the threshold variable, δ is the threshold to be estimated, and $I(\cdot)$ is the indicative function. $\ln(ecomomy)_{it}$, $\ln(ecomomy)^2_{it}$, $\ln(efficiency)_{it}$, $\ln(innovation)_{it}$, $opening_{it}$, $urbanization_{it}$, and $ownership_{it}$ are the control variables in this study [31]. β is the impact coefficient of the explanatory variables in different zones, and γ is the impact coefficient of each control variable. $\varepsilon_{it} \sim iid(0, \sigma^2)$ are the random disturbance terms.

Variables and Data

This research focuses on carbon emissions resulting from tourism, computed as outlined in Section 3.2. The digital economy serves as the key explanatory factor in this research. In assessing the digital economy, the majority of existing research relies on a solitary metric like the count of Internet users, with a minority developing a comprehensive indicator system for its measurement [32]. This document develops an all-encompassing assessment index for the digital economy encompassing three aspects: the evolution of informatization, the growth of the internet, and the evolution of digital transactions, subsequently employing principal component analysis to gauge the digital economy's extensive development index. Included in these is the dimension of informatization development, encompassing factors like the overall telecommunication sector, income from software businesses, proportion of informatization staff, density of cell phone base stations, and density of fiber optic cables; conversely, the aspect of Internet development involves variables such as the rate of Internet, cell phone, and mobile Internet usage. Peking University Digital Finance Research collaboratively created the digital universal finance index for digital transaction development as a surrogate indicator. Peking University Digital Finance Research Center and Ant Financial Services Group collaboratively create the index.

There are two main threshold variables in this study, namely the level of tourism agglomeration and the density of the resident population in the tourism area. Among them, tourism agglomeration level reflects the supply side, meaning the concentration or density of the local tourism industry, measured by the locational entropy index of the tourism industry. The density of resident population in a tourism area is reflected on the demand side, which means the concentration or density of local tourism consumers, and is measured by the deep resident population per unit area of the tourism area. To facilitate the calculation, this paper assumes that the total tourism revenue of region i in period t is $turism_{it}$, the gross product is GDP_{it}, the size of the resident population is POP_{it}, and the geographical area is $area_{it}$. Thus, the tourism agglomeration level $agglomeration_{it}$ and the density of the resident population of the tourist place $density_{it}$ are as follows:

$$agglomeration_{it} = \frac{tourism_{it} \big/ \sum tourism_{it}}{GDP_{it} \big/ \sum GDP_{it}} \tag{6}$$

$$density_{it} = \frac{POP_{it}}{area_{it}} \tag{7}$$

Among all control variables, $\ln(ecomomy)_{it}$ represents the regional economic development level, measured as the natural logarithm of GDP per capita. The reason for controlling the regional economic development level and its quadratic variables is that, according to the environmental Kuznets theory, there is an inverted "U" shaped relationship between carbon emissions and economic development level. $\ln(efficiency)_{it}$ represents the regional energy use intensity, measured by the natural logarithm of energy use per unit of GDP. $\ln(innovation)_{it}$ represents technological innovation capacity, measured by the natural logarithm of the number of patents granted. $opening_{it}$ represents the degree of openness to the outside world, measured by the proportion of total imports and exports of goods to regional GDP. $urbanization_{it}$ represents the urbanization rate, measured by the proportion of urban resident population to total population. $ownership_{it}$ represents the ownership structure of the tourism industry, measured by the number of state-owned enterprises in star-rated hotels.

[2] The traditional classical panel econometric model only examines the linear effect of the independent variable on the dependent variable; Alternatively, by introducing the quadratic term of the independent variable, the U-shaped or inverted U-shaped relationship between the independent variable and the dependent variable can be examined. Compared to classical panel econometric models, nonlinear threshold models can examine the nonlinear effects of independent variables on the dependent variable within different ranges of threshold variables.

Table 1. Descriptive statistics.

