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Evaluation of regional low-carbon circular economy development: a case study in Sichuan province, China

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Abstract

Purpose – This paper aims to build a scientific evaluation index system for regional low-carbon circular economic development. Taking Sichuan Province as the empirical research object, the paper evaluates its low-carbon circular economy (LCCE) development level and proposes policy recommendations for climate change improvement based on the evaluation results.

Design/methodology/approach – This paper, first, built an evaluation index system with 30 indicators within six subsystems, namely, economic development, social progress, energy consumption, low-carbon emissions, carbon sink capacity and environmental carrying capacity. Second, develop an "entropy weight-grey correlation" evaluation method. Finally, from a practical point of view, measure the development level of LCCE in Sichuan Province, China, from 2008 to 2018.

Findings – It was found that Sichuan LCCE development had a general downward trend from 2008 to 2012 and a steady upward trend from 2012 to 2018; however, the overall level was low. The main factors affecting the LCCE development are lagging energy consumption and environmental carrying capacity subsystem developments.

Research limitations/implications – This paper puts forward relevant suggestions for improving the development of a low-carbon economy and climate change for the reference of policymakers.

Originality/value – This paper built an evaluation index system with 30 indicators for regional low carbon circular economic development. The evaluation method of "entropy weight-grey correlation" is used to measure the development level of regional LCCE in Sichuan Province, China.

Keywords Policy recommendations, Development evaluation, Low-carbon circular economy

Paper type Research paper

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1. Introduction

Rapid economic and social development has caused significant environmental problems, such as climate change, ozone layer destruction and air pollution, threatening global sustainable development (Lu *et al.*, 2019; Li *et al.*, 2020). Climate change appears to be an environmental issue, but in essence, it is a development issue. To environmental protection, the "Circular Economy (CE)" concept was proposed by the American economist Boulding in the 1960s (Boulding, 1966) as part of his "Spaceship Theory." The CE is defined as an economic model with the core principles of reducing, reusing and recycling (Winans *et al.*, 2017). Subsequently, at the beginning of the 21st century, the British Government introduced the "Low-Carbon Economy (LCE)" concept in its first energy white paper (DTI, 2003). This concept received support from other developed nations, such as the USA, Japan and the European Union countries. A LCE refers to the efficient use of resources, the development of clean energy, reducing environmental pollution and obtaining more economic output. As a typical developing country, China is right in the rapid process of industrialization and urbanization; therefore, the total amount and the rate of greenhouse gas emission have increased tremendously (Jiang *et al.*, 2010). And as urbanization is accelerating and the economy continue to expand, the demand for resources and energy is expected to rise commensurately (Geng *et al.*, 2016). Figure 1 shows the carbon dioxide (CO_2) emissions trends and growth rate over the 40 years of reform and opening in China, from which China's CO_2 emissions increased sharply at the beginning of the 21st century, slightly slowed in 2012, but continued to rise after 2015. Therefore, transforming the traditional economic development model to a circular, low-carbon sustainable economic development path has become inevitable (Mathews and Tan, 2016). In November 2012, the Chinese Government implemented the circular LCE as the means to transform its development model (Hu, 2012) through projects, such as low-carbon park construction, new energy developments, waste classification and recycling and the active exploration of low-carbon circular development models based on regional characteristics (Wang and Chang, 2014; Bocken *et al.*, 2016).

Since the LCE and CE theories were put forward, scholars have attracted much attention (Kirchherr *et al.*, 2017; Korhonen *et al.*, 2018a) and become policy foci (Zink and Geyer, 2017; Li *et al.*, 2012). It is now commonly acknowledged that to promote the low-carbon CE

