Heliyon 9 (2023) e21683

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Correlation analysis of regional carbon emission intensity and green industry development-A case study of Chengdu-Chongqing region

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A R T I C L E I N F O

Keywords:
Carbon emission
Green industry development
Chengdu-Chongqing region
EWM-TOPSIS
Quantile regression

A B S T R A C T

Industrial structure markedly affects the level of carbon emissions generated in a region. It is imperative to study the industrial structure of the Chengdu-Chongqing region to obtain information to achieve regional high-quality development by promoting low-carbon development. We selected 16 cities in Chengdu-Chongqing area as the research object in this study. The total carbon emissions (CE), carbon intensity (CI) and per capita carbon emissions (PCE) were calculated for each city. The green industry development (GI) evaluation indexes were then extracted, and the comprehensive evaluation value was determined using the entropy weight-TOPSIS model (EWM-TOPSIS). The green industry development was used as the core explanatory variable to construct a system representing the dynamic relationship between green industry development and carbon intensity using the quantile regression (QR) model. The results of the study showed that: (1) the total carbon emissions of Chengdu-Chongqing region increased whereas the carbon intensity decreased from 2010 to 2020. (2) The green industry development evaluation results showed that Chengdu-Chongqing had unevenly distributed green industry development during the study period, and Chengdu and Chongqing cities had higher green industry development values than other cities. (3) The green industry development of the region had a significant negative effect on carbon intensity at low quantile and a significant positive effect on carbon intensity at high quantile. Energy supply (ES) was positively correlated with the carbon intensity of the region at 1 % level of significance, whereas urbanization rate (U) and power consumption (PEC) were negatively correlated with the carbon intensity at 1 % level of significance. We comprehensively evaluated the development of green industry and introduced it as a core explanatory variable into the quantile regression model to explore the relationship between regional carbon emission intensity and industrial development. The results provide a reference for designing strategies to promote high-quality development in the cities in the Chengdu-Chongqing region.

1. Introduction

Increase in fossil-based energy consumption mainly caused by extensive industrialization results in increased carbon dioxide

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https://doi.org/10.1016/j.heliyon.2023.e21683
Received 4 July 2023; Received in revised form 23 October 2023; Accepted 25 October 2023
Available online 28 October 2023

production [1]. Climate change mainly caused by excessive carbon emissions is a major concern globally and a significant threat to the environment [2]. As a result, more than 130 countries and regions, including China, have proposed development strategies that ensure low carbon emission [3]. Currently, production and manufacturing processes are the main sources of carbon emissions, so it is important to explore the relationship between carbon emissions and industrial structure to design strategies for achieving high-quality regional development [4]. Cities and regions are interdependent and exhibit mutually relationships with each city having a corresponding economic region. The cities in a country and the corresponding economic territories constitute a complete set of regional economic network, so it is imperative to include the cities in the study area as the research object to study the relationship between carbon emission and industrial structure of the entire region [5].

The CI indicator reflects the carbon emission efficiency during regional economic development [6], and the CI is more objective and reliable than CE in evaluating the unbalanced relationship between economic development and environmental conservation [7]. The traditional methods of economic development and irrational industrial structure are associated with a significant increase in carbon emissions [8], thus it is challenging to achieve sustainable economic development. The combination of economic and low-carbon development has become the focus of the government and academics since the "carbon peaking and carbon neutrality goals" were proposed. In addition, several scholars have carried out research on the decoupling and interactive effects of industrial structure and carbon emissions, the dynamic relationship between industrial structure upgrading, economic growth and carbon emission reduction, and the direction and degree of the impact of green finance on industrial structure upgrading [9–11].

Carbon emissions are influenced by various factors. Previous research has mainly focused on the following areas: (1) Urbanization development, whereby several people migrate to cities due to urbanization development, and of the urban lifestyle promotes carbon emissions [12]. On the contrary, urbanization promotes higher carbon emission efficiency and technological progress, which significantly reduces carbon emissions [13]. (2) Energy intensity, population size, and economic development scale are all positively correlated with CO_2 emissions [14–16]. Use of fossil energy, increase in population, and economic development promote increase in CO_2 emissions. (3) A negative correlation is observed between ecological conservation and CO_2 emissions, as well as energy structure and CO_2 emissions [17,18]. Ecological conservation significantly reduces CO_2 emissions by promoting the upgrade of industrial structures. Use of clean energy in the energy sector, such as electricity, not significantly reduces CO_2 emissions compared with non-renewable fossil energy sources and ensures sustainable development of green energy.

Quantitative analysis of the relationship between carbon emissions and various factors that affect carbon emission levels is necessary for establishing the relevant policies. A variety of methods have been applied to study the association between various factors and carbon emissions, including the Logarithmic Mean Divisia Index (LMDI) [19], Long-range Energy Alternatives Planning System (LEAP) [20], and optimization model [21]. In addition, some scholars have also studied the drivers of carbon emissions based on traditional econometric methods, such as multivariable linear regression model [22], spatial econometric methods [23], and ridge regression [24]. Panel quantile regression models have also been gradually applied in the recent past to explore the factors that affect carbon emissions. For example, Lin et al. (2023) systematically evaluated the potential heterogeneity and asymmetry of the direct and moderating effects of environmental regulations on the efficiency of industrial carbon emissions at the urban scale in China using a panel quantile regression approach [25]. Cheng et al. (2022) utilized quantile regression techniques to comprehensively explore the potential heterogeneous effects between energy technology innovation and carbon emission intensity, considering the huge heterogeneity in China. The results showed that renewable energy technology innovation and fossil energy technology innovation have opposite effects on carbon emission intensity in the low quantile region compared with the high quantile region [26]. Guo et al. (2023) used a quantile regression model to evaluate the relationship between urbanization and energy carbon emissions based on inter-provincial panel data obtained from China between 1997 and 2019. The findings showed that the effect of urbanization on carbon emissions was more significant for provinces in the high quantile compared with provinces in the low and middle quantile [27].

However, previous research has some limitations and gaps as follows: 1) The core explanatory variables in the model are often represented by a single indicator that does not comprehensively represent the variables. 2) The selection of variables is generalized and rarely considers the characteristics of the region's development and is not fully described in previous studies. 3) Scholars do not comprehensively consider the distribution of the explanatory variables at different levels when the research object is a country or a region. To circumvent these limitations, we combined the industrial development advantages of Chengdu-Chongqing region and selected the corresponding indicators to improve the comprehensive evaluation of the current green industry development in region, and used it as the core explanatory variable. Moreover, we selected ES, U, PD and PEC as the control variables, and utilized the QR model to conduct a comprehensive analysis of the distribution of CI at different levels in the region. This paper is organized as follows: Section 1 comprises outlines a summary of the research progress on carbon emissions; Section 2, 16 cities in Chengdu-Chongqing region are introduced as the research objects, the data and methods used in the study are introduced and the process for construction of a GI evaluation index system is presented in this section; Section 3, the CI calculated based on the carbon emission factor and the GI obtained based on the EWM-TOPSIS measurement is used to evaluate the CI and GI from the spatial and temporal perspectives; and the dynamic relationship between GI and CI is explored using the quantile regression method. The conclusion of this study is presented in Section 4, and the discussion is presented in Section 5.

2. Overview of the study area and methodology

In this study, data were collected from 16 cities in the Chengdu-Chongqing region from 2010 to 2020. First, the spatial-temporal characterization of CE, CI and PCE was conducted. Secondly, the GI evaluation index system was established based on economic resources, social resources and environmental resources, and a GI evaluation model was constructed based on EWM-TOPSIS. Finally, the correlations between CI and GI, ES, U, PD and PEC were evaluated using the QR model. The study design is summarized below.

Step 1. Collection of data on total energy consumption and related data on economic resources, social resources and environmental resources for 16 cities in the Chengdu-Chongqing region from 2010 to 2020;

Step 2. Measurement of CE, CI and PCE using the standard coal CO_2 emission factors available on the BP China Carbon Emission Calculator based on the total energy consumption [28], and performing spatial-temporal characterization of carbon emissions;

Step 3. Establishing a comprehensive evaluation index system of GI, constructing a GI evaluation method based on EWM-TOPSIS, and conducting a comprehensive spatial-temporal characterization of GI in the Chengdu-Chongqing region;

Step 4. Use of the QR model to quantitatively evaluate the dynamic relationship between CI and GI, ES, U, PD and PEC.