Variable	N	Mean	SD	Min	Max
lncarbon	231	8.1784	0.9504	5.1417	10.7790
digital	231	0.2128	0.1342	0.0100	0.5320
ln(economy)	231	9.1194	0.6040	7.8867	10.5800
ln(efficiency)	231	0.9748	0.6297	0.3000	4.3100
ln(innovation)	231	7.3149	1.7764	3.7136	10.8175
opening	231	0.3076	0.3810	0.0285	1.6682
urbanization	231	0.5050	0.1694	0.2348	0.8960
ownership	231	0.3638	0.1745	0.1260	0.9460

The study explores the complex interplay between the digital economy and tourism-related carbon emissions, utilizing panel data from 11 different provinces and cities within China's Yangtze River Economic Belt between 2000 and 2019. The absence of a comprehensive analysis of the timeline post-2020 stems from a significant worldwide New Crown Pneumonia outbreak since that year, previously leading to a worldwide economic slowdown, with the Yangtze River Economic Belt in China being a prime example. Incorporating the timeframe post-2020 into this research would probably result in skewed conclusions. Consequently, the era of the New Crown Pneumonia outbreak was excluded from the study's timeframe in this paper. All variables in this research were initially sourced from various sources, including the China Economic and Social Big Data Research Platform on the China Knowledge Network, the China Statistical Yearbook, Tourism Statistics Almanc, the Statistical Yearbook of Chinese Cultural Relics, the China Domestic Tourism Market Sentiment Report, and the Ministry of Culture and Tourism of the People's Republic of China Culture and Tourism Development Statistical Bulletin. Additionally, missing data were supplemented with regional Statistical Yearbooks, the Statistical Bulletin of National Economic and Social Development, and the government's annual work reports. To achieve stronger estimation outcomes, certain variables based on values are adjusted in line with this paper's 2000 base period, followed by the application of natural logarithm values. The descriptive statistical results of various variable data are shown in Table 1.

Results and Discussion

Existence Test of Threshold Effect

Prior to calculating the model, it's essential to ascertain the structure of the panel threshold model, namely, the presence of threshold effects and the count of thresholds. Consequently, this document establishes the theories of no threshold, a single threshold, a double threshold, and a triple threshold, sequentially conducting regression analysis on the threshold model based on various suppositions, and subsequently evaluating the panel threshold model's presence and threshold count based on the regression model's relevance. Given that this research includes two critical factors: the degree of clustering in tourism industries and the concentration of inhabitants in tourist areas, they are categorically analyzed in the existence test for the threshold effect.

This document presents the F-statistic and p-values for the threshold effect tests related to the two threshold variables, derived 1000 times using the

Table 2. Results for threshold effect test.

Threshold variable	Type	F stat.	Prob.	Crit 10	Crit 5	Crit 1
The level of tourism industry agglomeration	Single	24.94^{**}	0.04	18.0174	21.6501	27.5200
	Double	15.26	0.11	15.4135	23.8512	29.2598
	Triple	23.77	0.26	54.5461	66.9146	75.9842
The density of resident population	Single	39.31^{**}	0.04	25.4001	36.0628	44.2501
	Double	13.89	0.26	18.4020	27.7478	34.7733
	Triple	23.51	0.28	30.3795	38.1199	49.4579

Note: *** P<0.01, ** P<0.05, * P<0.1, robust standard errors in parentheses (the same below).

Bootstrap technique (Table 2). The outcomes of the tests, considering the tourism industry agglomeration level's threshold variable, reveal: a single threshold effect holds significance at the 5% level, with respective F-statistic values of 24.94 and 0.04; double threshold and triple threshold effects lack statistical importance, with corresponding F-statistic values of 15.26 and 23.77. The outcomes of the tests, considering the threshold variable for the density of resident populations in tourist areas, reveal: a notable single threshold impact at the 5% significance level, with associated F-statistic figures and p-values of 39.31 and 0.04, respectively; the effects of double and triple thresholds are statistically negligible, and the respective F-statistic figures are 13.89 and 23.51. To summarize, the key factors such as the level of tourism industry clustering and the density of tourist localities both exhibit notable singular threshold figures, leading to the adoption of a unified threshold model as the measurement model.

Threshold Estimation and Interval Division

Once the panel threshold model's structure is established, it becomes essential to calculate the threshold figures and their respective confidence ranges, which relate to the two key factors: the level of tourism clusters and the concentration of inhabitants in tourist areas. This document, adhering to Hansen's approach, defines the threshold values for estimation based on the likelihood ratio statistic LR of 0. Furthermore, the pivotal figure for all LR values at a 5% significance threshold represents the confidence interval for every threshold estimate. Table 3 illustrates that the critical variable for tourism clustering equates to a singular threshold of 1.08, while the concentration of inhabitants in tourist areas is linked to a singular threshold of 389.90.