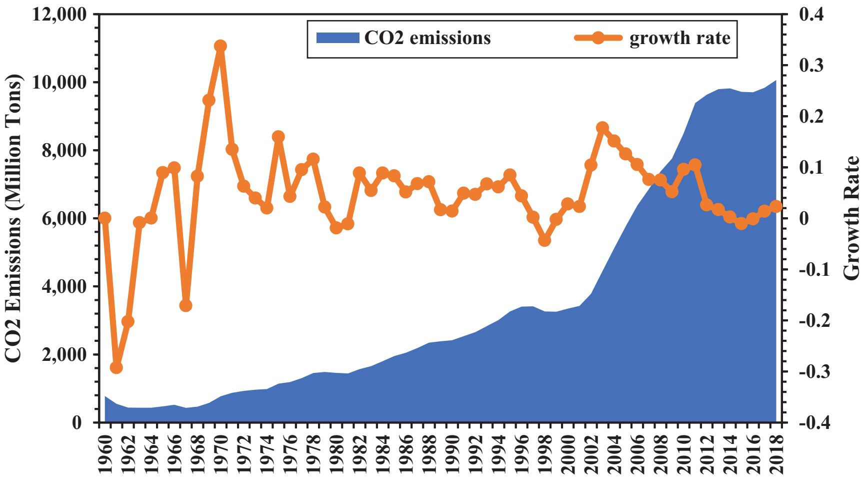

Figure 1. CO_2 emissions and growth rate in Mainland China from 1978 to 2018

(LCCE), the introduction of monitoring and evaluation tools like indicators to measure and quantify this progress becomes essential (Zhou *et al.*, 2015a, Elia *et al.*, 2017). Many indicator systems have been developed to analyse a city's sustainable development, but it requires a complicated set of input data often challenging to collect. Such as the green growth index system (OECD, 2011). The United Nations Environment Programmer (UNEP) also set a green economy measurement framework covering resource efficiency, economic transformation, social progress and human well-being (UNEP, 2012). The European Environmental Agency identifies the main policy questions concerning CE related to five areas in a lifecycle perspective: material input, eco-design, production, consumption and waste recycling (EEA, 2016).

In 2016, the National Development and Reform Commission and the National Bureau of Statistics of China formulated the "Green Development Index System," which mainly covers seven aspects: resource utilization, environmental governance, environmental quality, ecological protection, growth quality, green life and public satisfaction. China's recently issued "Evaluation Index System of Circular Economy Development (China, 2017 Edition)" (EIS2017) divides indicators into three categories: comprehensive indicators, special indicators and reference indicators. While this is being applied at a national level, it has not been adopted (nor has any other indicator system) at the urban level. Most cities do not collect sufficient statistical data (e.g. waste electronics or kitchen waste recycling rates) to assess CE development properly. Also, Tan *et al.* (2017) established an indicator framework for evaluating low-carbon cities from financial, energy, social and living, carbon and environment, urban mobility, solid waste and water.

In the past years, researchers and institutions' concept of LCCE has been widely explored as a possible path to increase our economic system's sustainability. And several case studies analyse its application in different contexts. However, state of the art shows that in-depth research on LCCE assessment and indicators still lacks regional level. There is no one-size-fits-all solution for assessing Regional LCCE (RLCCE) development. Bottlenecks in data availability (EIS2017), representativeness of selected indicators and accurate evaluation methods have restricted the calculation.

To bridge these gaps, this study makes several academic contributions to the field:

For one, based on previous research, a comprehensive evaluation indicator system of RLCCE is re-designed. It includes 30 indicators in six aspects: "economic development, social progress, energy consumption, low carbon emissions, carbon sink capacity, and environmental carrying capacity."

Secondly, combined the objectivity of the entropy weight method and the grey correlation method's computational simplicity to develop an "entropy weight-grey correlation" evaluation method. From a practical point of view, measure the development level of LCCE in Sichuan Province, China, from 2008 to 2018. And the evaluation results are divided into four grades: A, B, C and D.

Finally, through the evaluation results and discussion, this article puts forward relevant suggestions for improving the development of a LCE and climate change for the reference of policymakers.

Therefore, the remainder of this paper is organized as follows. Section 2 summarizes previous LCCE research. Section 3 introduces the circular low-carbon economic development evaluation index and models based on the entropy weight and grey correlations. Section 4 conducts an empirical analysis in Sichuan Province, China. Section 5 gives the calculation results and associated discussion and Section 6 concludes the paper and gives policy recommendations based on the evaluation results.