The research framework of the study is shown in Fig. 1.

2.1. Study area

The development of the western region of China plays a key role in the economy of the country. Chengdu-Chongqing region has become an important hub of economic development in the western region owing to several years of rapid development. Therefore, understanding the relationship between economic growth and carbon emissions in the Chengdu-Chongqing region can provide a reference for promoting high-quality development of other cities in the western region. The Chengdu-Chongqing region comprises 15 municipalities in Sichuan Province and 27 districts in Chongqing Municipality. We selected the entire city of Chongqing as the research object in our study owing to the availability of data and strategies for improving development in the region [29]. Therefore, the study area comprised 16 cities including Chongqing (CQ), Chengdu (CD) and Mianyang (MY). The construction of the Chengdu-Chongqing Economic Circle was first proposed in 2020, thus we chose 2010 to 2020 as the time frame for this study to ensure the findings were reliable and had practical significance. The resource-environmental and socio-economic data for the cities were obtained from the Sichuan Statistical Yearbook, the China City Statistical Yearbook and the statistical yearbooks of each city and state as well as the environmental bulletins of each city and state. The study area is shown in Fig. 2.

2.2. Data preprocessing

2.2.1. Explained variable

Carbon emission intensity (CI): Previous findings indicate that fossil energy is the most consumed type of energy in the industrial production and manufacturing [30], and the present study is on the industrial structure of Chengdu-Chongqing region. The Statistical Yearbook of Chengdu-Chongqing region prefectural and municipal cities does not have the detailed statistical information on the use of various types of fossil energy, therefore, we used the total amount of energy consumption in each prefectural and municipal city, which

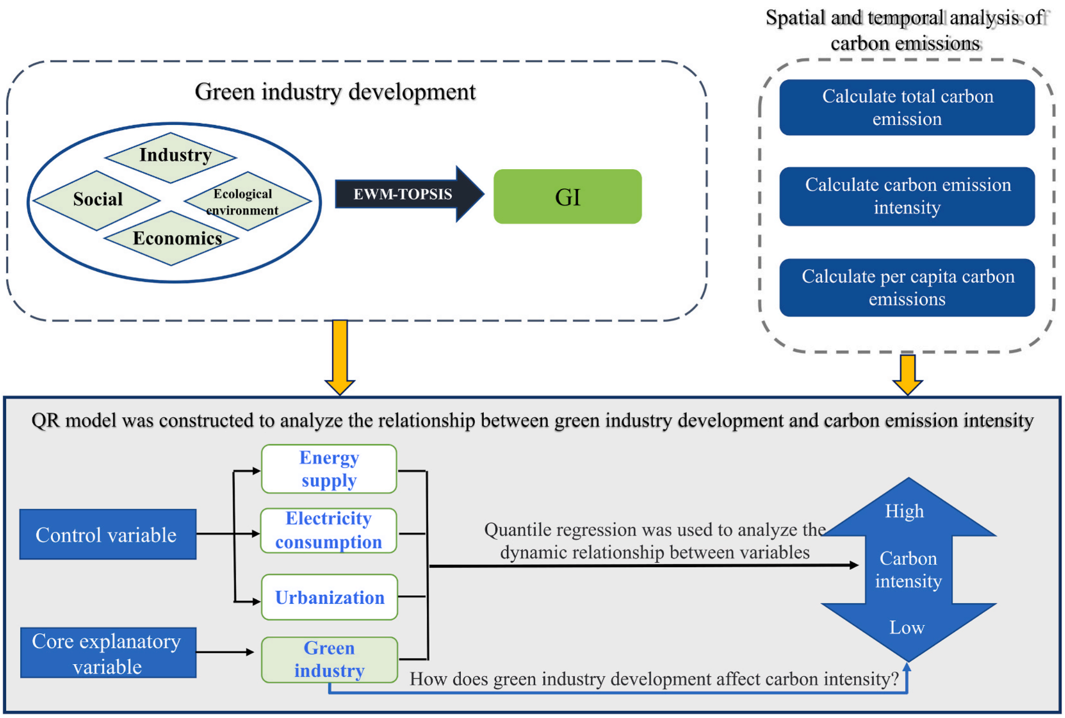

Fig. 1. Research framework diagram.

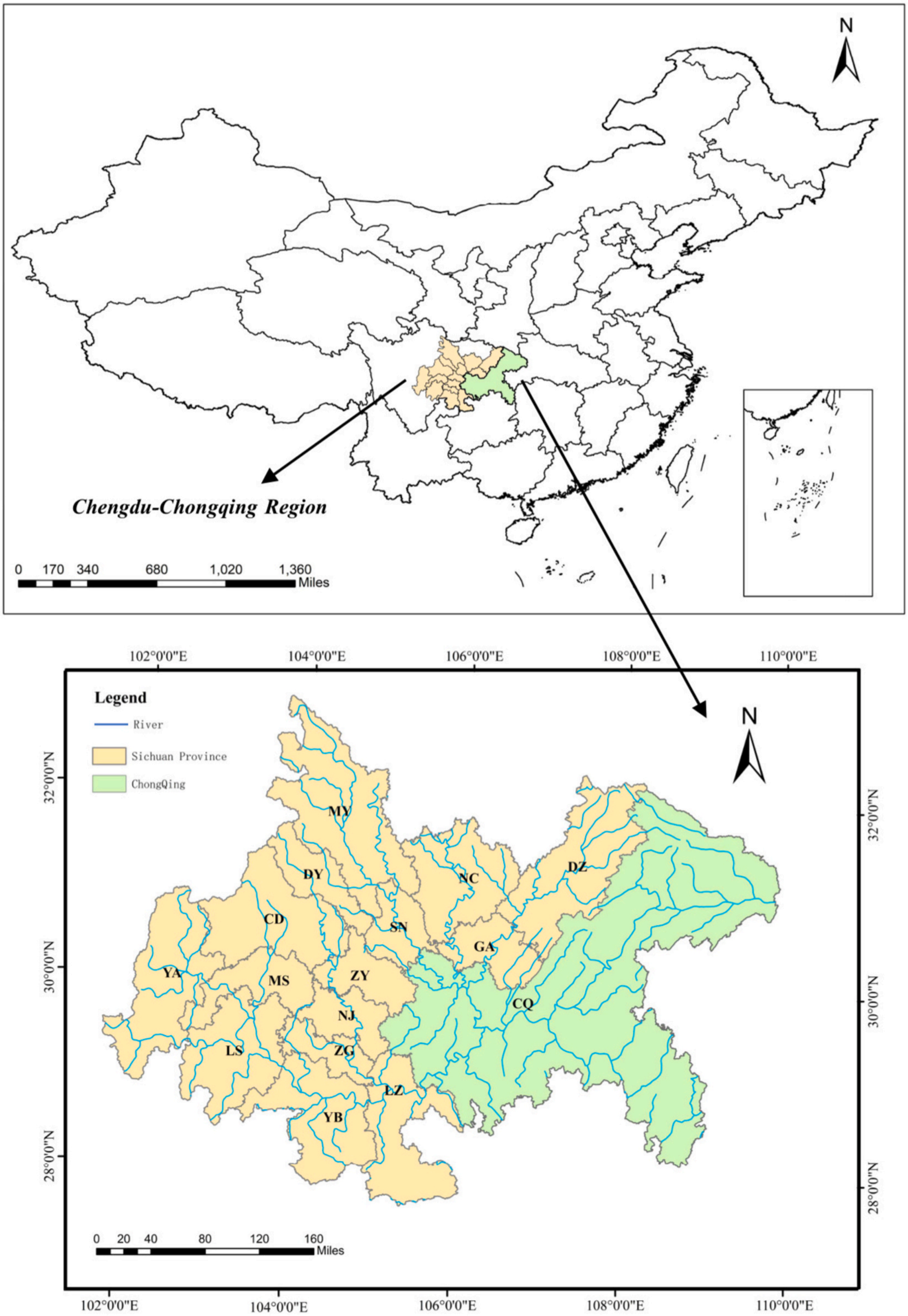

Fig. 2. Overview of the study area.