This study categorizes the research sample into various areas based on the singular threshold estimates of tourism cluster levels and the density of resident populations in tourist locales. Based on the tourism agglomeration level, it can be divided into low tourism agglomeration areas [0.5600, 1.0800), and high tourism agglomeration areas [1.0800, 3.2300]. The low tourism agglomeration area is mainly located in the upper reaches of the Yangtze River Economic Belt, while the high tourism agglomeration area is mainly located in the middle and lower reaches of the Yangtze River Economic Belt (Fig. 4, Left). According to the density of resident population in tourism places, it can be divided into low population density areas [100.6444, 389.9042), high population density areas [389.9042, 3949.5620]. In the Yangtze River Economic Belt, areas of low population density predominantly reside in its middle and upper segments, while areas of high population density are chiefly situated in its lower segments (Fig. 4, Right). Among the samples collected at varying threshold intervals, 118 were from areas with low tourism density, and 113 from areas with high tourism; 147 from regions with low tourism density, and 84 from

Table 3. Results for threshold estimation.

Threshold variable	Type	Threshold	Confidence interval	
			Lower limit	Upper limit
The level of tourism agglomeration	Single	1.0800	1.0500	1.1300
The density of resident population	Single	389.9042	387.3633	426.4137

Note: 95% confidence intervals are based on the Bootstrap method 1000 times.

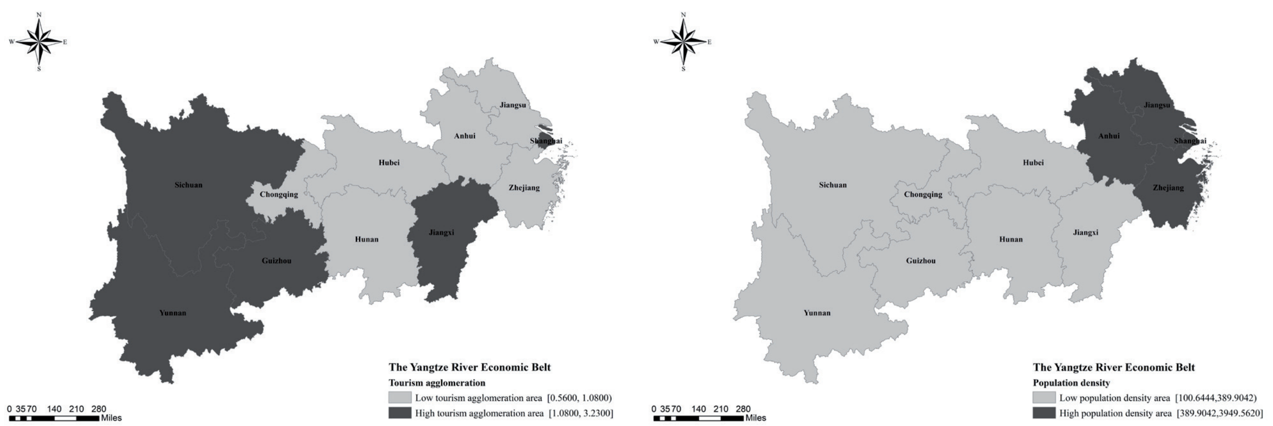

Fig. 4. Threshold interval division based on different threshold variables.

areas with high tourism density.

Threshold Effect Estimation and Discussion

Benchmark Regression Results

Given that the Hansen panel threshold model's estimation relies on a fixed effects model, verifying the presence of significant fixed effects in the panel threshold model is essential prior to regression estimation. For this purpose, the paper employs the Hausman test to evaluate the suitability of the fixed-effects model in estimating the panel threshold model. The outcomes of the tests indicate chi statistics figures for regression equations to be 42.52, 20.70, 66.66, and 10.19, in that order, with respective probability figures of 0, 0, 0, and 0.02, suggesting the dependability of the aforementioned four regression equations for estimations using the fixed-effects model.

This study empirically examined the overall impact of the digital economy on tourism's carbon emissions and its diverse features, using collective sample data from two variable groups, including the level of tourism agglomeration and the density of tourist localities (Table 4). From the estimation results of equations (1) and (2), the effect of the digital economy on the carbon emissions of the tourism industry under different agglomeration levels shows obvious threshold characteristics. Among them, the net effect of the digital economy on tourism carbon emissions is significantly positive in the band of low tourism agglomeration levels, i.e., when the tourism agglomeration level is below 1.08, indicating that the expansion of the digital economy scale intensifies tourism carbon emissions. This is because the level of tourism agglomeration reflects the intensity of the tourism industry. When the level of tourism agglomeration is low, the scale effect of the digital economy is not fully released, and the

Table 4. Threshold effect estimation results.