2. Literature review

2.1 Evaluation index system of low-carbon circular economy

Due to the inconsistent understanding of low-carbon development and circular development from all walks of life, the index systems established by different institutions or scholars in this field are also quite different.

On the one hand, it selects indicators related to carbon emission reduction in various areas, such as economy, society and ecological environment, to establish an indicator system (Tan *et al.*, 2017). Hu *et al.* (2011) study the low-carbon development of China by giving an "Economy–Energy–Electricity–Environment" framework. Jia *et al.* (2012) evaluate the low carbon development level of the world's 47 countries from five aspects: emission status, carbon source's control level, carbon capture capacity, human development index and urbanization level. Wang *et al.* (2019) evaluate the low-carbon development of coal enterprise groups from four aspects: low-carbon energy consumption, economical, resource utilization and low-carbon environment. Compared with low-carbon growth, circular development has a more precise definition. Related research mainly establishes an indicator system from the CE's basic principles, but different studies have different understandings of the category of circular development. The CE evaluation index system mainly includes resource output indicators, resource consumption indicators, comprehensive resource utilization indicators and waste discharge indicators (Hu *et al.*, 2018; Tang *et al.*, 2020).

On the other hand, it is based on the Driving Forces-Pressure-State-Impact-Response (DPSIR) model to establish a low-carbon development indicator system. Zhou *et al.* (2015a) constructed a quantitative index system of low carbonization based on the DPSIR model. The DPSIR framework was used to analyse greenhouse gases emissions' socio-economic dynamics and their pressures on the environment, the state of the environment, related climate change impacts and society's responses.

2.2 Evaluation methods of low-carbon circular economy development

There are many methods to evaluate economic development, and the combination method is currently used. The indicators are weighted first and then assessed. The index weight is of great significance in the overall evaluation – the greater the weight, the more critical the index.

Generally, either objective weighting or subjective weighting methods are used. Subjective weighting, which has solid subjective arbitrariness, is typically represented using analytic hierarchy processes, fuzzy clustering methods or Delphi methods (Gustafson and Kessel, 1979; Linstone and Turoff, 1975; Saaty, 1988). Objective weighting, which has a solid theoretical mathematical basis, is generally determined through the relationships with the initial data to avoid weighting subjectivity, with the usual methods being the coefficient of variation and the entropy value method (Reed *et al.*, 2002; Gray, 2011). The entropy weight method has been found to have higher precision, a better ability to explain the obtained results, greater adaptability and can be used in any process that requires weight determination (Delgado and Romero, 2016). Several comprehensive evaluation methods have been widely used, such as fuzzy extensive evaluation methods, the technique for order of preference by similarity to ideal solution and the grey correlation method, each of which has advantages and disadvantages (Dong *et al.*, 2020; Kutlu Gündoğdu and Kahraman, 2019). The grey correlation method has a simple structure and low data quantity, and data distribution system requirements. It requires less calculation. Consequently, it has been widely used in agriculture, industry, economics, management and other disciplines and has achieved remarkable results (Wang *et al.*, 2015; Delgado and Romero, 2016; Lu *et al.*, 2008; Ren *et al.*, 2020). Therefore, this paper combines an objective entropy weight method and grey correlation to develop an entropy weight-grey correlation evaluation method to measure China's LCCE development.

Most scholars construct an indicator system from a single concept of the green economy, LCE and CE from previous studies. The current LCCE development indicators are difficult to obtain. The existing index system rarely considers the environmental carrying capacity in the circular index. In addition, concerning the research object, the current research is mainly aimed at the national scale or the specific representative area, and there is less research on the provincial perspective. Also, there is a lack of empirical analysis from a regional perspective.