mainly includes raw coal and crude oil and its products, natural gas, and electricity to calculate the level of carbon emissions using the carbon emission coefficient method. The BP China Carbon Emissions Calculator calculates the level of CO_2 emissions through a "top-down approach", i.e., by counting a country's fossil energy consumption and multiplying that consumption by a conversion factor to obtain the level of CO_2 emissions. Therefore, we utilized the standard coal CO_2 emission coefficients obtained using the BP China Carbon Emission Calculator to get the CE, CI and PCE indicators [28], which were calculated using Equation (1) (2) and (3):

$$CE = 2.493 \times E \tag{1}$$

$$CI = CE/GDP \tag{2}$$

$$PCE = CE/P \tag{3}$$

where CE, CI and PCE represent the total carbon emission, carbon emission intensity and per capita carbon emission of the prefecture-level cities, respectively; E denote the total energy consumption of prefecture-level cities; GDP and P represent the regional GDP and population of prefecture-level cities, respectively; 2.493 is the CO_2 emission factor of standard coal obtained from the BP China Carbon Emission Calculator.

2.2.2. *Control variables*

Energy supply (ES): ES refers to per capita energy consumption, and is defined as the average amount of primary commodity energy consumed per person per year in a country or region. ES is a key indicator of the level of development of a country or region [31]. The industries in the Chengdu-Chongqing region are mainly manufacturing industries, with a several secondary industries and high energy consumption.

Urbanization rate (U): Urbanization rate is also known as the level of urbanization. Urbanization comprises a wide range of components, including migration of people to cities, urban expansion, and urban economic growth. In this study, we defined U as the proportion of urban population in each city [32]. The construction of the Chengdu-Chongqing economic circle has promoted improved modernization of cities and towns in the region.

Population density (PD): PD is the ratio of the year-end household population to the land area of an administrative area. It is an important indicator of the distribution of population in a country or region. Population density is used to determine the effect of population aggregation on carbon emissions [33].

Power consumption (PEC): PEC refers to per capita electricity consumption. It is defined as the ratio of electricity consumption of the whole society to the annual population of the region. High electricity consumption indicates a significant increase in use of clean energy, but electricity production is a major source of global carbon emissions [34].

The descriptive statistical analysis of the variables for the study period 2010–2020 is presented in Table 1.

2.2.3. *Core explanatory variables*

Green industrial development (GI): Green development is a strategy of economic growth and social development that aims at efficiency, harmony and sustainability. Green development is currently an important feature in the world. Several countries advocate for development of green industries as an important initiative to promote economic restructuring, highlight the concept and connotation of green economy, and ensure that carbon neutrality is achieved [35]. The actual status and characteristics of industrial development in Chengdu-Chongqing region were obtained through literature review. Subsequently an evaluation index system suitable for GI in the research area of this study was constructed based on the research results and data obtained from previous studies. Green industry development is affected by three aspects: economic, social and environmental. Therefore, we constructed a GI evaluation index system by selecting indicators from three subsystems: economic, social and environmental aspects [36]. Four indicators were selected in the economic subsystem namely labor productivity (ratio of regional GDP to total employment), capital productivity (ratio of regional GDP to social fixed asset investment), industrial agglomeration (locational entropy) and the degree of openness to the other countries (ratio of total imports and exports to regional GDP). Two indicators were selected in the social subsystem namely energy conservation and environmental protection expenditure (ratio of total environmental protection expenditure to general public budget expenditure) and science expenditure (the proportion of total science expenditure to general public budget expenditure). Three indicators namely, industrial wastewater emission per unit GDP, sulfur dioxide emission per unit GDP and greening coverage of construction areas were selected for the environmental subsystem. The evaluation index using the specific indicators was established as shown in Table 2.

Table 1
Descriptive statistical analysis of the study variables.

Type	Name	Unit	Mean	Min	Max	SD
Explained variable	CI	t/ 10^4 yuan	1.92	0.76	4.48	0.82
Control variable	ES	t/people	2.51	0.85	4.99	0.79
	U	%	46.98	29.07	78.77	9.33
	PD	people/ km^2	478.979	95	1461	243.746
	PEC	kW·h/people	1685.59	247.50	8339.69	1514.43

Table 2
Green industry development evaluation index system.

Objective layer	Rule layer	Indicator layer	Unit	Attribute	Code	Literature
GI	Economy	Labor productivity	million yuan/person	+	x1	[37]
		Capital productivity	%	+	x2	[38]
		Industrial agglomeration	%	+	x3	[39]
		The degree of openness to the other countries	%	+	x4	[40]
	Social	Energy conservation and environmental Protection expenditure	%	+	x5	[41]
		Science expenditure	%	+	x6	[42]
	Environment	Industrial wastewater emission per unit GDP	t/million yuan	−	x7	[43]
		Sulfur dioxide emission per unit GDP	t/billion yuan	−	x8	[44]
		Greening coverage of built-up areas	%	+	x9	[45]

The "+" symbol indicates that the indicator is promoting GI; The "-" symbol indicates that the indicator is inhibitory to GI.

2.3. Research methods

2.3.1. EWM-TOPSIS model

The TOPSIS superior-inferior solution distance method is a common comprehensive evaluation method that effectively extracts information from raw data, and the results from the method accurately indicate the difference between evaluation schemes [46]. The entropy weight method was used to obtain the index weights to explore the relationship between the data levels in this study after considering the objectivity of the construction of the index system. The data were first normalized, followed by evaluation of the information entropy and coefficient of differentiation for each indicator, then the weights of each indicator were calculated [47]. The size of the value of C_i determined by TOPSIS reflects the level of green industry development of the *i-th* city in Chengdu-Chongqing region. A C_i value closer to 1 indicates higher level of green industry development of the *i-th* city. A flowchart showing the steps of the EWM-TOPSIS method is shown in Fig. 3.

2.3.2. Quantile regression

The main focus of most previous regression models was on the effect of the explanatory variables on the conditional expectation of the explanatory variables, describing concentrated trends and often ignoring the changes in the coefficients under conditional random probability distributions. Researchers may be interested in other important quantiles of the distribution in empirical analysis. For example, studying the difference in the role of environmental regulatory constraints on carbon intensity in different regions requires evaluating the effect of environmental regulation on carbon intensity at low and high carbon intensity levels [48]. Roger and Gilbert (1978) proposed that the quantile regression method can be effectively used to solve this challenge [49]. This method does not make any assumptions about the distribution of random error terms unlike the least squares regression method. In addition, the results are

