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How to decouple tourism growth from carbon emissions? A case study of Chengdu, China

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ABSTRACT

The world has witnessed unparalleled tourism growth over the past decades but accompanied by significant carbon emissions. Therefore, addressing the conundrum that is to decouple tourism growth from carbon emissions is of great significance for achieving sustainable tourism. In this paper, we extend the framework of decoupling analysis by introducing the logarithmic mean Divisia index (LMDI) decomposition model and an innovative accounting approach into the Tapio decoupling index model. The results show that (1) during the observed period, an overall weak decoupling of tourism growth from carbon emissions and different influential factors played different roles in the decoupling process and that (2) various decoupling determinants are statistically linked, and maintaining the synergistic relationship among different decoupling strategies in the tourism industry should be an important issue to governmental authorities.

1. Introduction

As an environmentally sensitive industry, tourism is faced with a series of short-term external shocks such as terrorist attacks, natural disasters (e.g., earthquakes, floods), and epidemics (Barbhuiya & Chatterjee, 2020). Compared with these short-term external shocks, for at least the last 150 years there has been a growing awareness that the Earth's climate is changeable; indeed, the global climate has changed many times throughout history and prehistory, often with significant implications for human well-being and livelihoods (Toimil, Losada, Nicholls, Dalrymple, & Stive, 2020). Since the 1950s, anthropogenic emissions of greenhouse gases, particularly carbon dioxide, have given rise to unprecedented and ongoing changes in the state of the climate, such as increases in temperature, changes in precipitation patterns, changes in the occurrence of floods and droughts, sea-level rise, etc., while path dependence on fossil fuels and traditional economic development patterns makes decarbonisation targets difficult to achieve in the short term (Field & Barros, 2014). In this sense, coping with climate change via energy conservation and emission reduction has always been a long-term challenge for many industries in Mainland China, including the tourism industry (Hasselmann et al., 2003; Student, Lamers, & Amelung, 2020; Wang & Wang, 2018). The tourism industry is no longer considered a "smokeless industry", given the increasing environmental awareness of residents and the government (Gössling & Scott, 2018). Large-scale tourism activities and the operation of their supporting facilities inevitably lead to substantial resource consumption and carbon emissions (Zha, He, Liu, & Shao, 2019). The effect of tourism on the environment thus renders this industry a non-negligible contributor to anthropogenic climate change (Qiu, Fang, Yang, & Zhu, 2017). However, some scholars argue that policies that focus much on reducing carbon emissions may also increase the risk of tourism economic loss (Wang & Wang, 2018). The viewpoint that the tourism industry is faced with increasing pressure to balance economic growth with reducing carbon emissions has been acknowledged by many scholars (Gössling & Scott, 2018; Zha, Tan, Yuan, Yang, & Zhu, 2020). In light of this, addressing the conundrum that is to decouple tourism growth from environmental pressures is of great significance for achieving sustainable tourism development.

Decoupling analysis, initially applied by Zhang (2000) from the perspective of environmental economics, refers to tracking the temporal changes in the nexus between economic growth and environmental pollution (Wu et al., 2019). Because this technique can easily reveal the real-time pressure state between tourism growth and environmental quality, it has been widely applied in the tourism-environment system (Chen, Thapa, & Yan, 2018; Tang, Shang, Shi, Liu, & Bi, 2014). However, in the context of the sustainable development of the tourism industry, most of the extant literature on decoupling has focused only on the descriptive analysis of the tourism–environment decoupling status

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and evolution trends. The inner mechanism underlying the changes in the decoupling relationship between tourism growth and environmental pollution, to a large extent, has been neglected in the literature, failing to provide more targeted and effective policy implications to promote the decoupling evolution. Additionally, several methods, including the econometric method (Sun, 2016), Computable General Equilibrium (CGE) model (Zhang & Zhang, 2018), and decomposition approach (Liu, Feng, & Yang, 2011), have been used to identify the driving factors from the environmental economics perspective. Notably, an overwhelming majority of studies have concentrated only on the driving factors that influence tourism-related carbon emissions. Because policies that concentrate on only reducing carbon emissions may also increase the risk of tourism economic loss (Wang & Wang, 2018), these studies may reach a biased conclusion, which cannot offer effective guidance for balancing tourism economic growth and environmental protection. Thus, the purpose of our paper is to bridge the previously mentioned gap by providing a novel decoupling analytic framework for tourism–environment decoupling nexus, which not only allows for the exploration of the determinants of decoupling evolution but also for the clarification of the interactive relationship among determinants.

The contributions of this paper are as follows:

(i). We investigate the driving factors that influence the dynamic relationships between tourism growth and carbon emissions by using the Tapio decoupling index model and logarithmic mean Divisia index (LMDI) decomposition method. This work enriches the literature on tourism decoupling research and allows us to answer the question of why the decoupling status occurs, which can provide more reasonable and effective guidance for the sustainable development of the tourism industry.

(ii). We advance this strand of the literature by clarifying the interactive relationships among the previously mentioned determinants, by employing an innovative accounting approach (IAA) that includes forecast error variance decomposition (FEVD) and impulse response functions (IRFs). The results advance the understanding of how determinants influence each other.

Through its rapid development, the tourism industry has become a strategic pillar of the national economy in China. In 2017, it has contributed approximately 11.04% of the gross domestic product (GDP) and created more than 28.25 million jobs in China (China Tourism Academy-CTA, 2018). However, this large-scale expansion predominantly depended on the excessive use of resource inputs, thereby increasing carbon dioxide emissions (Liu, Shi, Hai, Zhang, & Li, 2018). This level of environmental degradation has further burdened China's national and regional governments to advance tourism growth while curbing carbon emissions. Consequently, the decoupling of tourism growth from carbon emissions has been one of the top priority issues of the Chinese government. However, due to the imbalanced levels of economic development, tourism resource endowment, and regional infrastructure, there is significant regional heterogeneity in tourism development—both in scale and potential—in China (Liu, Zhang, & Fu, 2017). This suggests that a "one-size-fits-all" policy for all regions would be ineffective. The city, as an important place for tourist activities, contains a large number of "high-energy-consuming and high-emission" tourism goods/services and the corresponding emissions account for a large proportion of the total tourism emissions (Rico et al., 2019). Meanwhile, with the accelerating urbanisation, the city inevitably faces more environmental pressure from burgeoning tourism. Thus, addressing the conundrum that is to decouple tourism growth from carbon emissions at the city level is of great significance for achieving sustainable tourism.

This study provides a comprehensive framework for investigating the decoupling relationship between tourism growth and carbon emissions and its inner mechanism. We take Chengdu, a typical city in Western China, as a case to examine the applicability of the proposed analytic framework and provide insights into the green development of the tourism industry. Based on an integrated methodology, we analyse the (1) dynamics of carbon emissions in the tourism industry over the observed period; (2) the decoupling relationship between tourism growth and carbon emissions; (3) the driving factors that influenced the historical decoupling evolution; and (4) interactive relationships among the driving factors. The remainder of this paper is organised as follows: The next section reviews the literature and then provides an overview of Chengdu, followed by an introduction to the proposed methodology and data sources. The empirical results and analysis are presented in the penultimate section, before we present our conclusions.

2. Literature review

Based on an extended decoupling analytic framework, this study attempts to investigate the dynamic relationship between tourism growth and carbon emissions as well as its inner mechanism. Thus, in this section, we aim at presenting a foundation for what this study seeks to accomplish, and Table 1 summarises some studies we reviewed in this article according to relevant dimensions.

2.1. Tourism-related carbon emissions

Since Gössling (2000) first proposed a measurement technique for tourism-related carbon emissions, related studies have attracted worldwide attention from academia (Becken & Patterson, 2006; Gössling & Hall, 2008). Geographically, scholars have applied a variety of methods to the measurement of such emissions at global (Lenzen et al., 2018), national (Becken & Patterson, 2006), regional (Munday, Turner, & Jones, 2013), and tourism destination (Sun, 2014) levels. Based on the internal structure of the tourism system, scholars have also quantified the carbon emissions associated with the specific subsectors of the tourism industry, such as transportation (Peeters, Szimba, & Duijnisveld, 2007) and accommodation (Chan, 2005). Furthermore, the scope of research on tourism-related carbon emissions is no longer confined only to the measurement of carbon emissions in recent years. For instance, some scholars have forecasted the growth trend of tourism-related carbon emissions under different scenarios (Dubois & Ceron, 2006). Others have considered such emissions as an indicator to represent the environmental pressure from tourism growth and, thus, explored the causal relationship among variables such as economic development, tourism growth, and environmental pressure (Katircioglu, 2014).

Due to the lack of special statistics as well as the complexity of the tourism system, there is no standard and unified method to account for the carbon emissions from the tourism system (Kuo & Chen, 2009). Studies on carbon emissions have mainly drawn on two approaches: the "top-down" method and the "bottom-up" method. The former mainly relies on publicly available data, such as tourism satellite accounts (TSAs) and national economic accounting, to estimate carbon emissions from the tourism industry (Liu et al., 2018). Scholars have combined this approach with the input–output model to estimate macro-emissions (Lenzen et al., 2018; Liu et al., 2011). Based on the perspective of commodity and service consumption in tourism, the latter approach estimates the tourism carbon emissions by dividing the tourism industry into several categories, such as transportation, accommodation, and tourism activities (Becken & Patterson, 2006; Qiu et al., 2017).

Specific to China, research on the tourism-related carbon emissions started later, but has yielded some rewarding achievements (Meng, Xu, Hu, Zhou, & Wang, 2017). Shi and Wu (2011) first applied the bottom-up approach to estimate emissions at the national level in 2008. With the help of the tourist consuming minus coefficient, Xie and Zhao (2012) subsequently constructed a rational method for measuring tourism-related carbon emissions based on the status of the Chinese tourism industry. Zhong, Shi, Li, Luo, and Luo (2014) established a carbon emissions measurement method for the Chinese tourism industry by

Table 1
Summary of relevant studies.

Dimensions	Authors	Method	Research objective (period)	Main findings
Tourism-related carbon emissions	Becken and Patterson (2006)	A bottom–up analysis & top–down analysis	New Zealand (1997–1998; 2000)	Both approaches result in similar estimates of the degree to which tourism contributes to national CO_2 emissions.
	Dubois and Ceron (2006)	Sensitivity analysis	France (2000)	"Business as usual" trends imply that French tourism and leisure Greenhouse Gas (GHG) emissions could increase by 90% by 2050, and passenger-kilometers by 200%.
	Katircioglu (2014)	Autoregressive distributed lag	Turkey (1960–2010)	Energy consumption and tourism are in a long-term equilibrium relationship with CO_2 emissions.
	Lenzen et al. (2018)	TSAs and the input–output model	160 countries (2009–2013)	Tourism's global carbon footprint accounts for approximately 8% of global greenhouse gas emissions.
	Meng et al. (2017)	TSA and the input–output model from productive industry	China (2002, 2005, 2007, 2010)	Indirect carbon emissions from other tourism sectors except the transport sector were 3–4 times their direct carbon emissions.
Decoupling analysis	Shuai et al. (2019)	Tapio decoupling analysis	133 individual countries (2000–2014)	Economic growth decouples from carbon intensity, carbon emission per capita, and total carbon emission in sequential order, and the proportion of the decoupling countries of higher income-level are higher than those of lower income-level.
	Ren and Hu (2012)	Laspeyres index approach & Tapio decoupling analysis	Chinese nonferrous metals industry (1996–2008)	The Chinese nonferrous metals industry has gone through four decoupling stages during the study period.
	Wang et al. (2017)	Tapio decoupling analysis	China (1996–2013)	Only three decoupling statuses occurred in the CO_2 emission–GDP decoupling during the study period.
	Tang et al. (2014)	Tapio decoupling analysis	Chinese tourism industry (1990–2012)	Decoupling of CO_2 emissions from economic growth in the tourism industry alternated between negative decoupling and weak decoupling during the study period.
	Chen et al. (2018)	Tapio decoupling analysis & LMDI decomposition	Yangtze River Delta's tourism (2001–2015)	The decoupling relation between tourism-related CO_2 emissions and economic growth, in general, was desirable, except in 2004.
Analysis of impact factors	Cansino et al. (2018)	LMDI decomposition & Vector autoregressive (VAR) model	Chile (1991–2013)	Energy intensity factor is the main compensating factor of Chile's CO_2 emission and carbon intensity react to shocks more significantly in the short term.
	Bianco (2020)	IDA-LMDI decomposition	Tourism sector in Italy (1995–2017)	Changes in electricity intensity and the industrial structure were responsible for an increase in the electricity consumption of 5.581 GWh, whereas the economic structure was responsible for a decrease of 1.337 GWh.
	Liu et al. (2011)	Input-output model & LMDI decomposition	Tourism industry in Chengdu, China (1999–2004)	Energy intensity, expenditure size, and industry size are generally