Therefore, different from previous research, this paper builds an evaluation index system with 30 indicators under six main subsystems: economic development, social progress, energy consumption, low carbon emissions, carbon sink capacity and environmental carrying capacity. Furthermore, the entropy weight-grey correlation evaluation method is used to measure the LCCE development level in Sichuan Province, China, from 2008 to 2018. The evaluation results allow for an analysis of the critical factors hindering LCCE development and the development of targeted policy recommendations for improving low-carbon circular economic growth in the future.

3. Material and methods

3.1 The low-carbon circular economy evaluation index system

3.1.1 Evaluation index system for regional low carbon circular economy. Based on LCE and CE concepts, a 30-evaluation indicator system is built that includes 6 subsystems: economic development, social progress, energy consumption, low-carbon emissions, carbon sink capacity and environmental carrying capacity. The specific indicator names and types are listed in Table 1:

Based on the index structure, the evaluation index system model for the RLCCE development level is shown in Figure 2.

3.1.2 Index system interpretation and the logical relationships. The quantitative, scientific and feasible evaluation index system measures the LCCE development level to guide regional assessments. In the following, the index system is explained based on the subsystem dynamics shown in Figure 3.

- *Economic development indicators*. The economic development system has four indicators: per capita regional gross domestic product (GDP), regional GDP growth rate and secondary and tertiary industries' added value to provincial GDP. GDP per capita is one of the evaluation indicators from the human development index and directly reflects the regional economy's quality. The GDP growth rate reflects the local economic growth rate and development level, and the ratio of the output value of the secondary and tertiary industries to regional GDP reflects the local industrial structure. The secondary sector is dominated by the industry and construction sectors, which depend primarily on fossil fuel energy; therefore, it has high energy consumption and high polluting characteristics, restricting the LCCE development. However, the tertiary industry has relatively low carbon emissions and resource use intensities; therefore, the higher the tertiary industry proportion, the more achievable the LCCE.
- *Social progress indicators*. In a CE, decoupling economic growth, resource use and environmental degradation are expected, simultaneously improving societal well-being (Geng *et al.*, 2016). The social progress system has five leading indicators: urbanization rate, urban and rural resident disposable income, research and development (R&D)

Table 1. Evaluation index system for RLCCE

Criterion layer	System layer	Indicator layer	Unit	Type	References
Developmental	Economic development (X1)	GDP per capita (X_{11})	CNY	+	(Tan *et al.*, 2017; Hu *et al.*, 2011)
		Regional GDP growth rate (X_{12})	%	+	(Krajnc and Glavič, 2005)
		The ratio of the added value of the secondary industry to regional GDP (X_{13})	%	–	(Li and Hu, 2012; Yang *et al.*, 2019)
		The ratio of the added value of the tertiary industry to regional GDP (X_{14})	%	+	"Green Development Index System"
	Social progress (X2)	Urbanization rate (X_{21})	%	+	(Yang *et al.*, 2018; Tan and Lu, 2016)
		Urban resident disposable income (X_{22})	CNY	+	"Green Development Index System"
		Rural resident disposable income (X_{23})	CNY	+	"Green Development Index System"
		R&D investment as a proportion of regional GDP (X_{24})	%	+	"Green Development Index System"
		Education expenditure as a proportion of regional GDP (X_{25})	%	+	(Nan and Yin, 2014)
Low carbon	Energy Consumption (X3)	Total energy consumption (X_{31})	10,000 tonnes of standard coal	–	(Iddrisu and Bhattacharyya, 2015) "Green Development Index System"
		Energy consumption intensity (X_{32})	Tonnes of standard coal/10,000 CNY	–	(Iddrisu and Bhattacharyya, 2015; Zhang and Su, 2016)
		Energy consumption elasticity coefficient (X_{33})	%	–	(Fei *et al.*, 2011; Price *et al.*, 2013)
		Industrial energy consumption (X_{34})	10,000 tonnes of standard coal	–	(Liu and Hao, 2018; Charfeddine, 2017)
		Building energy consumption (X_{35})	10,000 tonnes of standard coal	–	
		Transportation energy consumption (X_{36})	10,000 tonnes of standard coal	–	
	Low carbon emissions (X4)	Total carbon emissions (X_{41})	10,000 tonnes	–	(Ma *et al.*, 2019)
		Carbon emissions intensity (X_{42})	Tonnes per 10,000 CNY	–	(Zhang *et al.*, 2014)
Circular	Carbon sink capacity (X5)	Forest cover rate (X_{51})	%	+	"Green Development Index System"
		Forest stock (X_{52})	100 million m^3	+	"Green Development Index System"
		Afforestation area (X_{53})	10,000 hectares	+	(Lou *et al.*, 2019; Tan and Lu, 2016)
		Green coverage in built-up areas (X_{54})	%	+	(Longyu and Jing, 2018)
		Wetland areas (X_{55})	1,000 hectares	+	(Zhou *et al.*, 2015b)
			100m CNY	+	"Green Development Index System"