Variables	*Dependent variable: Total carbon emissions of tourism*			
	(1)	(2)	(3)	(4)
	Low tourism agglomeration area	High tourism agglomeration area	Low population density area	High population density area
digital	3.3046***	-3.9417**	2.3769*	-2.1776**
	(1.1653)	(1.7703)	(1.3785)	(0.9334)
ln(economy)	17.6113***	12.5350*	19.8674***	24.6291***
	(3.8259)	(6.9404)	(3.5612)	(7.1373)
ln(economy)^2	-0.8844***	-0.6458*	-1.0093***	-1.4254***
	(0.2039)	(0.3787)	(0.1866)	(0.4046)
ln(efficiency)	-0.3129*	-0.5532*	-1.8479***	-0.7620***
	(0.1990)	(0.3057)	(0.3226)	(0.1640)
ln(innovation)	-0.1103*	-0.2536**	-0.4289***	-0.1239*
	(0.0604)	(0.0936)	(0.0753)	(0.0706)
opening	0.0862	-0.2593	-0.1700	0.1764
	(0.4149)	(0.3588)	(0.2853)	(1.2493)
urbanization	-2.3732	-2.0508*	-0.9983	-3.9760**
	(1.5882)	(1.1016)	(0.8840)	(1.9719)
ownership	0.1675	0.6902	0.1780	0.0579
	(0.3703)	(0.5328)	(0.4392)	(0.4493)
cons	-79.0864***	-52.7264*	-92.7860***	112.6381***
	(18.3529)	(30.4583)	(17.3903)	(31.8682)
Region fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Obs.	118	113	147	84
R^2	0.8753	0.8891	0.8753	0.8566
F Stat.	249.500***	387.680***	249.500***	772.980***

growth of the own carbon emissions brought by the digital development of the tourism industry is not yet offset by the carbon emission reduction effect brought by agglomeration and the scale effect. Therefore, the digital development of the tourism industry not only does not promote carbon emission reduction, but also aggravates it. Moreover, every 1 percentage point increase in the digital economy will lead to a 3.3 percentage point increase in carbon emissions from the tourism industry. However, the net impact of the digital economy on tourism carbon emissions is significant in regions with high tourism industry agglomeration, i.e., regions with tourism industry agglomeration above 1.08, implying that the digital development of the tourism industry has contributed to the reduction of carbon emissions. At this point, due to the high level of concentration in the, tourism industry, the digital development of the scale of the effect has been fully developed, and the carbon emission reduction effect is gradually highlighted, offseting the expansion of the digital economy brought about by the increase in carbon emissions. At present, every 1 percentage point increase in the digital economy will lead to a 3.94 percentage point reduction in carbon emissions in the tourism industry.

From the estimation results of regression equations (3) and (4), the effect of the digital economy on tourism carbon emissions also shows obvious structural change characteristics in different zones of resident population density in tourism places. In the low density zone of the resident population in the tourism area, i.e., when the density of the resident population is below 389.90, there is a noticeable positive link between the digital economy and the tourism sector's carbon emissions, suggesting that the growth of the digital economy amplifies the tourism industry's carbon footprint. The reason lies in the unestablished scale effect of tourism consumers in sparsely populated regions, coupled with the carbon emissions generated by the development of the digital economy, rendering the promotion of digital tourism development during this era ineffective in meeting carbon emission reduction targets. Moreover, every 1 percentage point increase in the size of the digital economy at this time will lead to a 2.38 percentage point increase in total tourism carbon emissions. In addition, the scale effect of consumers in tourism is basically formed when the density of the resident population is higher than 389.90 in the higher zone of tourism. Furthermore, the impact of reducing carbon emissions through the scale effect greatly surpasses the growth effect of its own carbon emissions from the digital evolution of the tourism sector, suggesting that fostering the digital growth of this industry could aid in reducing carbon emissions. To sum up, the impact of the digital economy on tourism-related carbon emissions isn't confined to just one beneficial or detrimental influence, but rather a critical threshold effect. Particularly, once the level of tourism concentration, mirroring the supply aspect, and the density of the resident population, mirroring the demand aspect, attains a specific limit, the digital growth of tourism can fulfill its objectives of reducing carbon emissions effectively.