(continued on next page)

Table 1 (*continued*)

Dimensions	Authors	Method	Research objective (period)	Main findings
				found to be principal drivers of tourism-related emission growth, whereas energy share and consumption structure are not found to have a substantial influence on the growth of tourism industry emissions.
	Moutinho et al. (2015)	Decomposition analysis	Portuguese tourism industry (2000–2012)	The capital over labour productivity intensity effect has the strongest influence, while the carbon is at ion index exerts a positive influence on tourism-related CO_2 emissions.
	Alam et al. (2011)	Vector autoregressive (VAR) model	India (1971–2006)	Their findings provide evidence of the existence of bi-directional Granger causality between CO_2 emissions and energy consumption in the long-run but neither energy consumption nor CO_2 emissions causes movements in the variable of real income.
	Wang and Wang (2018)	Tapio decoupling analysis & LMDI decomposition	China (2000–2016)	Economic scale effect exerts a positive effect on carbon emissions, while energy intensity effect plays an inhibiting role. The effect of the population effect and carbon intensity effect was found to be negligible. And the energy intensity was a weak effect in decoupling effort.
	Karakaya et al. (2019)	Tapio decoupling analysis & LMDI decomposition	Turkey (1990–2016)	Economic growth and population effects are the main contributors in increases in carbon emissions in Turkey, and there is either no decoupling relationship between economic growth and carbon emissions in most of the years.

integrating the life cycle assessment theory, input–output analysis methods, and the national economic accounting system.

A macro-economic approach to the estimation of tourism-related carbon emissions is seldom preferred owing to the non-availability of statistical data and TSAs in China (Luo, Becken, & Zhong, 2018). The bottom-up method using tourism consumption data can overcome this dilemma to some extent (Shi & Wu, 2011). It can also offer relevant and detailed information on tourist behaviour, resource end-uses, and micro-level sources of carbon emissions, which can be useful for decision-making by both operators and policymakers (Becken & Patterson, 2006). Therefore, the bottom-up approach has become increasingly popular for estimating tourism-related carbon emissions (Chen et al., 2018; Qiu et al., 2017).

2.2. Decoupling of carbon emissions from economic output

The concept of "decoupling" first originated in the field of physics, then later introduced to the field of environmental science to reflect the temporal changes in the nexus between economic growth and environmental pollution (Wu et al., 2019). Zhang's (2000) seminal study was the first to apply decoupling in environmental studies to analyse the decoupling relationship between economic growth and carbon emissions. OECD (2002) proposed a "decoupling indicator" and divided the decoupling states into absolute and relative decoupling. Tapio (2005) further employed the OECD decoupling model to overcome the dilemma of base period selection, and then formed a new decoupling index based on the decoupling elasticity theory to distinguish between eight types of decoupling states. Since then, the Tapio decoupling index model has attracted much attention from scholars and has been widely applied to analyse the decoupling relationship of economic growth and carbon emissions at the national level (Shuai, Chen, Wu, Zhang, & Tan, 2019). Furthermore, within the national economic system, this model has been employed to investigate the decoupling status of different industries, such as transportation (Wang, Li, & Zhang, 2017; Zhao, Kuang, & Huang, 2016), manufacturing (Ren & Hu, 2012), construction (Wu et al., 2018), and agriculture industries (Han, Zhong, Guo, Xi, & Liu, 2018).

Within the research field of tourism, studies on the decoupling linkage between carbon emissions and tourism growth have come to the fore in recent years. For example, Tang et al. (2014) applied the decoupling theory to measure the relationship between tourism economic growth and carbon emissions in China. With the help of the decoupling index, Chen et al. (2018) measured the relationship between tourism, energy consumption, and carbon emissions in the Yangtze River Delta and found the existence of a weak decoupling state during the sample period. Furthermore, by applying the LMDI decomposition method, they investigated factors influencing tourism-related carbon emission in the Yangtze River Delta.

Although some studies have performed decoupling analysis in the tourism industry and provided references for this study, they have several latent drawbacks. Diakoulaki and Mandaraka (2007) stated that the diversity of sources of economic growth, coupled with the effect of environmental externalities, results in a complex inner mechanism of the decoupling evolution. Specifically, some factors influencing decoupling evolution coexist in a dynamic, variable, interrelated economic–environmental system and may interact, thus forming a complex inner mechanism underlying the decoupling evolution. When studying the issue of tourism–environment decoupling, it may be difficult to provide detailed information for policy development without considering this mechanism (Wu et al., 2019). However, extant tourism–environment decoupling analysis can only identify the dynamic relationship between the two indicators, not its inner mechanism. Although some studies have combined the decoupling model and decomposition method to investigate the relationship between tourism growth and environmental pollution (Chen et al., 2018), they focused on investigating factors influencing carbon emission, not the decoupling evolution in the tourism industry. Therefore, to promote the sustainable development of the tourism industry, it is imperative to clarify the inner mechanism of decoupling evolution by extending the traditional decoupling model.

2.3. Decomposition approach and econometric methodology

In sustainable development research, the decomposition approach and econometric methodology can effectively address the conundrum of "economic development versus environmental degradation" (Cansino, Sanchez-Braza, & Rodriguez-Arevalo, 2018).

First, the decomposition approach was introduced to identify the evolution of energy consumption at the spatial or sectoral level, after the two major energy crises in the 1970s (Roinioti & Koroneos, 2017). Mainstream decomposition approaches are currently divided into structural decomposition analysis (SDA) and index decomposition approach (IDA). SDA is based on the input–output model, and IDA is adopted for decomposing indicator changes at the sectoral level (Rose & Casler, 1996). Su and Ang (2012) compared these two decomposition methods and concluded that IDA is more widely applied in the field of energy consumption and environmental protection than SDA. Further, the LMDI is preferred in IDA for its mature technology, different forms, ease of calculation, and absence of residual decomposition (Zhang & Da, 2015). Therefore, this technique has been introduced into the field of tourism to investigate the factors influencing tourism-related carbon emissions. For example, Bianco (2020) identified seven factors to quantify and explain the drivers that cause the variation in electricity consumption in the tourism sector, by providing an IDA–LMDI decomposition analytic framework. Additionally, some scholars have mentioned that this method has better interpretation capabilities in developing countries undergoing rapid economic and policy changes because it can better explain the effects of variables (Cansino et al., 2018; Xu et al., 2017). Recently, scholars have attempted to investigate the driving factors of the decoupling in different regions or sectors by using the LMDI decomposition method (Karakaya, Bostan, & Özçağ, 2019; Wang & Wang, 2019; Wu et al., 2018). Nevertheless, few studies have combined the LMDI method with decoupling techniques to explore the factors influencing tourism–environment decoupling evolution. Undoubtedly, not performing further LMDI decomposition based on the decoupling index might lead to biased results.

Second, another research orientation in academia is to use the econometric methodology to explore the interaction relationships among variables within the fields of economics, environment, and energy. For example, Alam, Begum, Buysse, Rahman, and Van Huylenbroeck (2011) applied the generalised impulse response function and Granger causality to investigate the causal relationship between energy consumption, CO_2 emissions, and revenue in India. Based on the econometric method, Lee and Chiu (2011) examined the relationship between nuclear energy consumption, actual oil prices, oil consumption, and real revenue in highly industrialised countries. Cansino et al. (2018) further confirmed the applicability for incorporating the econometric model into the decoupling–decomposition system, advancing the understanding of the inner mechanism of various decomposition indicators.

In conclusion, as reviewed, although the aforementioned studies have advanced extant literature, gaps remain. The tourism–environment decoupling studies have focused solely on the assessment of decoupling statuses, while the determinants of different decoupling statuses and how they interact have not been investigated. Additionally, formulating scientific policy requires determining the inner mechanism underlying the complex relationship, including potential influencing factors and interactive relationships among these factors (Alves & Moutinho, 2013). In other words, the extant tourism–environment decoupling literature has not provided a systematic decoupling analytic framework that helps investigate the inner mechanism of decoupling evolution and provides additional insights into alleviating environmental pollution while maintaining tourism growth. Therefore, by introducing the LMDI decomposition technique and IAA approach into the Tapio decoupling index model, this study provides an innovative analytical framework for the study of tourism–environment decoupling nexus that is a guide for policymakers endeavouring to develop sustainable tourism.

3. Study area

Chengdu is the capital city of Sichuan Province, China. It locates between latitude $30^\circ05'$N $\sim$ $31^\circ26'$N and longitude$102^\circ54'$E $\sim$ $104^\circ53'$E, with an area of 14,335 km^2 and a population of 16 million (see Fig. 1). As an important economic centre in Western China, Chengdu has a long history of over 2300 years. Due to its richness in both natural and cultural resources, tourism has become an important economic sector of Chengdu. According to the statistics of the Chengdu Tourism Bureau, tourist arrivals increased from 8.96 million in 1991 to 239.77 million in 2018, and tourism receipts increased from RMB 0.62 billion to RMB 371.3 billion. Currently, Chengdu is one of the most representative tourist cities in China, and its development to a large extent is the epitome of the development of Chinese tourist cities. Therefore, because of its popularity and typicality, Chengdu is selected as a case to demonstrate the applicability of the proposed analytic framework. Furthermore, because most Chinese tourist cities are within the same context of policy and macroeconomy, the findings derived from this study might offer valuable implications for other tourist cities in devising policies to resolve the conundrum of how to balance tourism growth and environmental protection.

4. Methodology and procedure

Based on the above-listed research objectives, the research methods to be adopted in this paper mainly encompass the following parts: One is a method for measuring tourism-related carbon emissions; the second is a decoupling index model to measure the emissions–growth nexus in the tourism system; the third is the decomposed decoupling index by LMDI decomposition model to clarify the driving factors behind the decoupling relationship; the fourth is innovative accounting approach based on the vector autoregression model to clarify the interaction relationships among the above determinants.