(*continued*)

Criterion layer	System layer	Indicator layer	Unit	Type	References
	Environmental carrying capacity (X6)	Environmental pollution control investment (X_{61})			
		Industrial wastewater discharge (X_{62})	10,000 tonnes	–	(Tan and Lu, 2016) EIS2017
		Industrial solid waste generation (X_{63})	10,000 tonnes	–	(Tan and Lu, 2016) EIS2017
		Comprehensive industrial solid waste utilization rate (X_{64})	%	+	(Tan and Lu, 2016; Wang *et al.*, 2018)
		Sewage discharge (X_{65})	10,000 m^3	–	(Kirchherr *et al.*, 2017)
		Sewage treatment rate (X_{66})	%	+	EIS2017
		Domestic waste removal volume (X_{67})	10,000 tonnes	–	(Kirchherr *et al.*, 2017)
		Harmless domestic waste treatment rate (X_{68})	%	+	(Tan *et al.*, 2017) “Green Development Index System”

Table 1.

investment as a percentage of regional GDP and education investment as a percentage of regional GDP. As the main activity centre in a region, cities and towns attract increasing populations. That is, the higher the urbanization rate, the stronger the social development ability. Resident disposable income plays a decisive role in their consumption levels and, therefore, characterizes the residents' living standards in a region. R&D investment signifies a region's investment in science and technology, and its scale and intensity can reflect a region's scientific and technological strength, which plays an essential role in promoting social development. Finally, the proportion of educational investment in a region's GDP indicates regional cultural, educational and social development.

- *Energy consumption indicators*. The reduction is the first principle of a CE. It requires improved management technology in the production process to reduce the material and energy entering the production and consumption process (Korhonen *et al.*, 2018b). The energy consumption system has six indicators: total energy consumption, intensity, energy consumption elasticity coefficient, industrial energy consumption, building energy consumption and transportation energy consumption. The total energy consumption is the sum of all energy consumed in a region in a certain period and

Figure 2.
RLCCE development evaluation index system

directly reflects the energy consumption. Energy consumption intensity is the energy consumed per unit of GDP and reflects energy efficiency and economic structure changes. The elasticity energy consumption coefficient reflects the energy consumption growth rate and the regional GDP growth rate. Industry and construction are the major secondary industry energy-consuming industries, and transportation is the most energy-intensive tertiary industry.

- *Carbon emissions index*. Current global resource use, waste disposal and emissions led to critical climate change and environmental degradation (Velenturf *et al.*, 2019). The carbon emissions system includes two leading indicators: total carbon emissions and carbon emissions intensity. The total carbon emissions directly characterize the regional carbon emissions level and are among the main reference indicators for carbon emissions reduction. Carbon emissions intensity is the CO_2 emissions generated per unit area of GDP and is a widely recognized indicator for low-carbon economic development.
- *Carbon sink capacity index*. The construction of a LCE should reduce carbon emissions and maximize carbon sink capacity (Millward-Hopkins and Purnell, 2019). The carbon sink capacity system has five indicators: forest coverage, forest stock, afforestation area, green coverage in built-up and wetland areas. In 2017, the State Forestry Administration of China announced the "Provincial Forestry 2017–2018 Work Plan for Climate Change," which stated that there needed to be an increase in the carbon sink assessment indicators, such as forest carbon and stable wetland carbon sinks. Forests are the largest terrestrial carbon storage ecosystems and play significant roles as carbon sinks; therefore, forest coverage, afforestation areas and forest stock volumes are essential indicators for measuring carbon sink levels. The greening rate in built-up areas estimates the efforts to improve the living environment and enhance carbon sink capacity. Wetlands are also known as the "Kidneys of the Earth" and play an essential role in carbon sequestration; therefore, the wetland area is also an important indicator for measuring the carbon sink level.