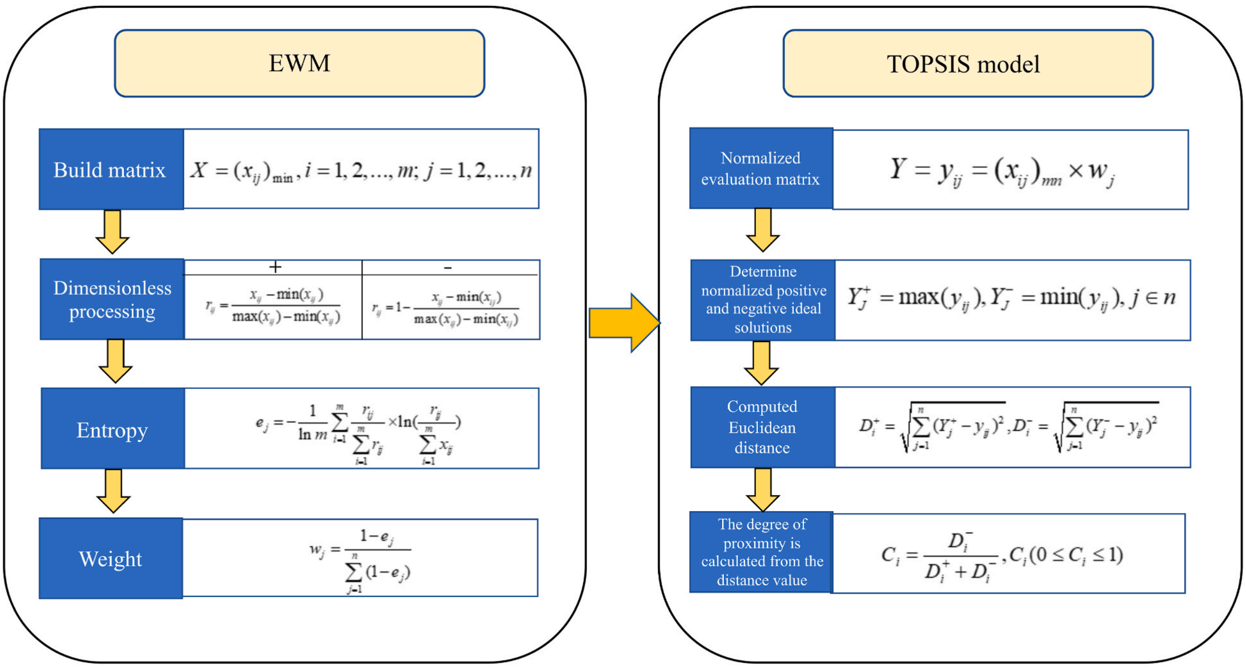

Fig. 3. A flowchart representation of the EWM-TOPSIS method.

not easily affected by extreme values and the regression is more robust. As a result, the quantile regression method reflects the data information more comprehensively. The formula for the panel data used in this paper is presented below in Equation (4):

$$Q_{Y_{it}}(\tau|X_{it}) = \alpha_i + X_{it}^T\beta(\tau), (\mathrm{i} = 1, 2, ..., \mathrm{n}; \mathrm{t} = 1, 2, ..., \mathrm{T}) \tag{4}$$

where $Q_{Y_{it}}$ represents the conditional quantile function; i denotes the different sample individuals; t represents the sample observation period; n denotes the sample size; T represents the learning period; τ denotes the set of quantile used in this study, ranging between (0,1); α_i is a constant term; β_τ represents the influence coefficient under τ quantile, and the weighted least squares influence coefficient β was used as shown below in Equation (5).

$$\beta(\theta) = \min_{(\alpha,\beta)} \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{t=1}^{T} w_k \rho_{\tau_k}\left[Y_{it} - \alpha_i - X_{it}^T\beta(\tau_k)\right] \tag{5}$$

where $\beta(\theta)$ represents the influence coefficient; k is the k-th group of quantiles; q represents the quantile groups; w_k denotes the weight coefficient of the k-th quantile; ρ_{τ_k} is a quantile loss function; β_{τ_k} represents the influence coefficient of the k-th quantile.

3. Results

3.1. Spatial-temporal evolution of carbon emissions in Chengdu-Chongqing region

3.1.1. Total carbon emissions in Chengdu-Chongqing region

The total carbon emissions of cities in the Chengdu-Chongqing region showed an increase from 2010 to 2020 (Fig. 4). The total amount increased from 520 million tons to 660 million tons at a growth rate of about 14 million tons/year. The results show that Chengdu and Chongqing had the accounted for the highest levels of emissions, with 20 % and 27.8 % of the total amount of emissions, respectively. On the contrary, Ya'an and Ziyang had relatively low levels of emissions accounting for 1.6 % and 1.4 % of the total amount of emissions, respectively. Chongqing and Ya'an had the highest growth rate of emissions with 52.8 % and 77.8 % increase over the study period, respectively. Currently, the focus of the region is ensuring rapid economic development, and as a result, carbon emissions are on the rise. But the growth rate of the total carbon emissions in the Chengdu-Chongqing region has decreased since 2014, indicating that the decision-makers are paying attention to environmental protection while promoting economic development in the region.

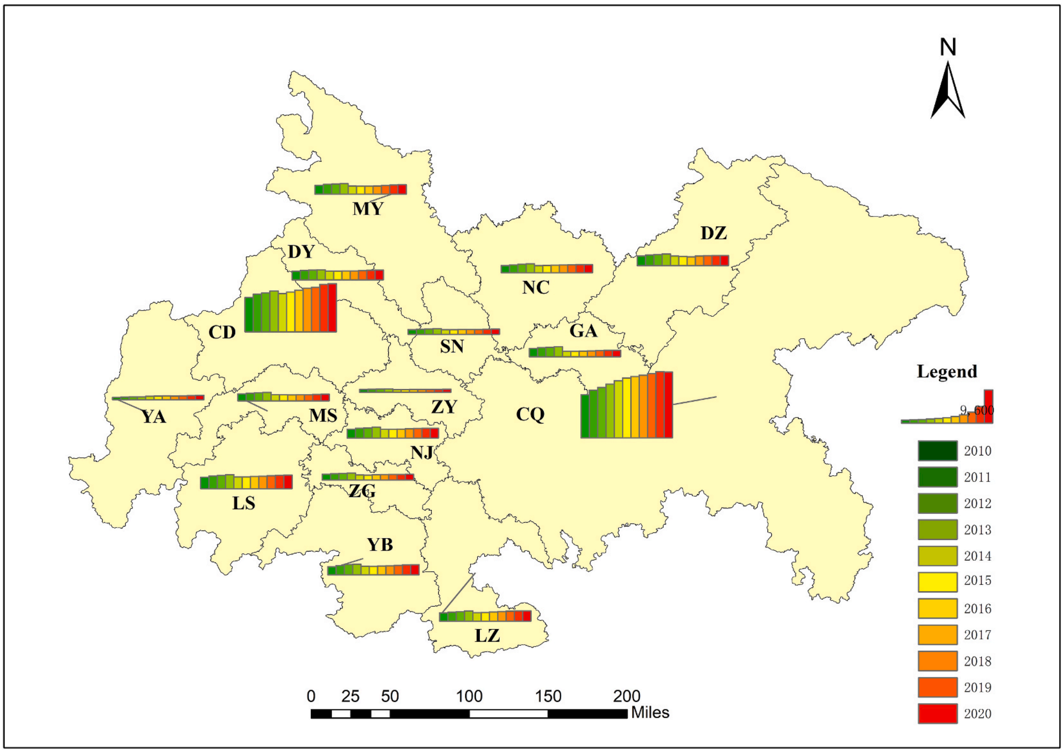

Fig. 4. Total carbon emissions (ten thousand tons) of the cities in Chengdu-Chongqing.

3.1.2. Carbon emission intensity of Chengdu-Chongqing region

The carbon emission intensity of cities in the Chengdu-Chongqing region shows decreased with time and there were no significant differences among cities (Fig. 5). Leshan showed the highest carbon emissions per unit GDP with a decrease from 4.5 tons/ten thousand yuan in 2010 to 2 tons/ten thousand yuan in 2020. Chengdu and Chongqing exhibited the minimum values of carbon emissions per unit of GDP over the years, whereas the emissions in other regions were mainly between 1 ~ 4.5 tons/ten thousand yuan. The carbon intensity of the other cities overall, with the exception of Chengdu and Chongqing, is higher, which is the opposite of the total amount of carbon emissions analyzed above. This further suggests that Chengdu and Chongqing are causing an increase in carbon emissions because of their economic development.

3.1.3. Carbon emissions per capita in Chengdu-Chongqing region

The carbon emissions per capita calculated based on the total carbon emissions and the annual resident population of each city were not significantly different among the cities (Fig. 6). Leshan had the highest carbon emissions per capita in the region, with an increase from 10 tons/person in 2010 to 12 tons/person in 2020. Ziyang had the lowest per capita carbon emission in the region. The average carbon emission per capita of the study area increased from 5.7 tons/person in 2010 to 6.7 tons/person in 2020. The per capita carbon emissions of the remaining cities, with the exception of Ya'an and Chongqing, generally displayed a clear downward trend after 2014, which is related to the decrease in the growth rate of total carbon emissions in the Chengdu-Chongqing region after 2014, as previously examined.