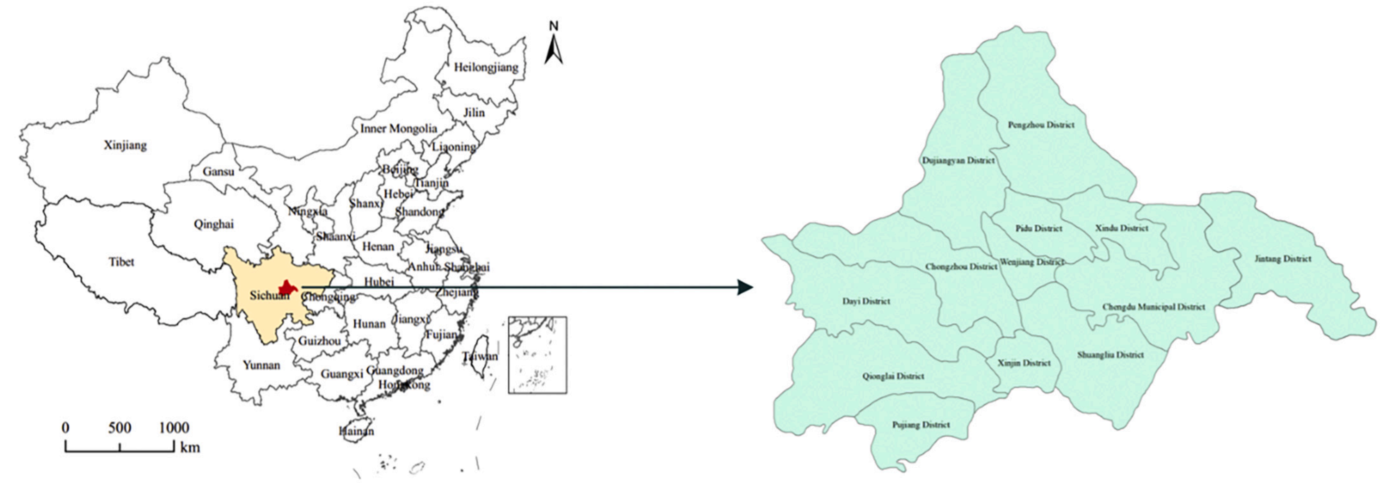

Fig. 1. Study area.

4.1. Method for estimating tourism-related carbon emissions

For the estimation of tourism-related carbon emissions, previous studies have mostly adopted "top-down" and "bottom-up" approaches, which are mainly from the perspective of "production" and "consumption".In contrast, the top-down method is suitable for evaluating the direct and indirect carbon emissions of tourism as an industry within a national economic system, while the bottom-up method is best suited for assessing the direct carbon emissions of tourism in small regions (Meng et al., 2017). Considering that this study focuses on the decoupling relationship between direct emissions and economic growth within the tourism system, and following Becken and Patterson (2006) and Qiu et al. (2017), we use the bottom-up approach to estimate tourism-related direct carbon emissions, which can be specified as follows:

$$C = C_T + C_H + C_F + C_A \tag{1}$$

where C indicates the amount of direct tourism-related carbon emissions. C_T, C_H, C_F, and C_A represent the carbon emissions from transportation, accommodation, catering, and tourism activities, respectively.

First, carbon emissions generated from tourism transportation can be estimated as follow:

$$C_T = \sum_{s=1}^{4} D_S \times F_S \times \beta_S \tag{2}$$

where S is the mode of transport (air, rail, car, and ferry), D_S is the amount of tourism turnover of mode S Passenger-Kilometers (pkm); F_S is the number of tourists of mode S (persons); $\beta_S$is the carbon emission factor of mode$S$(g/pkm).

Following Qiu et al. (2017), we argue that domestic tourists choose to travel by airplane, train, car, and ship, whereas all international tourists choose to travel by airplane. Based on the extant literature (Becken & Patterson, 2006; Shi & Wu, 2011), we formulated the factors of the carbon emission of aviation, rail, car, and ferry (see Table 2).

Second, carbon emissions generated from tourism accommodation can be estimated as follow:

$$C_H = \sum_{i}^{2} \sum_{x=1}^{2} G_{ix} \times \delta_x \times \varepsilon \tag{3}$$

where i is the type of tourists (domestic or inbound tourists), x is the type of accommodation (star hotels or other hotels), G_{ix} is the total residence days (bed nights); δ_x is the energy consumption per bed per night (MJ/per bed night); ε is the carbon content per unit of calorific value (gC/MJ).

The types of accommodation choices for tourists are divided into star hotels and other hotels herein. Based on the extant literature (Gössling, 2000; Wang & Xie, 2014), we set the energy consumption factor of the star hotel to 130 MJ/per bed night and of other hotels at 40 MJ/per bed night. The carbon content per unit calorific value is set to 43.2 gC/MJ.

Third, carbon emissions generated from tourism catering can be estimated as follow:

$$C_F = \sum_{k}^{6} N \times F_k \times \mu_k \tag{4}$$

where $k$indicates the type of edible food (grain, pork, beef and mutton, poultry, egg, and milk), N is the total tourist days (days), F_k is the consumption of the food per person per day (kg/per day), and $\mu_k$denotes the factors of carbon emission of edible food (g/kg).

We assume that the average daily food consumption of tourists is consistent with the average food consumption of urban residents based on Qiu et al. (2017). Further, as per Tan (2011), we represent the factors of carbon emission of various foods in Table 3.

Finally, carbon emissions generated from tourism activities can be estimated as follow:

$$C_A = \sum_{i}^{2} \sum_{y=1}^{5} G_{iy} \times \xi_y \tag{5}$$

where i is the type of tourists (domestic tourists or inbound tourists), y is the type of tourism activity (leisure vacation, sightseeing, business conferences, visiting relatives/friends, or others), G_{iy} is the number of the tourists to various types of tourism activities (persons), and ξ_y

Table 2
Factors for different transport modes.

Transport mode	Aviation	Rail	Car	Ferry
Emission factor (g/pkm)	396	65	132	63

Table 3
Factors for different types of food.

Food type	Grain	Pork	Beef and Mutton	Poultry	Egg	Milk
Emission factor (g/kg)	1740	1670	25,080	550	810	1530

denotes the factors of carbon emission of the various tourism activities (g/person).

Based on the extant literature (Becken & Patterson, 2006), we formulated the carbon emission factors as shown in Table 4.

4.2. Tapio decoupling index model

As per Tapio (2005), the decoupling index ($D_{C,\,G}$) of carbon emission from tourism growth can be estimated as follows:

$$D_{C,G} = \frac{\Delta C/C}{\Delta G/G} \tag{6}$$

where C, G denotes the tourism-related carbon emissions and tourism receipts, respectively. Based on the extant literature and the status quo in China, the $D_{C,\,G}$ classification and evaluation criteria are lists in Table 5.

4.3. Decomposed decoupling index by LMDI decomposition model

According to Kaya (1990), Eq. (1) can be expressed as the extended Kaya identity as follow:

$$C = \sum_i \frac{C_i}{E_i} \times \frac{E_i}{Y_i} \times \frac{Y_i}{Y} \times \frac{Y}{S} \times S \tag{7}$$

where C is the tourism-related carbon emissions, C_i denotes the carbon emissions of the tourism sector i, E_i is the energy consumption of the tourism sector i, $Y_i$denotes the receipts of the tourism sector i, Y denotes the total tourism receipts, and S is the number of tourists.

Let $e_i = \frac{C_i}{E_i}$, $f_i = \frac{E_i}{Y_i}$, $g_i = \frac{Y_i}{Y}$, $q = \frac{Y}{S}$, and $r = S$. Among them, $e_i$is the energy structure factor, f_i is the energy intensity factor, g_i is the income structure factor, q is the consumption level factor, and r is the tourist scale factor. The tourism-related carbon emissions in the initial year and the target year are set as C_0 and C_t, respectively. Thus, the tourism-related carbon emissions changes from the initial year to the target year as follows:

$$\begin{aligned} &\Delta C = C_t - C_0 \\ &= \sum_i e_i^t \times f_i^t \times g_i^t \times q^t \times r^t - \sum_i e_i^0 \times f_i^0 \times g_i^0 \times q^0 \times r^0 \\ &= \Delta Ce + \Delta Cf + \Delta Cg + \Delta Cq + \Delta Cr \end{aligned} \tag{8}$$

The effects of each driving factor on tourism-related carbon emissions from the initial year to the target year based on the LMDI method are as follows:

Table 4
Factors for different types of tourism activities.

Type of tourism activity	Emission factor (g/person)
Leisure vacation	1670
Sightseeing	417
Business conferences	786
Visiting relatives/friends	591
Others	172

Table 5
Classification and evaluation criteria for decoupling state.

Decoupling state		$\Delta C/C$	$\Delta G/G$	$D_{C,\,G}$
Decoupling	Strong decoupling	<0	>0	<0
	Weak decoupling	>0	>0	(0,1)
	Declining decoupling	<0	<0	>1
Negative decoupling	Expansion negative decoupling	>0	>0	>1
	Weak negative decoupling	<0	<0	(0,1)
	Strong negative decoupling	>0	<0	<0

$$\begin{aligned} \Delta Ce &= \sum_i \frac{C_i^t - C_i^0}{In(C_i^t) - In(C_i^0)} In\left(\frac{e_i^t}{e_i^0}\right) \\ \Delta Cf &= \sum_i \frac{C_i^t - C_i^0}{In(C_i^t) - In(C_i^0)} In\left(\frac{f_i^t}{f_i^0}\right) \\ \Delta Cg &= \sum_i \frac{C_i^t - C_i^0}{In(C_i^t) - In(C_i^0)} In\left(\frac{g_i^t}{g_i^0}\right) \\ \Delta Cq &= \sum_i \frac{C_i^t - C_i^0}{In(C_i^t) - In(C_i^0)} In\left(\frac{q^t}{q^0}\right) \\ \Delta Cr &= \sum_i \frac{C_i^t - C_i^0}{In(C_i^t) - In(C_i^0)} In\left(\frac{r^t}{r^0}\right) \end{aligned} \tag{9}$$

By integrating Tapio decoupling model and LMDI decomposition method, we decompose the decoupling index as follows:

$$\begin{aligned} D_{C,G} &= \frac{\Delta C/C}{\Delta G/G} = \frac{\Delta C}{C} \times \frac{G}{\Delta G} = \Delta C \times \frac{G}{C \times \Delta G} \\ &= (\Delta Ce + \Delta Cf + \Delta Cg + \Delta Cq + \Delta Cr) \times \frac{G}{C \times \Delta G} \\ &= \frac{\Delta Ce/C}{\Delta G/G} + \frac{\Delta Cf/C}{\Delta G/G} + \frac{\Delta Cg/C}{\Delta G/G} + \frac{\Delta Cq/C}{\Delta G/G} + \frac{\Delta Cr/C}{\Delta G/G} \\ &= De + Df + Dg + Dq + Dr \end{aligned} \tag{10}$$

De、Df、Dg、Dq、Dr represents the decoupling index of energy structure, energy intensity, income structure, consumption level, and tourist scale factor, respectively. Considering that the ΔG was more than 0 during the observed period, it can be found that, the smaller the decoupling index, the better the decoupling effect. If the value of decoupling index was more than 0, it was a negative driving factor for decoupling process. On the contrary, if the value of decoupling index was less than 0, it was a positive driving factor for decoupling process.

4.4. Innovative accounting approach based on the vector autoregression model

As an effective econometric model for dealing with multiple related time-series variables and predictive analysis, the vector autoregression (VAR) model is utilised to yield the dynamic shock of the stochastic error to the time-series system and, thus, explain the impact of this dynamic shock on each time-series variable (Johansen, 1995). Following Alves and Moutinho (2013), we introduce the five driving factors that influence the decoupling process into the VAR system as endogenous variables in order to explore the long-run and short-run relationships among the driving factors.

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t \tag{11}$$

where$\{y_t\} = [De_t\, Df_t\, Dg_t\, Dq_t\, Dr_t]$is a series of time; A is a constant number in this equation, p denotes the maximum number of the lag of criterion variable and ε_t is a pure white noise error term.