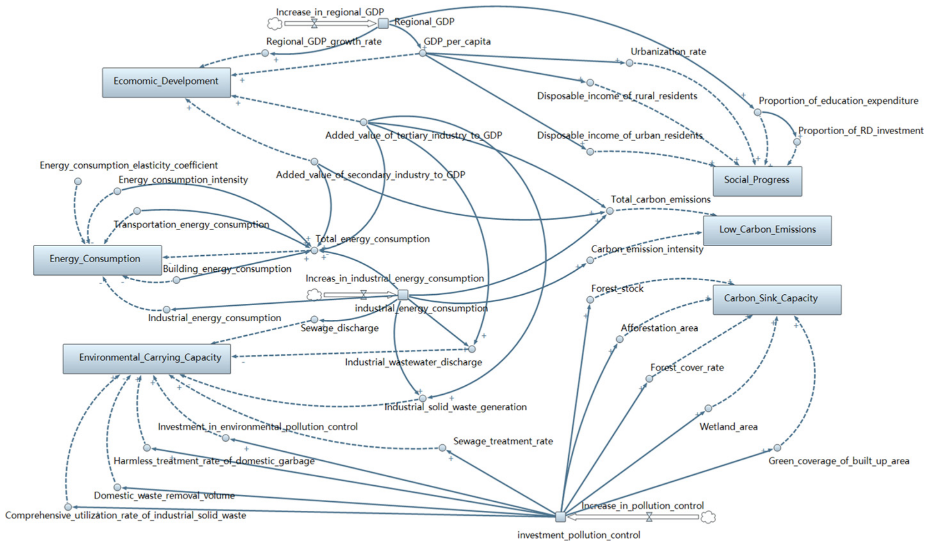

Figure 3.
System dynamic model

- *Environmental carrying capacity index*. The environmental carrying capacity is an essential concept in ecological science, reflecting the interaction between the environment and humans (Zhang *et al.*, 2019). The environmental carrying capacity system has eight indicators: investment in environmental pollution control, industrial wastewater discharge, industrial solid waste generation, sewage discharge, domestic waste removal volume, comprehensive industrial solid waste utilization rate, sewage treatment rate and the harmless domestic waste treatment rate. CE development is a specific measure to enhance the environmental carrying capacity, ecologically sustainable development and low-carbon development. Based on the Circular Economic Promotion Law requirements and other documents, the National Development and Reform Commission of China issued a Circular Economic Development Evaluation Index System in 2017. The indicators were resource consumption, waste discharge intensity, waste recycling rate and pollutant disposal rate.

3.2 "Entropy weight-grey correlation" evaluation model

3.2.1 Entropy weight method. The entropy weight method, an objective weighting method that eliminates any subjective factors' influence, uses each evaluation object's index value to construct a judgment matrix, normalized and the index entropy weight for each index calculated. The final entropy value indicates the degree of system disorder, with the smaller the indicator information entropy, the greater the amount of information it provides and the more significant the role it plays in the evaluation (Delgado and Romero, 2016).