From the estimation results of the control variables, in the estimated equations (1) to (4), The calculated coefficients for key economic development variables show a notable positive trend, while those for secondary variables display a significant negative trend, suggesting a clear inverse "U" type correlation in Kuznets between regional economic growth and tourism-related carbon emissions. Put differently, with the rise in regional economic growth, there's a pattern of escalating and subsequently diminishing carbon emissions in the tourism sector. The rationale is that during the initial phases of development, the escalation in economic magnitude and developmental stage results in a rise in carbon emissions. Once these levels are attained, the scale effect begins to manifest, fostering a decrease in carbon emissions. The calculated values for the energy consumption intensity factor show a notable negative trend across all four equation groups, suggesting that increased energy consumption per GDP unit aids in lowering carbon emissions. The calculated coefficient for the variable of technological innovation capacity is notably negative across all four equation sets, suggesting that greater technological innovation capacity amplifies the impact on reducing carbon emissions in the tourism sector. In all four equation sets, the calculated coefficients for the degree of external openness variable show no significant impact, suggesting the influence of external openness on tourism's carbon emissions is insignificant. The projected values for the urbanization rate factor show a notable negative trend exclusively in regions where tourism is densely populated and the population density in tourist locales is high, a trend not observed in other areas. This suggests that a rise in urbanization rates can only lead to a decrease in carbon emissions once the concentration of the tourism sector or its consumers reaches a specific threshold. The calculated values for the tourism sector's property rights structure factor show no notable significance across all calculated formulas, suggesting that the substantial presence of government-owned businesses in luxury hotels doesn't markedly impact the tourism industry's carbon footprint.

From the significance test results of the regression equations, the F-statistic values of equations (1) to (4) are 249.5, 387.68, 249.5, and 772.98, respectively, and the corresponding probability values are all zero, indicating that the econometric model is well set. Moreover, the goodness-of-fit values of the four sets of equations are 0.875, 0.889, 0.875, and 0.857. This suggests that the aforementioned regression formulas are capable of elucidating roughly 88% of the data linking the dependent and independent variables.

Tourism Carbon Emissions Decomposition

Earlier studies indicate that the primary sources of carbon emissions from tourism are threefold:

transportation, lodging, and tourism-related activities. Thus, which area is crucial for reducing carbon emissions through a digital economy? The study breaks down carbon emissions from tourism into those from transportation, lodging, and tourism, and additionally conducts empirical evaluations of how the digital economy impacts carbon emissions across various tourism sectors.

The data in Table 5 reveals that in areas with low tourism, the digital economy's overall impact on carbon emissions from tourism transport and lodging is negligible, whereas it's notably beneficial for tourism activities. This suggests that the digital economy's influence on carbon emissions from tourism activities is minimal in these low-tourism regions. Within areas with a high concentration of tourism, the digital economy markedly lowers carbon emissions in tourism transport, transportation, and related activities. Furthermore, the impact of reducing emissions on tourism transport and its operations is notably substantial. It is evident that in areas densely populated by tourists, the digital economy primarily concentrates on reducing carbon emissions in the tourism transport and tourism sectors.

Furthermore, across various threshold periods segmented by the density of tourist spots, the findings align with the estimated formulas, suggesting that the digital economy aids in lowering carbon emissions in densely populated regions, primarily through the enhancement of carbon emission reduction in tourism transportation and activities. To sum up, the impact of the digital economy on diminishing carbon emissions within the tourism sector predominantly occurs in areas with dense populations and dense urban centers, with the key strategy being the advancement of carbon emission reduction in tourism transportation and related activities.

Heterogeneity Analysis of Tourism Carbon Emissions

Besides measuring carbon emissions from tourism, this study substitutes variables related to tourism carbon emissions with variables like tourism carbon emission intensity, per capita carbon emission, and carbon emission intensity for analyzing heterogeneity (Table 6). Within this context, the intensity of carbon emissions from tourism is quantified by the amount of carbon released per GDP unit, while the density of carbon emissions is determined by the amount of carbon emitted per area unit.

Results from the heterogeneity analysis reveal that the digital economy exhibits a reversed 'V' threshold impact on the intensity, per capita, and density of carbon emissions in tourism, irrespective of whether these are segmented into threshold ranges based on the level of tourism agglomeration or the density of resident populations. Particularly at lower thresholds, the digital economy has markedly enhanced the intensity, per capita, and density of carbon emissions in the tourism

Table 5. Structural decomposition results.