3.2. Spatial and temporal evolutionary characteristics of green industry development

3.2.1. Green industry development index weights of the study area

The weights of the indicators were calculated using the EWM and the weights of these indicators were arranged in order (Fig. 7). The weight of the degree of openness to the other countries (x4) which was in the economic subsystem ranked first and the weight of this indicator was significantly different from the weights of the other indicators. Expenditure on science (x6) in the social subsystem ranked second, and the contribution of indicators x4 and x6 was close to 50 % of the overall, indicating that they are important factors that affect the GI. In contrast, the environment subsystem's indicators of industrial waste emissions (x8, x7) and greening coverage (x9) are given minimal weights, with weight values totaling no more than 10 % of the overall.

3.2.2. Green industry development evaluation results

We conducted GI evaluation using the EWM-TOPSIS method. The GI levels of the 16 cities were evaluated from the perspective of time from 2010 to 2020. The results showed significant differences in GI levels in the 16 cities (Fig. 8). Neijiang and Suining exhibited

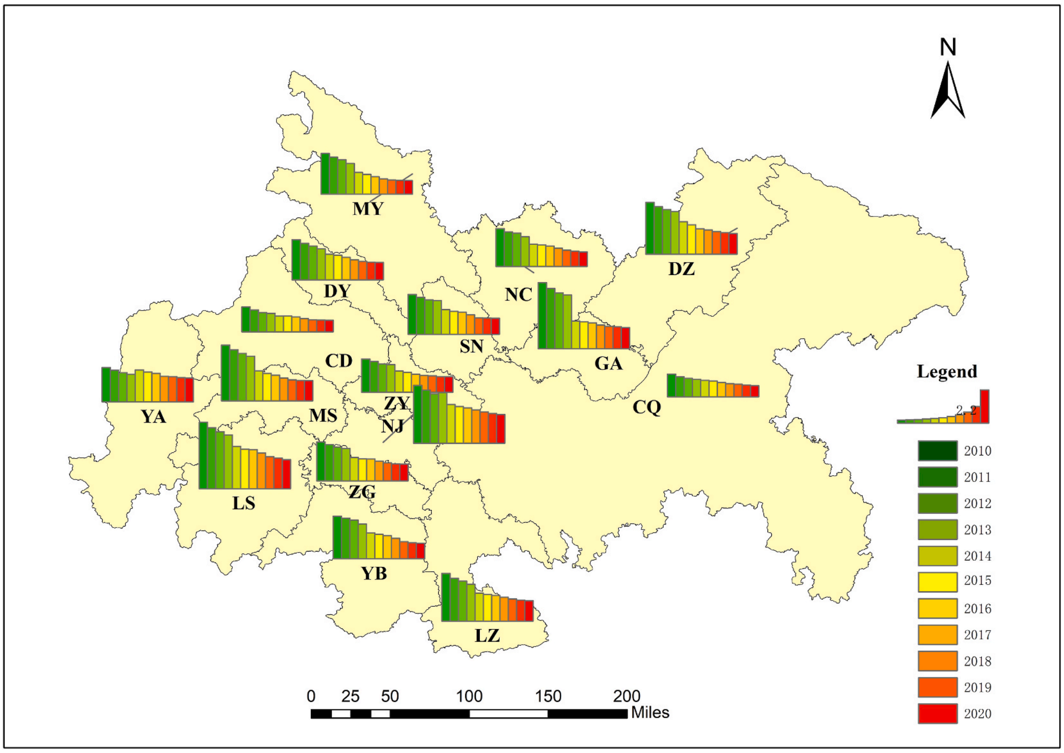

Fig. 5. Carbon emission intensity (ton/million yuan) of cities in the study area.

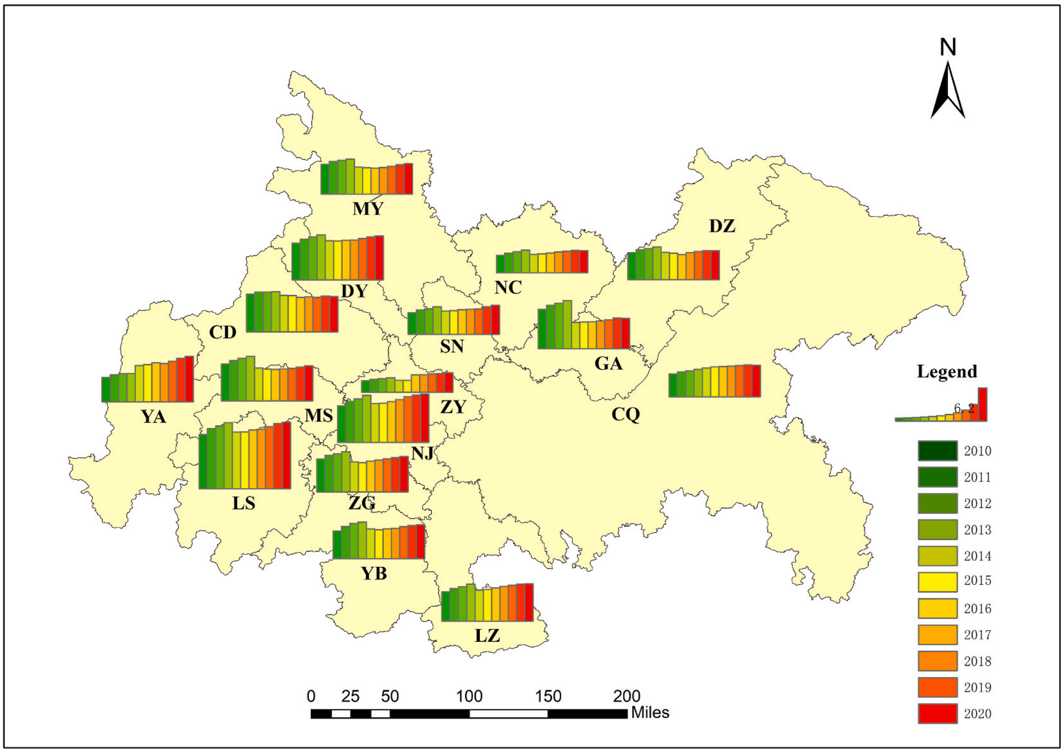

Fig. 6. Carbon emissions per capita (tons/person).

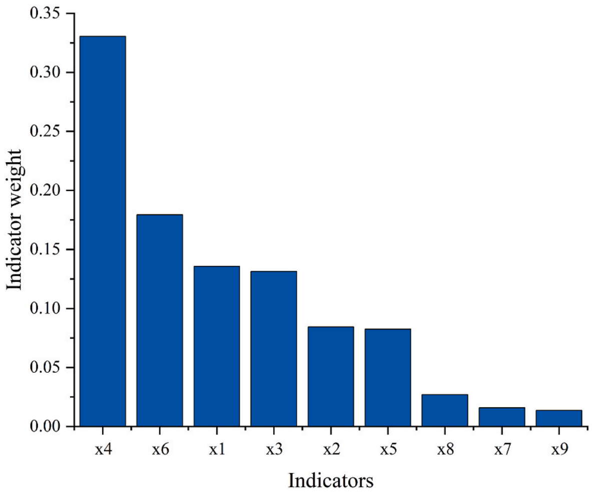

Fig. 7. Weight ranking of GI evaluation indicators in Chengdu-Chongqing region.

the lowest GI level and did not have significant fluctuation, whereas the other showed significant fluctuation. Mianyang, Chengdu and Chongqing had high GI levels, with Chengdu having the highest and consistent GI level.

The distribution of GI across cities is presented in Fig. 9. Chengdu and Chongqing had significantly higher GI levels than the other cities. Mianyang and Deyang cities neighbor Chengdu city and also has high GI levels. Ziyang, located between Chengdu and Chongqing, also had a higher level of GI, indicating that the development of the green industry exhibits a spillover profile, extending from areas with a high level of development to the surrounding areas.