The IAA that includes FEVD and IRFs is proven to be an efficient method to identify the long-run and short-run relationships among variables and how they could influence each other in the future (Alves & Moutinho, 2013). First, FEVD can explain the degree to which the forecast error variance of a specific effect variable is described by innovations generated from another effect variable in a system over various time horizons. Herein, the forecast error of step h is:

$$x_{t+h} - E_t x_{t+h} = \sum_{i=0}^{\infty} \psi_i (\varepsilon_{t+h-i} - E_t x_{t+h-i}) = \sum_{i=0}^{h-1} \psi_i \varepsilon_{t+h-i} \tag{12}$$

Therefore, the forecast error variance can be expressed as follow:

$$\begin{aligned} E(x_{t+h} - E_t x_{t+h})^2 &= \sum_{i=0}^{h-1} \psi_i \sum \psi_i' \\ &= \sum_{i=1}^{m} \left(p_j p_j' + \psi_1 p_j p_j' \psi_1' + \ldots + \psi_{p-1} p_j p_j' \psi_{p-1}' \right) \end{aligned}$$

$$\psi_i = \sum_{k=1}^{p} \psi_{i-k} A_k, \quad \Phi_i = \psi_i \Gamma_0, \quad \psi_i = I_n, \quad \Phi_n = (\varphi_{n,ij}) \tag{13}$$

where, $p_j p_j' + \psi_1 p_j p_j' \psi_1' + \ldots + \psi_{p-1} p_j p_j' \psi_{p-1}'$ is the contribution rate of the variable I to the forecast error of the period h.

Second, using the IRFs, we offer a rough analysis of the dynamic responses of time-series to a one-period standard deviation shock and indicate the direction of the response to each shock. Thus:

$$\Phi_n(\varphi_{ik,n}) = \sum_{j=1}^{n} \Phi_{n-j} A_j, n = 1, 2, \ldots \tag{14}$$

where, $\Phi_0 = I_m$, $A_j = 0$ is subjected to$j > p$; $\varphi_{ik,\ n}$is the ik^{th}element of Φ_n, which indicates the reaction of variable y_i to an initial fluctuation of a variable before the period n.

4.5. Data sources

In our study, we select the time series from 1991 to 2018 due to the availability and credibility of data. The original data sources for this study are as follows: Data on tourist arrivals, tourism receipts, and passenger turnover volume are drawn from *the Statistical Yearbook of Chengdu city (1992–2019)*; the data on average daily food consumption of residents are taken from the *China Statistics Yearbook (1992–2019)*. Besides, the data on the proportion of tourists that stay overnight and day-trippers; accommodation percentage for star hotels and other hotels of domestic (inbound) tourists; the average duration of stay of domestic (inbound) tourists; and finally the data on activity percentage for leisure vacation, sightseeing, business conferences, visiting relatives/friends and others are collected from the *Domestic Tourism Sample Survey Report of Chengdu*, and *the Inbound Tourism Sample Survey Report of Chengdu*; the data on expenditure structure of domestic (foreign) tourists are derived from the *Sichuan Tourism Statistics Fact Sheet(1996–2019),* and based on an in-depth interview with the Chengdu Tourism Bureau, and we extrapolated the missing data about this indicator in individual years from the available year data.

5. Results and analysis

5.1. Total amount of tourism-related carbon emissions in Chengdu

As shown in Fig. 2, the growth curve of tourism-related carbon emissions in Chengdu can be divided into two stages: a relatively slow growth stage from 1991 to 2008 and a rapid growth stage from 2008 to 2018. During the first stage, the tourism-related carbon emissions increased from 92.4 million kg to 1100.4 million kg, with a relatively slow average annual growth rate of 13.75%. In the second stage, the carbon emissions associated with tourism increased faster than the former stage and finally reached 13,743.2 million kg, with an average annual growth rate of 25.80%. This phenomenon is easy to explain. With the implementation of the Great Western Development Strategy, the Chinese government has increased its support of the development of transport in backward western provinces in recent years (Zha, Tan, Fan, Xu, & Ma, 2020). In addition, the improvement of living standards and the increase in leisure time stimulated tourist travel demand. Under this circumstance, tourism-related carbon emissions generated from the transport sector have recently experienced rapid growth, leading to the increment of tourism-related carbon emissions in the second stage.

With respect to the sectoral emission structure, transport is the main contributor to tourism-related carbon emissions, accounting for 88.77% of total tourism emissions. In stark contrast, the proportions of accommodation, catering, and tourism activities are relatively small: 5.80%, 3.30%, and 2.13%, respectively. Empirical results have supported the finding that tourism-related carbon emission varies by subsector in the tourism system (Liu et al., 2011; Shi & Wu, 2011). These findings also demonstrate to some extent the rationality of the tourism-related carbon emission estimation in this study. Furthermore, the significant differences in the carbon emissions between tourism subsectors show that emission reduction in tourism requires differentiated carbon reduction policies. For instance, curbing the carbon emissions generated from

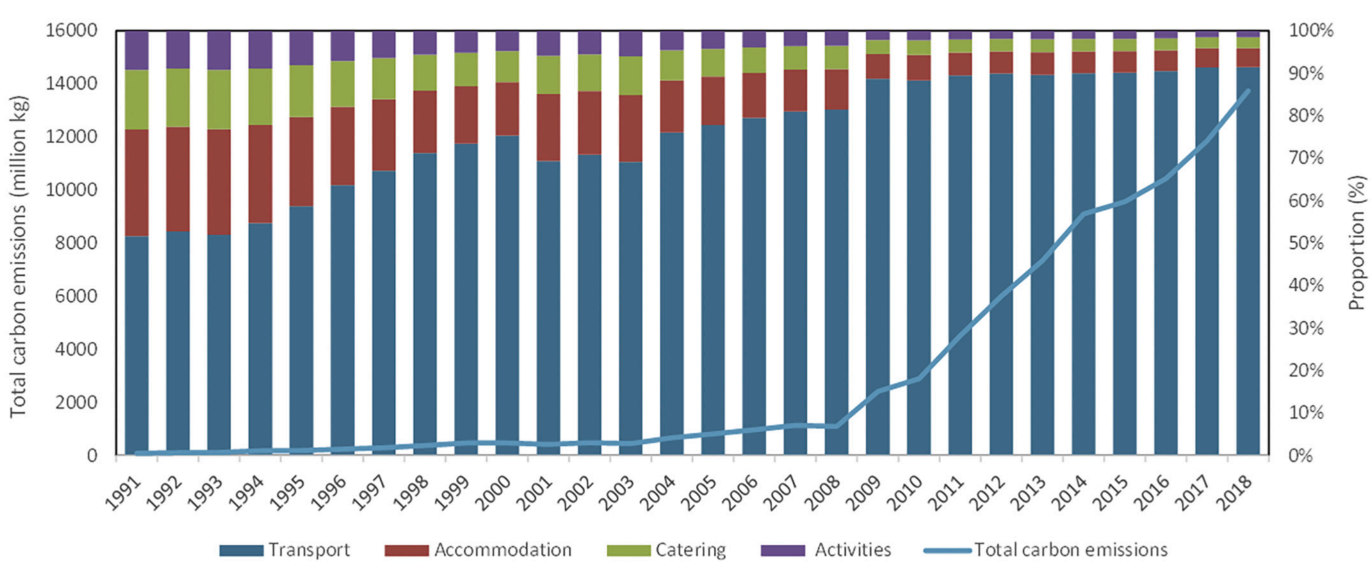

Fig. 2. Total tourism-related carbon emissions in Chengdu (1991–2018).

transport is a critical step towards achieving sustainable development in tourism (Becken & Patterson, 2006), which should be a priority of government authorities and scholars.

5.2. Decoupling tourism growth from carbon emissions in Chengdu

According to the Tapio decoupling index model, Fig. 3 illustrates the decoupling relationship between tourism growth and carbon emissions in Chengdu. In general, we observe a weak decoupling, with an average decoupling index value of 0.806 during the observed period; that is, the growth trend of tourism receipts marginally outstripped the growth trend of tourism-related carbon emissions. Four states of decoupling appear in the tourism economy system of Chengdu during the observed period: weak, expansive negative, strong, and weak negative decoupling.

Specifically, even though the decoupling state exhibits a volatility trend over most of the observed period, we can roughly divide the evolution of decoupling states into three stages, namely, a fluctuating weak decoupling stage from 1991 to 2003, an overall expansive negative decoupling stage from 2003 to 2012, and a stable weak decoupling stage from 2012 to 2018.

In 1991–2003, with the implementation of policy established at the 14th Communist Party Congress, the tourism receipts in Chengdu have been initially increased under the socialist market economy context (Tsang & Hsu, 2011). Correspondingly, the growth of tourism-related carbon emissions in this stage presented a relatively slow rate. Although there were some fluctuations during 1997–1999 and 2002–2003 due to unexpected socio-economic events such as the Asian financial crisis and the severe acute respiratory syndrome (SARS), overall, the decoupling tourism growth from carbon emissions in Chengdu presented a weak decoupling state.

From 2003 to 2012, joining in the World Trade Organization (WTO) and the radical economic policy formulated by the government authorities with the aim of stimulating domestic economic growth and rising national income level have promoted the prosperity of China's tourism economy to a large extent (Luo, Becken, & Zhong, 2018; Chinese State Council, 2010). However, it is noteworthy that less attention has been paid to the energy-saving and emission-reduction work in the tourism industry during this period, causing the rapid growth of tourism receipts and tourism-related carbon emissions. Thus, tourism growth and carbon emissions were in an expansive negative decoupling state during this period.

In 2012–2018, China's economic development entered a new era, and pursuing the sustainable and low-carbon economy became an important goal of socio-economic development. Regarding the tourism industry, consistent with the requirement of economic transformation and upgrading, a series of policies on saving energy and reducing carbon emission have been successively issued by the government authority, such as *Instructive Opinions Regarding Further Promotion of the Energy Saving and Emission Reduction Work of Tourism Industry*, which has accelerated the optimisation of industrial structure and the improvement of energy efficiency in the tourism industry. As such, the weak decoupling state followed a stable trend and the decoupling index followed a downward trend during this stage.

5.3. Analysis of the driving factors of the decoupling index

Considering that the Tapio decoupling index fails to identify the driving factors behind the process, we now explore the driving factors that influence the decoupling of tourism growth from carbon emissions in Chengdu by combining the LMDI decomposition method and the Tapio decoupling index model.

5.3.1. Fluctuating weak decoupling stage (1991–2003)

As shown in Table 6, *Dq* was the essential factor inhibiting the decoupling process during this stage, with an average decoupling index value of 0.82, meaning that a significant accretion in tourism consumption level will not only stimulate the tourism growth but also give rise to substantial growth in tourism-related carbon emissions. *Dr* had a strong restraining effect on the decoupling process, whereas *Df* played a promoting role. Furthermore, *De* and *Dg* played an insignificant role in the decoupling process. Notably, only *Df* played a consistently promoting role in the decoupling process during this stage. This finding highlights the importance of the reduction of energy intensity for a sustainable tourism economy, as it can reasonably control carbon emissions without damaging the steady tourism growth.