Dependent Variables	*Independent variable: Digital economy*			
	(1)	(2)	(3)	(4)
	Low tourism agglomeration area	High tourism agglomeration area	Low population density area	High population density area
Carbon emissions from tourism transportation	1.1178 (1.1843)	-6.4959*** (1.3528)	0.5243 (1.0348)	-3.0311*** (1.3587)
Carbon emissions from tourist accommodation	0.1719 (1.1628)	-2.1129** (0.9208)	1.3246 (0.9524)	-1.2675* (0.6616)
Carbon emissions from tourism activities	3.1147* (1.8588)	-5.0362*** (1.9794)	1.4510** (0.6344)	-2.9130** (1.5064)

Table 6. Heterogeneity analysis results.

Dependent Variables	*Independent variable: Digital economy*			
	(1)	(2)	(3)	(4)
	Low tourism agglomeration area	High tourism agglomeration area	Low population density area	High population density area
Carbon emission intensity	1.8413*** (0.6177)	-1.4601*** (1.2080)	1.3893* (0.8298)	-1.1299*** (0.2665)
Per capita carbon emissions	3.6453** (1.3536)	-5.6735*** (1.8370)	3.8348*** (0.9532)	-5.8234*** (2.0448)
Carbon emission density	3.9898*** (1.4886)	-5.7655*** (2.1059)	1.3753*** (0.4759)	-2.1709*** (0.4480)

sector; at higher thresholds, it markedly diminishes these aspects of the industry. Contrarily, the digital economy exerts a more significant peripheral impact on the tourism sector's per capita carbon emissions and their density, suggesting that in areas with elevated threshold levels, advancing the digital economy is more effective in diminishing the tourism industry's per capita and carbon emission densities.

Conclusions

Employing both the carbon footprint and "bottom-up" approaches, this study quantified the carbon emissions from tourism in the Yangtze River Economic Belt of China, focusing on the trio of tourism transportation subsystems: accommodation and activities. Ultimately, an econometric model with a nonlinear panel threshold was developed to concretely examine how the digital economy impacts tourism carbon emissions and its diversity. Key findings included: firstly, determining if the concentration of tourism industries or the density of permanent residents in tourist areas serves as the benchmark variable; and secondly, analyzing the digital economy's influence on carbon emissions from tourism in the Yangtze River Economic Belt reveals a uniform threshold effect. Additionally, the critical figures for clustering tourism industries and the density of permanent residents in tourist areas stand at 1.08 and 389.90, in that order. Furthermore, as tourism clusters and the density of residents in tourist spots rise, the digital economy's overall impact on tourism carbon emissions manifests as an inverted "V" type single threshold. This growth in both tourism concentration and resident density in tourist areas aids the digital economy in reducing carbon emissions in tourism. As a third point, the impact of the digital economy on diminishing carbon emissions within the tourism sector primarily focuses on transportation and tourism-related activities. As a fourth point, the digital economy markedly influences the intensity of carbon emissions in tourism, per capita carbon emissions, and their density, while exerting a more pronounced marginal impact on both per capita carbon emissions and their density.

The digital economy acts as a two-sided blade, capable of lowering carbon emissions in the tourism sector and naturally emitting carbon dioxide. Consequently, indiscriminately advancing the digital economy or advocating for the digital overhaul of the tourism sector places the local tourism industry in a quandary of superior development and cutting carbon emissions. Specifically, in areas characterized by sparse tourism clusters and sparse populations, actively fostering the digital growth of the tourism sector will prove challenging to achieve substantial economic gains and exert pressure, while also leading to substantial rises in carbon emissions and environmental hazards, complicating the avoidance of the "inefficiency" dilemma. Consequently, to achieve a harmonious interplay between tourism's digital evolution and the diminution of carbon emissions, it's imperative that we meticulously strategize and cultivate the digital economy with a focus on scientifically evaluating tourism carbon emission laws and also dismantle the inflexible trend of ineffective grouping of tourism carbon emissions by judiciously directing tourism businesses and demographic grouping. Consequently, this enhances the impact of the digital economy on reducing carbon emissions, leading to the superior growth of tourism and creating a mutually beneficial scenario for both the enhancement of tourism quality and the decrease in carbon emissions.

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Conflict of Interest

Authors declare no conflict of interest.

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