The specific entropy weight calculation steps are as follows:

- *Construct an indicator judgement matrix*. Assume that there are n measurement objects and m indicators and construct the matrix $X = (X_{ij})_{n\times m}$ (i = 1,2,3, . . ., n; j = 1,2,3, . . ., m). Where X_{ij} is the m-index n-year LCCE development level judgement matrix, that is, the value of the j-th index in the i-th year.
- *Normalize the data*. The data normalization transforms each indicator into computable data of the same magnitude and dimension, making the evaluated object's quantitative calculation easier. Because of the different indicator natures, the indicators are divided into efficiency indicators and cost indicators, the specific calculation formulas for which are as follows:

For the efficiency indicators, the larger the indicator value, the better. The normalized procedure for which is:

$$f_{ij} = \left[\frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}}\right] \times 0.9 + 0.1 \tag{1}$$

For the cost indicators, the smaller the indicator value, the better. The normalized formula for which is:

$$f_{ij} = \left[\frac{maxX_{ij} - X_{ij}}{maxX_{ij} - minX_{ij}}\right] \times 0.9 + 0.1 \tag{2}$$

- Calculate the entropy weight of the j-th index in the year i. Based on the definition, the entropy e_j and the entropy weight w_j are:

$$b_{ij} = \frac{f_{ij}}{\sum_{i=1}^{n}(f_{ij})} \tag{3}$$

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n}[b_{ij} ln b_{ij}] \tag{4}$$

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m}(1-e_j)} \tag{5}$$

where b_{ij} is the proportion of the standardized value for the j-th indicator in the i-th year in the entire evaluation year series, e_j is the entropy of the j-th indicator and w_j is the entropy weight for the j-th indicator, with the constraint being $0 \le w_j \le 1$ and $\sum w_j = 1$.

- Calculate the system layer weight.

$$w_o = \sum_{j=1}^{a} w_j \tag{6}$$

3.2.2 Grey correlation method. The grey relational model assesses the consistencies between two systems and is therefore suitable for evaluating dynamic change processes. As each system in the model is a grey system with incomplete information and messy data characteristics, the grey correlation model can comprehensively assess the complete system information by analyzing and researching the "partly known poor information" within the grey system (Kuo *et al.*, 2008). The LCCE's multiple subsystems: economic development, social progress, energy consumption, low-carbon emissions, carbon sink capacity and environmental carrying capacity: are subject to synergy and have internal interactive and uncertain relationships. Therefore, the relationships between the various systems are defined as grey relationships, for which a grey correlation model is used to measure the LCCE development level, as follows:

- *Determine the analysis sequence*. The reference data column is composed of the optimal value for each index and recorded as $X'_0 = \left(x'_0(1), x'_0(2), \cdots, x'_0(m)\right)$.
- *Non-dimensional processing of the index data*. After processing, the index data is combined with the analysis sequence to form the following matrix:

$$(X_0, X_1, \cdots, X_n) = \begin{pmatrix} x_0(1) & x_1(1) & \cdots & x_n(1) \\ x_0(2) & x_1(2) & \cdots & x_n(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_0(m) & x_1(m) & \cdots & x_n(m) \end{pmatrix} \tag{7}$$

- Calculate the difference sequence, maximum difference and minimum difference. Calculate the absolute difference between the evaluated target index sequence and the reference sequence to form the following difference sequence matrix:

$$\begin{pmatrix} \Delta_{01}(1) & \Delta_{02}(1) & \cdots & \Delta_{0n}(1) \\ \Delta_{01}(2) & \Delta_{02}(2) & \cdots & \Delta_{0n}(2) \\ \vdots & \vdots & & \vdots \\ \Delta_{01}(N) & \Delta_{02}(N) & \cdots & \Delta_{0n}(N) \end{pmatrix}_{N\times n} \quad (8)$$

where $\Delta_{0i}(k) = |x_0(k) - x_i(k)|$, $i = 0,1,\ldots,n$; $k = 1,2,\ldots,N$

The maximum and minimum differences are the maximum and minimum numbers in the different sequence matrix:

$$\underset{\substack{1\le i\le n\\1\le k\le N}}{max}\{\Delta_{0i}(k)\} \triangleq \Delta(\max) \quad (9)$$

$$\underset{\substack{1\le i\le n\\1\le k\le N}}{min}\{\Delta_{0i}(k)\} \triangleq \Delta(\min) \quad (10)$$