5.3.2. Overall expansive negative decoupling stage (2003–2012)

Statistically, the expansive negative decoupling state during this stage can be mainly explained by the rising value of *Dr* (from 0.26 to 0.70). This finding echoes the point stated by Tao, Huang, Wu, Yu, and Wang (2014), who noted that the growth of the tourist scale is not only the engine of the tourism economy but also the reason for the rise of tourism-related carbon emissions. Meanwhile, the lack of awareness of the conflicts between tourism consumption and ecological protection in this stage (Liu et al., 2011) makes *Dq* a crucial factor in suppressing the decoupling with an average decoupling index value of 0.26. Furthermore, the effects of *Df*, *De*, and *Dg* on the decoupling process were less optimistic, and represented inhibition, despite their relatively low absolute values. This demonstrates that the industrial restructuring and energy efficiency improvement were far away from their anticipated decoupling effect during this stage, and thus, have substantial room for

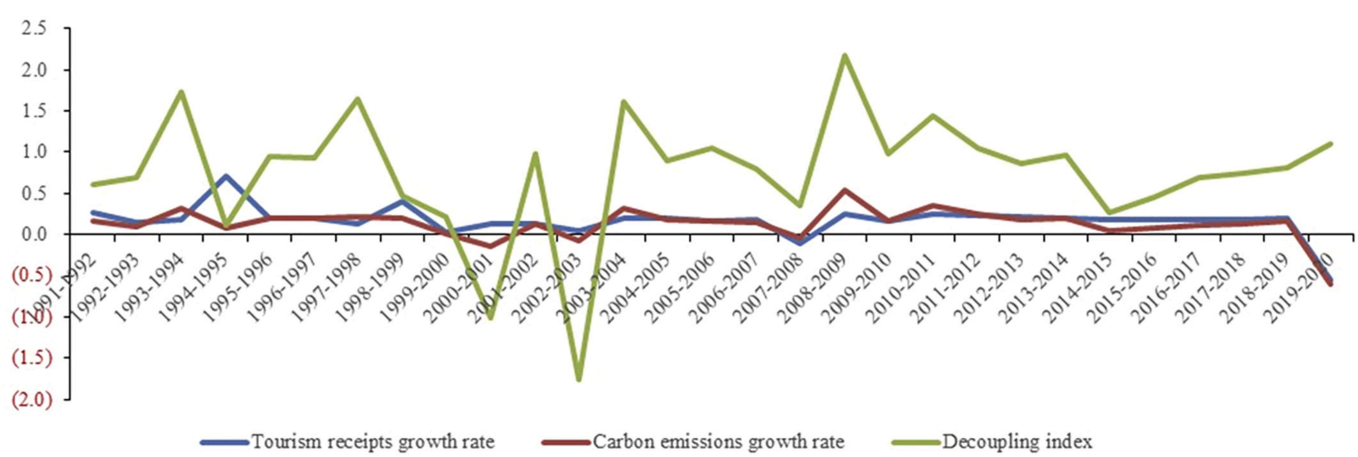

Fig. 3. Relationship between tourism growth and carbon emissions (1991–2018).

Table 6
Decomposition of the decoupling tourism growth from carbon emissions.

Time period	*De*	*Df*	*Dg*	*Dq*	*Dr*	$D_{C,G}$
1991–1992	0.02	−0.57	0.10	0.55	0.51	0.61
1992–1993	0.05	−0.85	0.47	0.14	0.89	0.69
1993–1994	−0.01	1.59	−0.77	−0.65	1.56	1.73
1994–1995	0.00	−1.61	0.04	1.68	−0.01	0.11
1995–1996	−0.02	−0.12	0.09	0.61	0.39	0.96
1996–1997	−0.02	0.19	−0.25	0.54	0.47	0.93
1997–1998	−0.04	0.83	−0.09	0.18	0.77	1.65
1998–1999	0.00	−0.91	0.23	0.85	0.30	0.48
1999–2000	0.07	−0.71	−0.15	4.09	−3.08	0.22
2000–2001	0.15	−2.12	−0.18	0.51	0.63	−1.01
2001–2002	0.05	−0.09	0.01	0.40	0.60	0.98
2002–2003	−0.16	−2.63	−0.02	0.90	0.16	−1.76
2003–2004	−0.05	0.79	−0.05	0.40	0.52	1.62
2004–2005	0.04	−0.14	−0.02	0.48	0.53	0.90
2005–2006	0.05	0.13	−0.12	0.40	0.59	1.05
2006–2007	0.07	−0.23	−0.07	0.69	0.33	0.79
2007–2008	0.23	−0.98	0.13	0.57	0.40	0.35
2008–2009	−0.01	1.32	0.06	−0.01	0.80	2.17
2009–2010	0.05	−0.29	0.22	−0.15	1.16	0.98
2010–2011	0.04	0.25	0.22	−0.16	1.09	1.44
2011–2012	0.00	0.01	0.06	0.12	0.88	1.06
2012–2013	−0.01	−0.18	0.04	0.00	1.02	0.86
2013–2014	0.03	−0.01	−0.05	0.18	0.82	0.97
2014–2015	0.08	−1.09	0.20	0.93	0.14	0.26
2015–2016	−0.04	−0.49	−0.08	0.82	0.24	0.45
2016–2017	0.27	−0.56	−0.07	0.78	0.26	0.68
2017–2018	−0.05	−0.27	0.02	0.28	0.28	0.74

Abbreviations: *De*, the decoupling index of energy structure factor; *Df*, the decoupling index of energy intensity factor; *Dg*, the decoupling index of income structure factor; *Dq*, the decoupling index of consumption level factor; *Dr*, the decoupling index of tourist scale factor; $D_{C,\ G}$, the decoupling index of carbon emission from tourism growth.

improvement.

5.3.3. Stable weak decoupling stage (2012–2018)

The value of *Df* showed an obvious downward trend during the stage (from 0.10 to −0.43) and became the main driving force for stable weak decoupling. This is attributed to the reduction of energy intensity caused by the optimisation of tourism industry structure and innovation of technology in recent years, which effectively promoted the transition from expansive negative decoupling to weak decoupling (Tang et al., 2014). The suppression effect of *Dq* on the decoupling process was strengthened during this stage, and its decoupling index value increased from 0.26 to 0.50. This phenomenon can be explained by the rapid growth of national tourism consumption, in line with the improved living standards, transport infrastructure, and its associated facilities. The excessive growth of tourism consumption expenditure has become the main obstacle factor for the achievement of strong decoupling, which was corroborated by the finding of Chen et al. (2018). In general, although the downward trend of weak decoupling in this stage shows that tourism growth has reduced its dependence on carbon emissions to a certain extent, there is still a substantial gap between the goal of achieving the ideal state of strong decoupling and the levels of practice in the tourism industry of Chengdu.

5.3.4. The overall observed period (1991–2018)

In general, only *Df* played a promoting role in the decoupling, whereas *Dr* and *Dq* had a strong restraining effect for the observed period. However, *De* and *Dg* played an insignificant role. Specifically, the results from Table 6 indicate that *Dq* had the greatest negative effect on the decoupling process, with an average value of 0.56. This is mainly because of the continuously increased resident income and the desire to improve living standards, which promote more tourist consumption and generate a large amount of carbon emissions. Thus, the sustained growth of per capita tourism consumption is primarily responsible for the continuous growth in tourism-related carbon emissions (Liu et al., 2011). It also proves that tourism activities have "high energy and carbon intensity" attributes, which are different from daily activities (Gössling & Hall, 2008). *Dr* played a minor negative role in the decoupling process relative to *Dq*. The annual average decoupling elastic coefficient value reached 0.47 because long-run rapid tourism growth exponentially increased energy consumption and carbon emissions. Although the value of *Df* did not exhibit a consistent direction—changing from −2.630 to 1.593—it still has the only positive effect on the decoupling. The energy intensity in the tourism industry follows a recent downward trend with the rise in energy-saving and emissions-reducing technology as well as greater environmental awareness among tourists. The fluctuation in the value of *Df* also indicates that it still has the potential for the overall decoupling in the future. In addition, though the values of *De* and *Dg* hover near zero, they still have a non-negligible effect on the decoupling process in the low-carbon development context.

5.4. IAA analysis among the driving factors

5.4.1. VAR system stability test

To avoid the problem of spurious regressions, we must assess the stationarity properties of the variables employed. Thus, we employ the augmented Dickey–Fuller (ADF) unit root tests to examine the stationarity (Table 7). The results demonstrate the null hypothesis, that is, each variable has a unit root that is rejected at the 1% level, indicating that each variable in the VAR model is a stationary variable.

Five criteria are provided by the VAR model system to evaluate the optimal lag period: the continuously modified LR test statistic criterion (LR), the final prediction error criterion (FPE), the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SC), and Hannan Quinn Information Standards (HQ). As shown in Table 8, the results indicate that the optimal lag order number of the VAR model was 3.

In a multivariate framework, we can use the Granger causality test to identify the causal relationship between variables (Granger, 1969). Performing a test to verify the existence of causality relationship between variables is a prerequisite for VAR model estimation. The conclusions of Granger causality tests between variables are presented in Table 9. *Dr* and *Dq* Granger cause *De* at the 1% level of significance. *Dg* Granger causes *De*, *Dq*, and *Dr* at 10%, 5%, and 5% levels of significance, respectively. *De* and *Df*, *Df* and *Dq*, *Df* and *Dr*, and *Dq* and *Dr* present bidirectional causality in Granger causality tests. Furthermore, except for *Dg*, all joint equation tests demonstrate Granger causality between variables with at least 5% significance, indicating that *Dg* is exogenous to the VAR system and that the remaining variables are endogenous to the system. One of the reasons could be the negligible effect of *Dg* on the decoupling process. Additionally, the study area is located in Western China, far from the main source of tourists (i.e. Eastern China), and transport accounts for a large share of tourist expenditure, resulting in a relatively stable tourism expenditure structure. This economic reality might be another reason for the exogenous nature of *Dg*.

Given the results derived from the Granger causality test, we reconstruct the VAR model by setting *De*, *Df*, *Dq*, and *Dr* as endogenous variables, and *Dg* as an exogenous variable. To ensure the rigour and validity of the VAR model, we apply the AR root test to verify the stability of the VAR model. Fig. 4 presents the results that all eigenvalues

Table 7
Unit root test results.

Variable	ADF value	1% critical value	5% critical value	10% critical value	Conclusion
De	−3.5360	−4.0044	−3.0989	−2.6904	Stationarity
Df	−5.1839	−3.9591	−3.0810	−2.6813	Stationarity
Dg	−11.3789	−4.8001	−3.7912	−3.3342	Stationarity
Dq	−4.6358	−3.7379	−2.9919	−2.6355	Stationarity
Dr	−4.6788	−3.7379	−2.9919	−2.6355	Stationarity

Table 8
Lag order selection criteria.

Lag	Log L	LR	FPE	AIC	SC	HQ
0	18.58631	NA	2.00e-07	−1.235119	−0.987155	−1.176706
1	48.22257	43.10729*	1.41e-07	−1.656597	−0.168812	−1.306120
2	74.55702	26.33445	1.90e-07	−1.777911	0.949695	−1.135369
3	139.2013	35.26052	2.24e-08*	−5.381937*	−1.414510*	−4.447330*

Note: * indicates lag order selected by the criterion.

Table 9
Granger causality/block exogeneity.

	Dependent variable				
	De	*Df*	*Dg*	*Dq*	*Dr*
De	–	6.626*	3.853	0.568	0.346
Df	6.768*	–	1.050	7.131*	7.183*
Dg	7.095*	4.248	–	8.723**	10.680**
Dq	13.893***	12.205***	1.849	–	11.676***
Dr	13.213***	13.290***	1.562	9.798**	–
All	25.484**	49.026***	16.717	29.189***	32.028***

Note: The null hypothesis that the variables in a column are not significant in explaining the variables in the row is tested. 'All' denotes the causality test set for all independent variables. The symbols *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

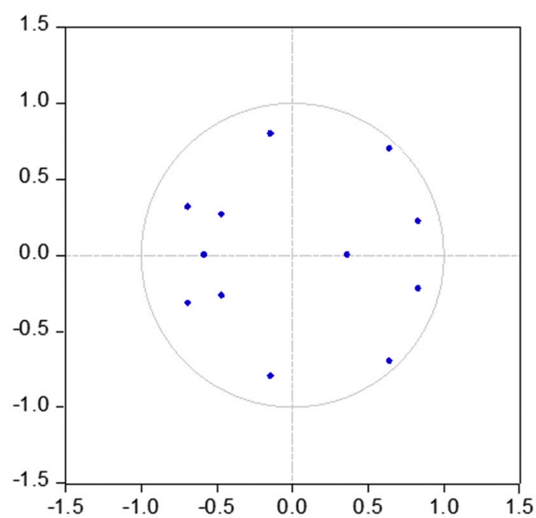

Fig. 4. Inverse roots of the AR characteristic polynomial.

were within the unit circle. Thus, the VAR model is stable.