The findings presented in Table 3 show that: 1) The mean GI value for the 16 cities in the Chengdu-Chongqing region was 0.206, and the standard deviation was 0.206, indicating that the overall level of GI in the Chengdu-Chongqing region was weaker and less stable. 2) The results on specific cities indicate that Chengdu and Chongqing had a GI value more than 0.4. Dazhou and Nanchong had the lowest GI levels among all the cities, and their stability was relatively average. Suining and Neijiang had high GI stability and

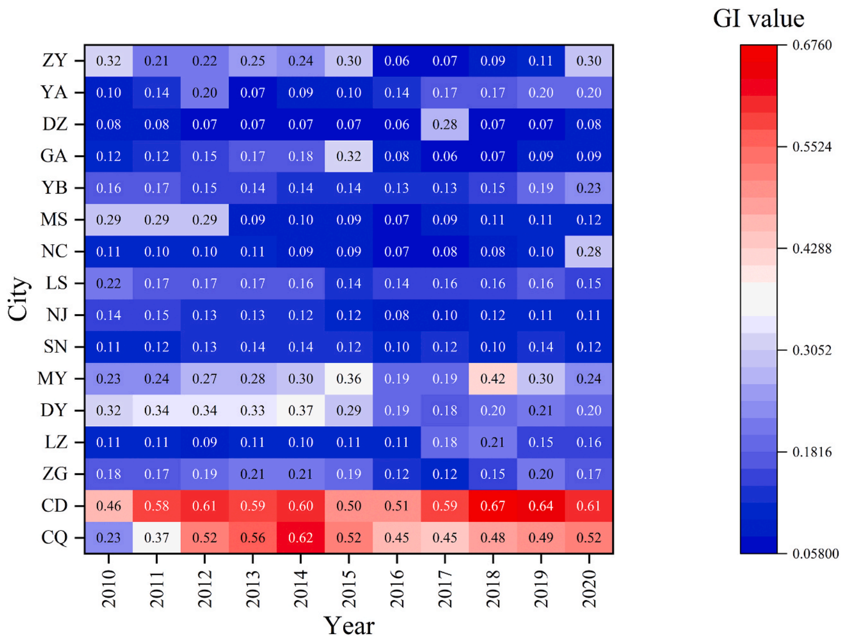

Fig. 8. Visualization of green industry development of cities in the study area

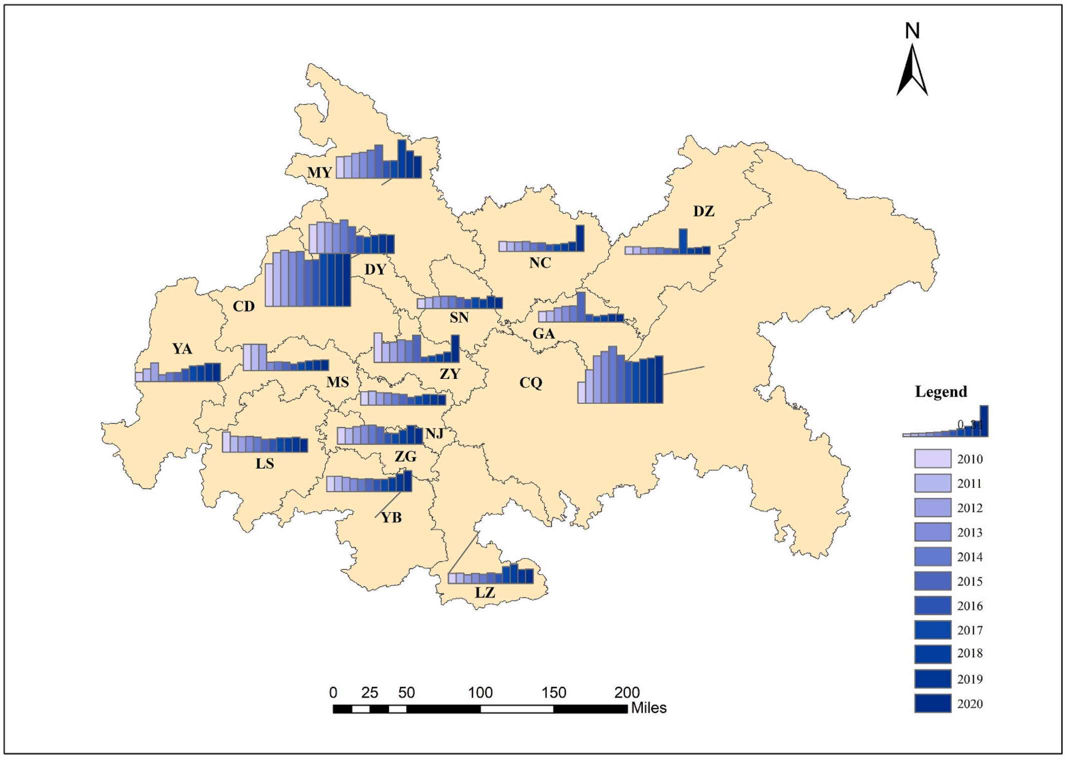

Fig. 9. Regional GI distribution.

average GI levels.

3.2.3. Temporal trends of carbon emission intensity and green industry development

The results on the CI and GI values of Chengdu-Chongqing region from 2010 to 2020 (Fig. 10) showed that:1) The carbon emission

Table 3
GI mean, mean ranking, standard deviation and stability ranking of cities in Chengdu-Chongqing region.

Region	Mean	Mean ranking	SD	Stability ranking
CQ	0.474	2	0.104	16
CD	0.580	1	0.063	10
ZG	0.174	6	0.032	5
LZ	0.132	11	0.038	6
DY	0.269	4	0.073	12
MY	0.274	3	0.070	11
SN	0.120	13	0.013	1
NJ	0.120	14	0.020	2
LS	0.164	7	0.021	3
NC	0.111	15	0.059	8
MS	0.148	9	0.090	14
YB	0.158	8	0.029	4
GA	0.132	12	0.075	13
DZ	0.092	16	0.062	9
YA	0.144	10	0.048	7
ZY	0.197	5	0.097	15
Research area	0.206	–	0.206	–

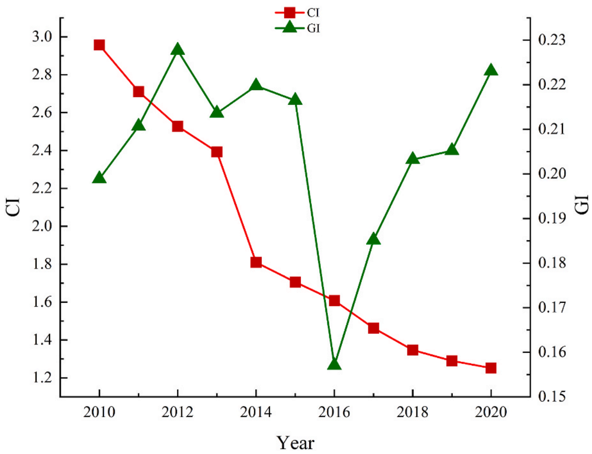

Fig. 10. Time variation of CI and GI values.

intensity has steadily decreased in the past 10 years, and the GI value fluctuated significantly, with an abrupt decline in 2016.2) The GI values can be grouped into three stages based on the process of change. The first phase was an increasing trend from 2010 to 2012, then a fluctuating decreasing trend from 2012 to 2016, with a minimum level observed in 2016, and the third phase was a continuous increasing trend since 2016, which is likely to continue beyond the study period. 3) The rate of CI reduction decreased gradually since 2014, whereas the GI values exhibited a steep decrease from 2015 to 2016, then gradually increased to the average after 2019.