5.4.2. Analysis of long-run and short-run relationships among the driving factors

Fig. 5 represents the results of the IRFs for the four-decomposition factors. The horizontal axis indicates the years after the impulse shocks; the vertical axis measures the magnitude of the response. Table 10 presents the results of the FEVD over a ten-year period.

The empirical results from the IRFs indicate that *De* reacted more significantly to a one standard deviation shock in *Dq* and *Dr* than to shocks in other variables, which were first positive and then negative in the third and fourth periods, respectively, and disappeared in the long term. This result demonstrates that a low-carbon consumption pattern has a positive promotion effect on the decoupling process of the energy structure factor in the short run, supporting the conclusions of Meng et al. (2017). *Df* reacted significantly to the one standard deviation shock in all of the variables. The reaction from the shock of *Dq* was negative in the short run but turned positive and dissipated in the long run, and the reaction from the shocks of *De* was more placid but lasted for a long time. This finding, to some extent, highlights the importance of the optimisation of consumption patterns and the adjustment of the energy structure. That is, a low-carbon and environmentally friendly transformation of tourism consumption patterns and a sustainable energy structure will lower the energy intensity in the tourism industry in the long run (Moutinho, Costa, & Bento, 2015), to further stimulate the occurrence of decoupling. *Dq* and *Dr* reacted more sharply to a one standard deviation shock in *De*. The reaction of *Dq* from the shock of *De* was negative in the first period and positive in the fifth period and vanished in the long run, whereas the reaction of *Dr* from the shock of *De* had an opposite direction.

As shown in Table 10, the standard deviation shock in *Dq* and *Dr* was the variable that better explained the change of *De* in the long term, with an approximate percentage of 15.01% and 15.76%.

This result supports the claim in the IRF analysis that encouraging tourists to practice low-carbon consumption behaviour from the demand side will significantly affect the optimisation of the energy utilisation structure in the tourism industry. *De* and *Dq* were the main factors that explained the change in *Df* (50.31% and 25.35%, respectively). We can infer that the energy portfolio diversification and the innovation of energy conservation technologies in the tourism industry will lead to an obvious decrease in energy intensity in the long run. The change in *Dq* was affected by various factors, whereas *De*, *Dr*, and *Df* contributed 41.56%, 14.35%, and 6.47%, respectively. Therefore, we can infer that there is a bidirectional causality relationship between *De* and *Dq*, suggesting that the governmental authority should pay more attention to coordinating the interactive relationship between the transformation of energy structure and improvement in the consumption pattern to further facilitate the decoupling process in the tourism industry. Additionally, the change in *Dr* in the long run can be explained by *Dq* (41.19%), *De* (38.02%), and *Df* (7.55%).

The results of the IRFs and FEVD demonstrate that various factors influencing decoupling evolution are statistically linked. When formulating decoupling policies, ignoring the interactive relationship between determinants may undermine their effectiveness (Cansino et al., 2018). Therefore, the synergistic relationship among various decoupling strategies in the tourism industry should garner more attention.

6. Conclusions and discussion

In the context of demands for economic sustainability and environmental constraints, the tourism industry is faced with immense environmental pressure from burgeoning tourism (Zha et al., 2019). Consequently, addressing the conundrum that is to decouple tourism growth from environmental pressures is of great significance for achieving sustainable tourism development. A plethora of studies have been conducted on the decoupling relationship between tourism growth and carbon emissions in recent years (Chen et al., 2018; Tang et al., 2014). However, most studies are limited to assessing the decoupling states, which may not help in capturing the key path of tourism growth–carbon emissions decoupling. To this end, we extended the decoupling index model by introducing the LMDI decomposition method and the IAA approach into the Tapio decoupling model and examined Chengdu as a study case to explore the dynamic decoupling relationship between tourism growth and carbon emissions and its inner mechanism of decoupling evolution. This study enriches the literature

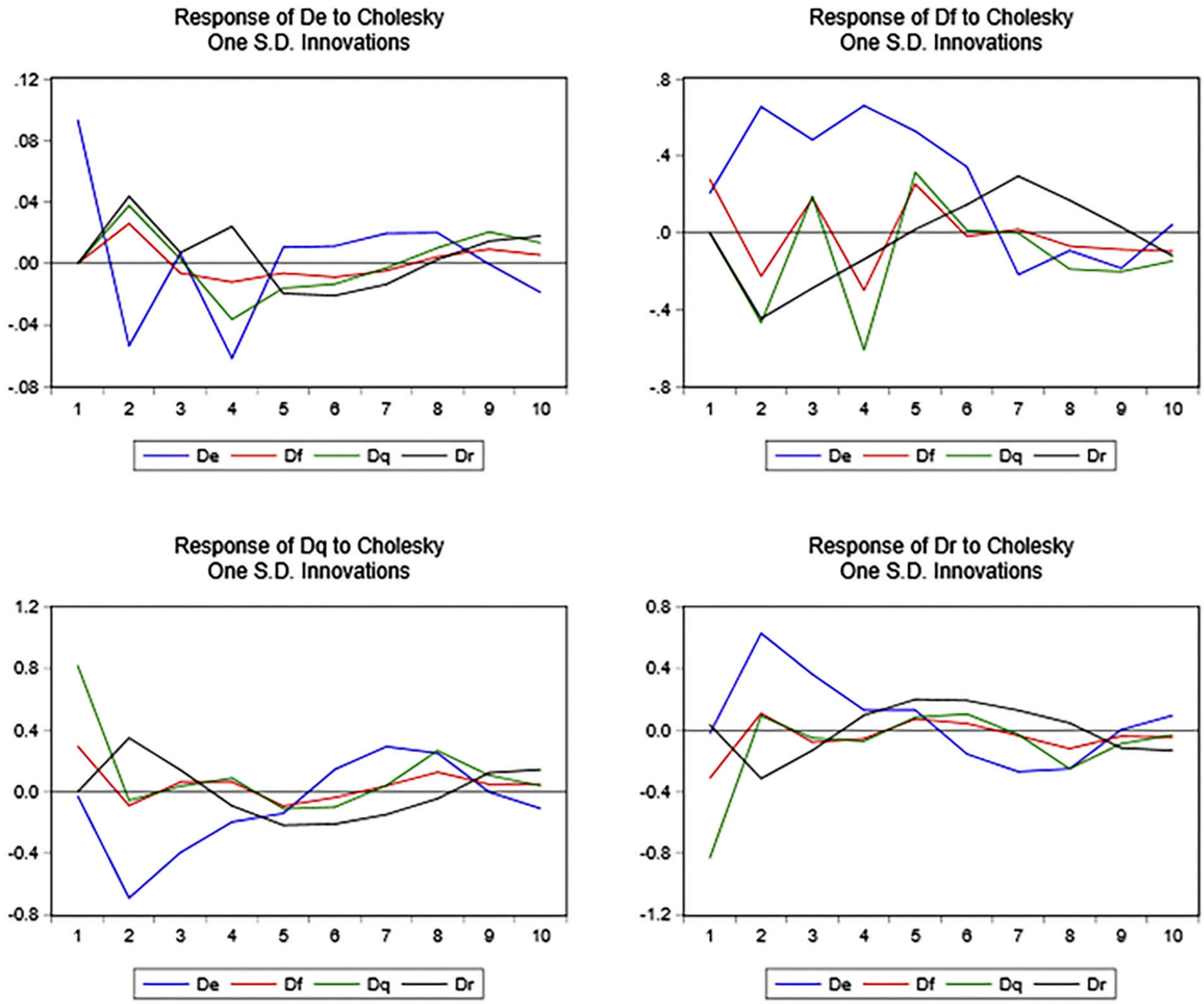

Fig. 5. Results of IRFs.

on sustainable tourism by providing an extended decoupling analytic framework. Although Chengdu is the only city selected as a case to demonstrate the superiority of the analytic framework, these findings may offer valuable implications for policymakers responsible for developing low-carbon tourism. The main findings are summarised as follows.

We empirically confirm that tourism-related carbon emissions in Chengdu maintained a relatively high growth trend during the observed period. Meanwhile, there is a significant discrepancy in carbon emissions among four tourism subsectors. Transport, accommodation, catering, and tourism activities contributed an average value of 88.77%, 5.80%, 3.30%, and 2.13% to the tourism-related carbon emissions, respectively. This finding is consistent with the conclusions drawn by Liu et al. (2011) and Chen et al. (2018).

The decoupling state of tourism growth from carbon emissions during the observed period was generally characterised by weak decoupling. The average decoupling index value was 0.806. The overall decoupling state shows a temporal evolution trend of "fluctuating weak decoupling – overall expansive negative decoupling – stable weak decoupling" during the observed period. It is worth noting that the weak decoupling is not perfect, as it only indicates a relative decrease in the dependence of tourism growth on environmental pollution over the sample period (Han et al., 2018). The average value of the decoupling index observed from Chengdu was close to the critical value between the weak and the expansive negative decoupling states, suggesting that there is still much room for improvement in the decoupling state of tourism growth from carbon emissions.

Besides, the above findings focus on the dynamic decoupling relationship between tourism growth and carbon emissions in a conventional context. It is worth noting that the COVID-19 pandemic that broke out in 2020 has already severely affected tourism, and these negative shocks are still ongoing globally, with the vast majority of countries or regions experiencing economic stagnation or even severe decline in tourism (Škare, Soriano, & Porada-Rochoń, 2021; Uğur & Akbıyık, 2020). Undoubtedly, a serious recession in the tourism economy would be accompanied by a corresponding reduction in carbon emissions (Cooper & Alderman, 2020), and changes in the structure of tourism consumption due to the epidemic may also lead to changes in the decoupling relationship between tourism growth and emissions (Kitamura, Karkour, Ichisugi, & Itsubo, 2020). Thus, it is essential to compare the decoupling relationship between tourism growth and carbon emissions before and after the epidemic and to discuss it in depth accordingly to highlight the robustness and significance of the conclusions drawn in this study.

Due to limitations of data availability, this paper can only examine the decoupling relationship between tourism growth and carbon emissions based on cursory estimates of tourism carbon emissions for 2019 and 2020. Based on data derived from the *Chengdu Municipal Government Work Report* for 2019 and 2020 and the *China Tourism Green Book* (2020–2021) (Tourism Research Center, Chinese Academy of Social Sciences, 2021), we can make rough estimates of tourism-related carbon emissions for 2019 and 2020. The results show that the carbon emissions

Table 10
the results of FEVD.

Period	*De*	*Df*	*Dq*	*Dr*
Variance decomposition of *De*				
1	100.0000	0.000000	0.000000	0.000000
2	74.31286	4.320694	9.092760	12.27368
3	73.91967	4.528154	9.067634	12.48454
4	71.48617	3.984015	12.70445	11.82536
5	69.48334	4.016952	13.38505	13.11466
10	64.84196	4.382287	15.01438	15.76137
Variance decomposition of *Df*				
1	35.39603	64.60397	0.000000	0.000000
2	46.26596	12.58860	21.57071	19.57473
3	50.28677	11.42579	18.18974	20.09769
4	49.28763	10.77115	26.96239	12.97882
5	51.51434	11.36461	26.20988	10.91116
10	50.30782	10.36883	25.34589	13.97746
Variance decomposition of *Dq*				
1	0.109194	11.52921	88.36159	0.000000
2	34.84715	6.986637	49.25460	8.911612
3	40.84654	6.422201	43.55328	9.177976
4	41.74403	6.437625	42.44808	9.370259
5	40.73835	6.610570	40.96629	11.68479
10	41.55642	6.471293	37.62210	14.35020
Variance decomposition of *Dr*				
1	0.060324	12.40705	87.37403	0.158596
2	30.54400	8.432466	53.33988	7.683652
3	36.23158	7.948272	47.77660	8.043551
4	36.54432	7.958577	46.99767	8.499435
5	36.01132	7.951369	45.34679	10.69052
10	38.01932	7.549944	41.19204	13.23869

from tourism reached 16,470.23 million kg in 2019, while the impact of the epidemic reduced tourism-related carbon emissions to 10,249.77 million kg in 2020. As the event that marked the large-scale outbreak of the COVID-19, that is, the Wuhan lockdown, occurred on January 23, 2020, the devastating impact of the epidemic on tourism in Chengdu was in 2020 rather than 2019. In this context, tourism-related carbon emissions in 2019 continued the growth trend of the previous stage, and the corresponding decoupling state of tourism growth from carbon emissions was characterised by weak decoupling. By contrast, tourism-related carbon emissions reduced by 37.77% in 2020 compared to 2019 due to the severe impact of the COVID-19 outbreak. Subsequently, with the epidemic largely under control, the tourism industry in Chengdu has gradually recovered from the pandemic crisis. Nevertheless, the pressure to prevent and control epidemics has led to significant changes in tourists' travel behaviour and preferences, such as changes in travel patterns (e.g., increased self-drive trips), declining frequency of travel, and shorter travel distances, which have had a significant impact on the sectoral emission structures; thus, the decoupling state of tourism growth from carbon emissions in Chengdu presented a declining decoupling state in 2020.

COVID-19 brought an economic and public health crisis to the world, and the response of governments and societies to address this crisis has significantly reduced energy consumption and its corresponding anthropogenic carbon emissions (Shan et al., 2021). As part of the economic system, the tourism economy has also been heavily affected by lockdown measures in many regions (countries) and significant restrictions on mass gatherings and travel, which in turn have led to dramatic reductions in tourism-related carbon emissions. Although tourism-related emissions are declining due to the impact of the pandemic, we should be aware of what the cost of this decline in emissions is to human life and the economy (Škare et al., 2021). As noted by Cooper and Alderman (2020), the reduction in emissions resulting from economy death is not sustainable tourism. Sustainable tourism means a completely durable and robust decoupling relationship between tourism growth and carbon emissions, thus cutting carbon emissions cannot and should not be the single goal of sustainable tourism. Furthermore, we should note that COVID-19 may offer an opportunity to decouple tourism growth from carbon emissions by shifting from the present "high resource consumption" mode to an 'environmentally friendly' mode (Sharma, Thomas, & Paul, 2021). For example, declining demand for aviation has led airlines to phase out outdated aircraft; restrictions on overseas travel for international students, business travellers, political leaders, and others have led to increased leverage for videoconferencing (Sharma et al., 2021). These changes are likely to reposition global tourism in a 'sustainable' way, with a greater focus on inclusive development rather than a mere notion of 'growth'. Meanwhile, we could also foresee a resurgence in consumption, including tourism, that is, once the pressure from the COVID-19 pandemic is gone and restrictions are lifted, countries would strive to rebuild their economies and individuals regain mobility. In this sense, the reduction in tourism-related carbon emissions due to the pandemic may be temporary, as there are no everlasting structural changes in the tourism destination, transport, and energy systems due to COVID-19.

The LMDI decomposition and IAA help us identify the driving factors that influence the historical decoupling process as well as the interaction relationships among the driving factors (Cansino et al., 2018). First, according to the empirical results of index decomposition, only the energy intensity factor consistently played a promoting role in the decoupling process, corroborating the finding of Robaina-Alves, Moutinho, and Costa (2016), who noted that the reduction of energy intensity exerted a strong positive impact on the process of tourism sustainable development. Therefore, to achieve the decoupling by reducing the energy intensity of the tourism industry, we strongly recommend that the government promote market-based energy reforms to incentivise innovation in the tourism subsectors (e.g., energy pricing mechanism reform, electricity marketisation reform, and energy fiscal and taxation system reform). Additionally, the government should enhance the execution of the Program of Environmental Protection Education because low-carbon education helps strengthen tourists' awareness of energy conservation and environmental protection (Tang & Ge, 2018). Furthermore, the tourist scale and consumption level factors had a strong restraining effect on the decoupling process over most of the observed period. However, achieving decoupling by curbing the scale growth of tourism, or the expenditure size, is impractical because the tourism industry is one of the strategic pillar industries in China (Chen et al., 2018). In the context of sustainable development, a low-carbon consumption model in the tourism process should be propagated and encouraged. In particular, feasible strategies in terms of policy, technology, and management should be proposed to curb the excessive growth of carbon-intensive commodities (e.g., airplanes, luxurious hotels) on the tourism demand side. In this regard, implementing a carbon tax on tourism revenue may be beneficial (Zhang & Zhang, 2018). Although the values of the energy structure and income structure factors hovered near zero, they still had a non-negligible effect on the tourism–environment decoupling state in the low-carbon development context. For instance, we argue that optimising the tourism energy utilisation structure by increasing the use of clean and renewable energy (e.g., wind, geothermal, and photovoltaic energy) could be helpful for achieving sustainable tourism (Zha, Fan, Yao, He, & Meng, 2020). Additionally, adjusting the tourism expenditure structure through increasing R&D investments in high value-added and environment-friendly tourism products might be another strategy to promote the decoupling evolution. In short, the improvement of tourism expenditure structure and low-carbon technology in tourism energy utilisation would help to deepen the degree of decoupling, which deserves much more attention for future decoupling in relevant regions.

Second, the IAA analysis explored the interactive relationship between the factors influencing decoupling evolution, furthering the understanding of the inner mechanism of decoupling evolution. Based on these findings, our conclusion is that various determinants of decoupling evolution are statistically linked. Therefore, to avoid undermining the effectiveness of different decoupling policies, establishing a comprehensive policy synergistic mechanism is necessary. Because tourism is regarded as an interrelated system, setting a clear, unified policy goal for various tourism policymakers is a prerequisite for achieving policy synergy in the tourism system (Fianto, 2020). To ensure the coherence of goals among policymakers, we argue that optimising the administrative structure and developing a macro plan are also necessary. For example, establishing a special management department to coordinate actions between tourism-related authorities and developing a long-term plan for low-carbon tourism might promote policy synergies among tourism-related sectors. Additionally, the asymmetric information between stakeholders regarding the trade of carbon emission may challenge the achievement of tourism sustainable development (Gössling & Buckley, 2016). Therefore, in response to these challenges, an information-sharing platform should be established by adopting more market-based initiatives (e.g., carbon label and low-carbon product supplier certificate). Finally, because of the interwoven link between tourism sectors, a combination of different policy instruments should be optimised in practice. For example, because of the bidirectional causality relationship between *De* and *Dq*, strategies to optimise the energy structure might be ineffective because tourist consumption patterns can also play a significant role in the use of various energies. In this circumstance, to optimise the energy structure in the tourism industry, we argue that administrative instruments (e.g., energy portfolio diversification), guidance instruments (e.g., low-carbon tourism promotion), and market instruments (e.g., carbon tax, carbon pricing) should work together. In summary, if the ideal state of strong decoupling in the tourism industry is achieved, promoting the complementarity of different strategies is necessary.

Author contributions

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Declaration of interest

There are no interest conflicts of the authors.

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References

Alam, M. J., Begum, I. A., Buysse, J., Rahman, S., & Van Huylenbroeck, G. (2011). Dynamic modeling of causal relationship between energy consumption, CO_2 emissions and economic growth in India. *Renewable & Sustainable Energy Reviews, 15*(6), 3243–3251.

Alves, M. R., & Moutinho, V. (2013). Decomposition analysis and innovative accounting approach for energy-related CO_2 (carbon dioxide) emissions intensity over 1996–2009 in Portugal. *Energy, 57*, 775–787.

Barbhuiya, M. R., & Chatterjee, D. (2020). Vulnerability and resilience of the tourism sector in India: Effects of natural disasters and internal conflict. *Tourism Management Perspectives, 33*, 100616.

Becken, S., & Patterson, M. (2006). Measuring national carbon dioxide emissions from tourism as a key step towards achieving sustainable tourism. *Journal of Sustainable Tourism, 14*(4), 323–338.

Bianco, V. (2020). Analysis of electricity consumption in the tourism sector. A decomposition approach. *Journal of Cleaner Production, 248*, 119286.

Cansino, J. M., Sanchez-Braza, A., & Rodriguez-Arevalo, M. L. (2018). How can Chile move away from a high carbon economy? *Energy Economics, 69*, 350–366.

Chan, W. W. (2005). Partial analysis of the environmental costs generated by hotels in Hong Kong. *International Journal of Hospitality Management, 24*(4), 517–531.

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

China Tourism Academy-CTA. (2018). *Annual report of tourism statistics in 2017 and prediction of tourism economic situation*. Retrieved from html/2018–12/2018-12-28-15-55-12622.html.

Chinese State Council. (2010). Views on the acceleration of the development of tourism industry. Retrieved from http://www.gov.cn/gzdt/2010-06/12/content_1626556.htm.

Cooper, J. A., & Alderman, D. H. (2020). Cancelling march madness exposes opportunities for a more sustainable sports tourism economy. *Tourism Geographies, 22*(3), 525–535.

Diakoulaki, D., & Mandaraka, M. (2007). Decomposition analysis for assessing the progress in decoupling industrial growth from CO_2 emissions in the EU manufacturing sector. *Energy Economics, 29*(4), 636–664.

Dubois, G., & Ceron, J. P. (2006). Tourism/leisure greenhouse gas emissions forecasts for 2050: Factors for change in France. *Journal of Sustainable Tourism, 14*(2), 172–191.

Fianto, A. Y. A. (2020). Community-based marine tourism development in East Java Province, Indonesia. *ABAC Journal, 40*(3), 1–26.

Field, C. B., & Barros, V. R. (Eds.). (2014). *Climate change 2014–impacts, adaptation and vulnerability: Regional aspects*. Cambridge: Cambridge University Press.

Gössling, S. (2000). Sustainable tourism development in developing countries: Some aspects of energy use. *Journal of Sustainable Tourism, 8*(5), 410–425.

Gössling, S., & Buckley, R. (2016). Carbon labels in tourism: Persuasive communication? *Journal of Cleaner Production, 111*, 358–369.

Gössling, S., & Hall, C. M. (2008). Swedish tourism and climate change mitigation: An emerging conflict? *Scandinavian Journal of Hospitality and Tourism, 8*(2), 141–158.

Gössling, S., & Scott, D. (2018). The decarbonisation impasse: Global tourism leaders' views on climate change mitigation. *Journal of Sustainable Tourism, 26*(12), 2071–2086.

Granger, C. W. J. (1969). Investigating causal relations by econometric models and crossspectral methods. *Econometrica, 37*(3), 424–438.

Han, H., Zhong, Z., Guo, Y., Xi, F., & Liu, S. (2018). Coupling and decoupling effects of agricultural carbon emissions in China and their driving factors. *Environmental Science and Pollution Research, 25*(25), 25280–25293.

Hasselmann, K., Latif, M., Hooss, G., Azar, C., Edenhofer, O., Jaeger, C. C., … Wokaun, A. (2003). The challenge of long-term climate change. *Science, 302*(5652), 1923–1925.