3.3. The dynamic relationship between carbon emission intensity and green industry development

QR model is a new analysis method for data that do not meet the assumptions of mean reversion. This implies that when determining the independent variables, more information about the data is mined at different levels of the dependent variable to accurately reflect the dynamic relationship between different variables and the dependent variable. Therefore, we estimated the dynamic relationship between GI and CI using the QR model. Multicollinearity test is carried out on the basis of quantile regression due to the possibility of multicollinearity between variables. Variables with cointegration are eliminated, and the GI, lnES, lnU, lnPEC of the study area are retained. In this study, we estimated the ordinary least squares model (OLS) to enhance the evaluation effect during comparison of the average regression coefficient with the traditional panel data model. Nine quantile indexes, namely, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 were used to evaluate the relationship between different influencing factors and CI under different distribution conditions.

3.3.1. Explanatory variable quantile regression results

The regression coefficients (slopes of the regression curves) were different for the different variables at different quartiles (Table 4). This implies that different variables had different degrees of influence on CI marginal effects at different quartiles. Analysis of the core

Table 4
Results for OLS and QR estimation.

Variable	OLS	QR								
		0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
lnGI	0.0640***	−0.0651***	−0.0202	−4.57e-06	0.0654*	0.0871***	0.0848***	0.114***	0.134***	0.160***
	(0.0230)	(0.0248)	(0.0407)	(0.0447)	(0.0383)	(0.0212)	(0.0280)	(0.0265)	(0.0201)	(0.0297)
lnES	0.844***	0.831***	0.837***	0.913***	0.936***	0.873***	0.869***	0.892***	0.891***	0.855***
	(0.0407)	(0.0529)	(0.0635)	(0.0795)	(0.0713)	(0.0598)	(0.0593)	(0.0306)	(0.0282)	(0.0579)
lnU	−1.591***	−1.291***	−1.240***	−1.251***	−1.603***	−1.706***	−1.691***	−1.774***	−1.834***	−2.031***
	(0.0962)	(0.130)	(0.164)	(0.171)	(0.150)	(0.0847)	(0.134)	(0.109)	(0.110)	(0.136)
lnPEC	−0.174***	−0.172***	−0.195***	−0.201***	−0.179***	−0.179***	−0.171***	−0.178***	−0.185***	−0.160***
	(0.0213)	(0.0359)	(0.0479)	(0.0507)	(0.0433)	(0.0294)	(0.0317)	(0.0186)	(0.0222)	(0.0280)
Constant	6.364***	4.775***	4.885***	4.992***	6.348***	6.878***	6.787***	7.221***	7.571***	8.277***
	(0.325)	(0.315)	(0.590)	(0.686)	(0.527)	(0.289)	(0.460)	(0.396)	(0.354)	(0.475)

Note: values in parentheses are *t*-test values; ***, **, and * represent significance at a confidence level of 1 %, 5 %, and 10 %, respectively.

explanatory variables indicated that the effect of GI on CI was largely positive at the 1 % level of significance in both OLS and QR models. The degree of contribution of GI to CI generally showed a V-shaped trend with increase in quantiles. The GI exhibited opposite effect on CI at low and high quantiles. The absolute value of the regression coefficient of GI decreased with increase in quantiles (0.10~0.30) at the lower quantiles, whereas the absolute value of the regression coefficient of GI increased with increase in the quantiles (0.40~0.90). This finding indicates that GI significantly affects CI, and the effect is more significant in the lower-quantile and higher-quantile municipal units than in the median-quantile municipal unit.

Analysis of control variables using the OLS and QR models showed that ES was positively correlated CI at a significance level of 1 % whereas U and PEC were negatively correlated with CI at a significance level of 1 %. The specific analyses are as follows.

(1) Energy supply: The regression coefficients of ES exhibited M-shaped fluctuation trend with increasing quantiles, and the values of the regression coefficients at the low and high quantiles were significantly lower than the values at the mid-quantiles. This is because utilization of fossil energy produces carbon dioxide, leading to increase in carbon emissions. However, the coefficient of ES showed a fluctuating trend because of the different levels of economic development in each region, but the fluctuation range was maintained within the confidence interval.
(2) Urbanization rate: The results showed a negative correlation between U and CI, indicating that an increase in regional U leads to a decrease in CI. The degree of U's influence on CI increased with increase in the number of quantiles, and the absolute value of the regression coefficients at the lower quantiles was lower than that at the higher quantiles, which indicates that the degree of U's contribution was higher at the higher quantiles than that at the lower quantiles. A high urbanization rate indicates a higher economic, cultural, and technological level of a city. The concept of sustainable development prompts the demand for alternative cleaner energy sources, thus the negative impact of U on carbon emission intensity becomes stronger. Therefore, increase in the level of urbanization is negatively correlated with carbon emission intensity at this stage.
(3) Electricity consumption: The relationship between PEC and CI exhibited a W-shaped fluctuation trend, but the range of fluctuation was not large. This is because electricity is a clean energy source and there are several water resources in Sichuan and Chongqing regions that can be used to generate electricity, and utilization of clean energy as the main energy source can reduce carbon dioxide emissions.

3.3.2. *The distribution of regression coefficients of each explanatory variable*

Curves for the confidence intervals of the quantile regression at different quantile levels were generate to explore the effect of different variables on CI (Fig. 11). The distribution of regression coefficients of the variables showed varying effect of influence of socio-economic and green industry development factors on CI at different quantile levels.

The upper and lower limits of the OLS estimation coefficient and the confidence interval were horizontal lines, and the coefficients and confidence intervals did not change with change in quantile level (represented as dotted lines in different colors in Fig. 11). Analysis of the QR model regression coefficients show that the regression coefficients of CI were different at different quantile levels (Fig. 11). The regression coefficients and confidence intervals of GI were initially less than 0, then they increased gradually to values greater than 0 with increase in quantiles. These findings indicate that GI had both positive and negative effects on CI and the effect on CI is more significant at the lower and higher quantiles. In contrast, the regression coefficients and confidence intervals of U and PEC were less than 0, and the confidence intervals of PEC gradually became narrower, indicating that the standard deviation of the coefficient estimates gradually decreased and the volatility of the coefficient estimates also decreased. All the coefficient estimates of the variables at different quartiles were not within the confidence intervals of the coefficients of the mean regression model, indicating that the mean regression model was not reliable so the quantile regression model explained the relationship between the variables better. The positive and negative impacts of ES, U and PEC estimated by OLS regression on the carbon emission intensity of the study area were more consistent compared with the results obtained using quantile regression, which shows the robustness of the QR model and reliability of the results.

4. Discussion

In this study, we calculated the carbon emission intensity based on the total amount of energy consumption, and we improved the evaluation of GI using the EWM-TOPSIS method combined with the location and industrial characteristics of Chengdu-Chongqing area, and finally analyzed the dynamic relationship between GI and CI using the QR model to provide a reference for the high-quality development of Chengdu-Chongqing area. The finding showed that total carbon emissions and per capita carbon emissions in the Chengdu-Chongqing region exhibited an increasing trend, but the rate of increase of total carbon emissions has slowed down since 2014. In addition, the carbon emission intensity of the Chengdu-Chongqing region has decreased over time. Comprehensive evaluation of GI showed that the GI level of Chengdu-Chongqing region fluctuates significantly, which can be attributed to the industrial adjustment made in the region to improve the industrial system. The GI had a negative effect on the CI of cities with low carbon intensity in the Chengdu-Chongqing region, and a positive effect on the CI of cities with high carbon intensity.