Johansen, S. (1995). *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford: Oxford University Press.

Karakaya, E., Bostan, A., & Özçağ, M. (2019). Decomposition and decoupling analysis of energy-related carbon emissions in Turkey. *Environmental Science and Pollution Research, 26*(31), 32080–32091.

Katircioglu, S. T. (2014). International tourism, energy consumption, and environmental pollution: The case of Turkey. *Renewable & Sustainable Energy Reviews, 36*, 180–187.

Kaya, Y. (1990). Impact of carbon dioxide emission control on GNP growth: Interpretation of proposed scenarios. In *Presentation to the energy and industry subgroup, Response strategies working group*. Paris: IPCC.

Kitamura, Y., Karkour, S., Ichisugi, Y., & Itsubo, N. (2020). Evaluation of the economic, environmental, and social impacts of the COVID-19 pandemic on the Japanese tourism industry. *Sustainability, 12*(24), 10302.

Kuo, N. W., & Chen, P. H. (2009). Quantifying energy use, carbon dioxide emission, and other environmental loads from island tourism based on a life cycle assessment approach. *Journal of Cleaner Production, 17*(15), 1324–1330.

Lee, C. C., & Chiu, Y. B. (2011). Oil prices, nuclear energy consumption, and economic growth: New evidence using a heterogeneous panel analysis. *Energy Policy, 39*(4), 2111–2120.

Lenzen, M., Sun, Y. Y., Faturay, F., Ting, Y. P., Geschke, A., & Malik, A. (2018). The carbon footprint of global tourism. *Nature Climate Change, 8*(6), 522–528.

Liu, G., Shi, P., Hai, F., Zhang, Y., & Li, X. (2018). Study on measurement of green productivity of tourism in the Yangtze River Economic Zone, China. *Sustainability, 10*(8), 2786.

Liu, J., Feng, T., & Yang, X. (2011). The energy requirements and carbon dioxide emissions of tourism industry of Western China: A case of Chengdu city. *Renewable & Sustainable Energy Reviews, 15*(6), 2887–2894.

Liu, J., Zhang, J., & Fu, Z. (2017). Tourism eco-efficiency of Chinese coastal cities - analysis based on the DEA-Tobit model. *Ocean and Coastal Management, 148*, 164–170.

Luo, F., Becken, S., & Zhong, Y. (2018). Changing travel patterns in China and 'carbon footprint' implications for a domestic tourist destination. *Tourism Management, 65*, 1–13.

Meng, W., Xu, L., Hu, B., Zhou, J., & Wang, Z. (2017). Quantifying direct and indirect carbon dioxide emissions of the Chinese tourism industry (reprinted from journal of cleaner production, vol 126, pg 586-594, 2016). *Journal of Cleaner Production, 163*, S401–S409.

Moutinho, V., Costa, C., & Bento, J. P. C. (2015). The impact of energy efficiency and economic productivity on CO_2 emission intensity in Portuguese tourism industries. *Tourism Management Perspectives, 16*, 217–227.

Munday, M., Turner, K., & Jones, C. (2013). Accounting for the carbon associated with regional tourism consumption. *Tourism Management, 36*, 35–44.

OECD. (2002). Indicators to measure decoupling of environmental pressure from economic growth. Retrieved from https://www.oecd.org/env/indicatorsmodelling-outlooks/1933638.pdf.

Peeters, P., Szimba, E., & Duijnisveld, M. (2007). Major environmental impacts of European tourist transport. *Journal of Transport Geography, 15*(2), 83–93.

Qiu, X. P., Fang, Y. P., Yang, X. T., & Zhu, F. B. (2017). Tourism eco-efficiency measurement, characteristics, and its influence factors in China. *Sustainability, 9*(9), 1634.

Ren, S., & Hu, Z. (2012). Effects of decoupling of carbon dioxide emission by Chinese nonferrous metals industry. *Energy Policy, 43*, 407–414.

Rico, A., Martinez-Blanco, J., Montlleo, M., Rodriguez, G., Tavares, N., Arias, A., & Oliver-Sola, J. (2019). Carbon footprint of tourism in Barcelona. *Tourism Management, 70*, 491–504.

Robaina-Alves, M., Moutinho, V., & Costa, R. (2016). Change in energy-related CO_2 (carbon dioxide) emissions in Portuguese tourism: A decomposition analysis from 2000 to 2008. *Journal of Cleaner Production, 111*, 520–528.

Roinioti, A., & Koroneos, C. (2017). The decomposition of CO_2 emissions from energy use in Greece before and during the economic crisis and their decoupling from economic growth. *Renewable & Sustainable Energy Reviews, 76*, 448–459.

Rose, A., & Casler, S. (1996). Input-output structural decomposition analysis: A critical appraisal. *Economic Systems Research, 8*(1), 33–62.

Shan, Y., Ou, J., Wang, D., Zeng, Z., Zhang, S., Guan, D., & Hubacek, K. (2021). Impacts of COVID-19 and fiscal stimuli on global emissions and the Paris agreement. *Nature Climate Change, 11*(3), 200–206.

Sharma, G. D., Thomas, A., & Paul, J. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives, 37*, 100786.

Shi, P., & Wu, P. (2011). A rough estimation of energy consumption and CO_2 emission in tourism sector of China. *Acta Geographica Sinica, 66*(2), 235–243 (In Chinese).

Shuai, C., Chen, X., Wu, Y., Zhang, Y., & Tan, Y. (2019). A three-step strategy for decoupling economic growth from carbon emission: Empirical evidences from 133 countries. *Science of the Total Environment, 646*, 524–543.

Škare, M., Soriano, D. R., & Porada-Rochoń, M. (2021). Impact of COVID-19 on the travel and tourism industry. *Technological Forecasting and Social Change, 163*, 120469.

Student, J., Lamers, M., & Amelung, B. (2020). A dynamic vulnerability approach for tourism destinations. *Journal of Sustainable Tourism, 28*(3), 475–496.

Su, B., & Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics, 34*(1), 177–188.

Sun, Y. Y. (2014). A framework to account for the tourism carbon footprint at island destinations. *Tourism Management, 45*, 16–27.

Sun, Y. Y. (2016). Decomposition of tourism greenhouse gas emissions: Revealing the dynamics between tourism economic growth, technological efficiency, and carbon emissions. *Tourism Management, 55*, 326–336.

Tan, Q. (2011). Greenhouse gas emission in China's agriculture: Situation and challenge. *China Population, Resources and Environment, 21*(10), 69–75 (In Chinese).

Tang, M., & Ge, S. (2018). Accounting for carbon emissions associated with tourism-related consumption. *Tourism Economics, 24*(5), 510–525.

Tang, Z., Shang, J., Shi, C., Liu, Z., & Bi, K. (2014). Decoupling indicators of CO_2 emissions from the tourism industry in China: 1990-2012. *Ecological Indicators, 46*, 390–397.

Tao, Y., Huang, Z., Wu, L., Yu, F., & Wang, K. (2014). Measuring carbon dioxide emissions for regional tourism and its factor decomposition: A case study of Jiangsu province. *Acta Geographica Sinica, 69*, 1438–1448 (In Chinese).

Tapio, P. (2005). Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transport Policy, 12*(2), 137–151.

Toimil, A., Losada, I. J., Nicholls, R. J., Dalrymple, R. A., & Stive, M. J. (2020). Addressing the challenges of climate change risks and adaptation in coastal areas: A review. *Coastal Engineering, 156*, 103611.

Tourism Research Center, Chinese Academy of Social Sciences. (2021). *Green book of China's tourism (2020–2021)*. Retrieved from https://baijiahao.baidu.com/s?id=1699098157442565410&wfr=spider&for=pc.

Tsang, N. K., & Hsu, C. H. (2011). Thirty years of research on tourism and hospitality management in China: A review and analysis of journal publications. *International Journal of Hospitality Management, 30*(4), 886–896.

Uğur, N. G., & Akbıyık, A. (2020). Impacts of COVID-19 on global tourism industry: A cross-regional comparison. *Tourism Management Perspectives, 36*, 100744.

Wang, M. C., & Wang, C. S. (2018). Tourism, the environment, and energy policies. *Tourism Economics, 24*(7), 821–838.

Wang, Q., & Wang, S. (2019). A comparison of decomposition the decoupling carbon emissions from economic growth in transport sector of selected provinces in eastern, central and western China. *Journal of Cleaner Production, 229*, 570–581.

Wang, Q., & Xie, F. (2014). Urban tourism situation analysis on CO_2 emissions and future low carbon scenarios based on decoupling theory and Kaya identities. *Tourism Tribune, 29*(8), 98–109 (In Chinese).

Wang, W., Li, M., & Zhang, M. (2017). Study on the changes of the decoupling indicator between energy-related CO_2 emission and GDP in China. *Energy, 128*, 11–18.

Wu, Y., Chau, K. W., Lu, W., Shen, L., Shuai, C., & Chen, J. (2018). Decoupling relationship between economic output and carbon emission in the Chinese construction industry. *Environmental Impact Assessment Review, 71*, 60–69.

Wu, Y., Tam, V. W. Y., Shuai, C., Shen, L., Zhang, Y., & Liao, S. (2019). Decoupling China's economic growth from carbon emissions: Empirical studies from 30 Chinese provinces (2001-2015). *Science of the Total Environment, 656*, 576–588.

Xie, Y., & Zhao, Y. (2012). Measuring carbon dioxide emissions from energy consumption by tourism in Yangtze River Delta. *Geographical Research, 31*(3), 429–438 (In Chinese).

Xu, S., Zhang, W., He, Z., Han, H., Long, R., & Chen, H. (2017). Decomposition analysis of the decoupling indicator of carbon emissions due to fossil energy consumption from economic growth in China. *Energy Efficiency, 10*(6), 1365–1380.

Zha, J. P., Fan, R., Yao, Y., He, L. M., & Meng, Y. Y. (2020). Framework for accounting for tourism carbon emissions in China: An industrial linkage perspective. *Tourism Economics*. https://doi.org/10.1177/1354816620924891.

Zha, J. P., He, L., Liu, Y., & Shao, Y. (2019). Evaluation on development efficiency of low-carbon tourism economy: A case study of Hubei Province, China. *Socio-Economic Planning Sciences, 66*, 47–57.

Zha, J. P., Tan, T., Fan, R., Xu, H., & Ma, S. (2020). How to reduce energy intensity to achieve sustainable development of China's transport sector? A cross-regional comparison analysis. *Socio-Economic Planning Sciences, 71*, 100772.

Zha, J. P., Tan, T., Yuan, W., Yang, X., & Zhu, Y. (2020). Decomposition analysis of tourism CO_2 emissions for sustainable development: A case study of China. *Sustainable Development, 28*(1), 169–186.

Zhang, J., & Zhang, Y. (2018). Carbon tax, tourism CO_2 emissions and economic welfare. *Annals of Tourism Research, 69*, 18–30.

Zhang, Y. J., & Da, Y. B. (2015). The decomposition of energy-related carbon emission and its decoupling with economic growth in China. *Renewable & Sustainable Energy Reviews, 41*, 1255–1266.

Zhang, Z. (2000). Decoupling China's carbon emissions increase from economic growth: An economic analysis and policy implications. *World Development, 28*, 739–752.

Zhao, Y., Kuang, Y., & Huang, N. (2016). Decomposition analysis in decoupling transport output from carbon emissions in Guangdong Province, China. *Energies, 9*(4), 295.

Zhong, Y., Shi, S., Li, S., Luo, F., & Luo, W. (2014). Empirical research on construction of measurement framework for tourism carbon emission in China. *China Population, Resources and Environment, 24*(1), 78–86 (In Chinese).

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