The key findings from the study are as follows: 1) The total carbon emissions, carbon emission intensity and per capita carbon emissions of the 16 cities in Chengdu-Chongqing region were calculated in this study. The results showed that the total carbon emissions increased whereas the carbon emission intensity decreased over the study period. These findings indicate that the future economic development of Chengdu-Chongqing region can be improved while reducing carbon emissions thus achieving the development of green economy. Spatial analysis showed that the total carbon emissions and carbon intensity of Chengdu and Chongqing cities were significantly different from other cities in the Chengdu-Chongqing region. This spatial difference in per capita carbon

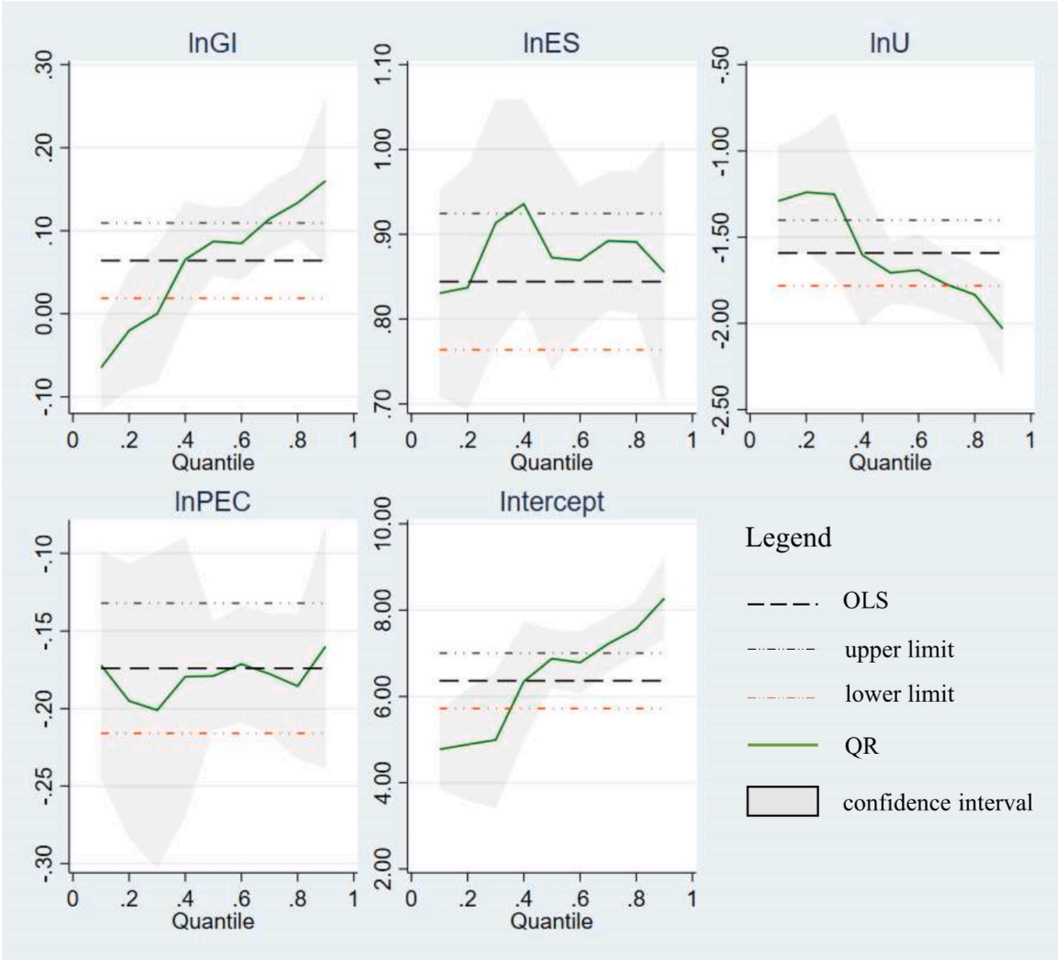

Fig. 11. The distribution of regression coefficients of each explanatory variable.

emissions was more significant in the western part of the Chengdu-Chongqing region, where per capita carbon emissions were significantly higher than in the eastern part. 2) The GI values obtained using EWM-TOPSIS method were used to comprehensively evaluate the degree of development of green industries in the 16 cities in the Chengdu-Chongqing region based on economic, social, and environmental dimensions. The results showed that the degree of openness in the economic subsystem markedly affects the GI of Chengdu-Chongqing region and the spatial distribution of the GI was uneven. In addition, the degree of openness and the degree of scientific and technological development were highly correlated with the development of green industry in the city; 3) The QR model was used to evaluate the dynamic relationship between the GI values and CI. The results using the QR model showed that the effect of each explanatory variable on the explained variables varied at different quantiles compared with the results obtained using the ordinary least squares regression method. The regression results showed that GI was negatively correlated with the carbon emission intensity in in the cities with low carbon emission intensity in Chengdu-Chongqing region, and positively correlated with the carbon emission intensity in the cities with high carbon emission intensity, and the positive effect was more significant at the low and high quantiles; The findings showed that ES was positively associated with CI, whereas U and PEC were negatively correlated with CI. These results show that Targeted upgrading of industrial structure by subregion can help achieve high-quality development in Chengdu-Chongqing region.

The findings indicate the unbalanced relationship between urban economic development and ecological environmental protection, but the study had some limitations: 1) The method of combining nighttime lighting data [50] can be used to determine the level of carbon emissions of each city and compare the results with the present results. Moreover, carbon emissions are present in the supply chain, and the network of transferring carbon emissions in the production process can be evaluated to identify the key sectors that contribute to carbon emissions [51]. 2) The development of Chengdu-Chongqing Economic Circle is highly linked, but the spatial spillover effect of carbon emissions was not considered in this study. It is imperative to conduct further studies and incorporate spatial information into the analytical model, taking into account the spatial correlation of carbon emissions, and considering the relationship between cities in Chengdu-Chongqing region to achieve effective reduction of emission in the region [52,53]. In summary, the methodological model established in this study can provide a reference for regional carbon emission research and economic development.

5. Conclusion

In this study, we collected total energy consumption and the total carbon emission data from 16 cities in the Chengdu-Chongqing region and evaluated per capita carbon emission and carbon emission intensity of each city. In addition, we combined with the industrial development parameters and spatial characteristics of Chengdu-Chongqing area. We used green industry indicators in Chengdu-Chongqing area to establish the GI measurement method based on EWM-TOPSIS methods, and analyzed the spatial and temporal evolution trend of GI in Chengdu-Chongqing area. We constructed a QR model with GI as the core explanatory variable and ES, U, and PEC as the control variables, and used it to evaluate the dynamic relationship between CI and GI. The main research findings of the study are presented below.

1) The total amount of carbon emissions in Chengdu-Chongqing area increased from 2010 to 2020, but the intensity of carbon emissions decreased during this period, indicating that the correlation between carbon emission and economic development in Chengdu-Chongqing area is weakening. The carbon intensity and per capita carbon emissions in Chongqing and Chengdu region were significantly lower than other cities, and the “dual-core leadership” of Chengdu and Chongqing will be crucial to the economy of the Chengdu-Chongqing region’s high-quality development.
2) The GI levels based on EWM-TOPSIS indicate that Chengdu and Chongqing had higher green industry development indexes than other cities. Chengdu and Chongqing are the economic and cultural centers of the Chengdu-Chongqing area so they are more open to the outside world, and the economic level of these two cities is higher than other cities in the Chengdu-Chongqing area. Moreover, the level of green industry development of these two cities is markedly higher than that of other cities in the region. The industrial development model developed in this study showed that GI suppressed the carbon emission intensity for cities with low carbon emission intensity, and promoted carbon emission intensity for cities with high carbon emission intensity. This is because the development of the Chengdu-Chongqing area is currently dominated by the secondary industry sector, and industrial agglomeration may lead to increased environmental pollution. The Chengdu-Chongqing region should upgrade its industrial structure, exploit its unique location because it connects the western region and Southeast Asia to promote the upgrading of traditional industries to green industries and establish new industrial clusters based on advances in information technology.
3) The results of the study on carbon emission intensity, electricity consumption and urbanization rate indicate that use of clean energy and modern urbanization have reduced the carbon emission intensity in the Chengdu-Chongqing area. Therefore, the society should increase the use of clean energy and construct modern cities to reduce carbon emission.

Data availability statement

Data associated with the study has not been deposited into a publicly available repository and data will be made available on request.

CRediT authorship contribution statement

Jiaqi Cao: Writing – original draft. **Siying Wang:** Methodology. **Xingyue Fan:** Conceptualization, Data curation. **Xiaoyi Yang:** Formal analysis, Methodology. **Huangyuying Zheng:** Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by Sichuan Science and Technology Program (2023NSFSC0807), Opening Fund of Sichuan Mineral Resources Research Center (SCKCZY2022-YB017) and the General Program of Sichuan Center for Disaster Economy Research (ZHJJ2022-YB002).

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