- Calculate the correlation coefficient.

$$\xi_{0i}(k) = \frac{\Delta(\min) + \rho\Delta(\max)}{\Delta_{0i}(k) + \rho\Delta(\max)} \quad (6.9) \quad (11)$$

Determine the correlation coefficient matrix:

$$\begin{pmatrix} \xi_{01}(1) & \xi_{02}(1) & \cdots & \xi_{0n}(1) \\ \xi_{01}(2) & \xi_{02}(2) & \cdots & \xi_{0n}(2) \\ \vdots & \vdots & & \vdots \\ \xi_{01}(N) & \xi_{02}(N) & \cdots & \xi_{0n}(N) \end{pmatrix}_{N\times n} \quad (6.10) \quad (12)$$

In general, the resolution coefficient ρ in the formula takes a value in (0,1) depending on the formula's data (3–11). ρ is usually 0.5.

- Calculate the degree of association.

$$r_{0i} = \sum_{k=1}^{m} W_k \cdot \zeta_i(k) \quad (13)$$

In the formula, W_k is the weight of each index, k = 1,. . .,m

4. Empirical analysis

4.1 Data sources

To examine China's regional LCCE development, Sichuan Province is taken as an empirical case in this section. The original case study data were extracted from the Sichuan Statistical Yearbooks, the China Energy Statistical Yearbooks and the China Environmental Statistics Yearbooks from 2008 to 2019. The CO_2 emissions were calculated from IPCC energy-related data. The carbon emissions intensities were calculated by dividing the total carbon emissions by regional GDP. The energy consumption intensity was calculated by dividing the total energy consumption by the provincial GDP. The remainder of the data were obtained directly from the statistical yearbooks.

4.2 Index weight coefficient calculation

The original data were normalized using formulas (1) and (2), and then the entropy weights of the various indicators and system layers were calculated using procedures (3) to (6), the results for which are shown in Table 2.

Target layer	Criterion layer	Weights	System layer	Weights	Indicator layer	Weights
Measurement of the development level of the LCCE	Developmental	0.3132	Economic development (X1)	0.1636	X_{11}	0.0303
					X_{12}	0.0591
					X_{13}	0.0425
					X_{14}	0.0317
			Social progress (X2)	0.1496	X_{21}	0.0299
					X_{22}	0.0332
					X_{23}	0.0369
					X_{24}	0.0218
					X_{25}	0.0278
	Low carbon	0.2478	Energy consumption (X3)	0.1969	X_{31}	0.0392
					X_{32}	0.0288
					X_{33}	0.0354
					X_{34}	0.0325
					X_{35}	0.0309
					X_{36}	0.0299
			Low carbon emissions (X4)	0.0509	X_{41}	0.0221
					X_{42}	0.0288
	Circular	0.4390	Carbon sink capacity (X5)	0.1848	X_{51}	0.0150
					X_{52}	0.0415
					X_{53}	0.0395
					X_{54}	0.0199
					X_{55}	0.0689
			Environmental carrying capacity (X6)	0.2542	X_{61}	0.0407
					X_{62}	0.0301
					X_{63}	0.0396
					X_{64}	0.0455
					X_{65}	0.0259
					X_{66}	0.0253
					X_{67}	0.0275
					X_{68}	0.0196

Table 2.
Evaluation index and system layer weight coefficients

4.3 Comprehensive index score

The weighted score table for the evaluation index, the system-level score for the evaluation targets, and the comprehensive score table were obtained using formulas (7) to (13) from the grey correlation order model shown in Tables 3 and 4.

4.4 Evaluation level calculation

The maximum reference score for each subsystem and the total evaluation value is based on the original data reference sequence, as shown in Table 5.

A four-level evaluation: A, B, C, D: was then determined based on maximum scores that were 90% and above, 75%–89%, 60%–74% and less than 60%, the evaluation rating table for which is shown in Table 6.

5. Results and discussion

5.1 Subsystem scoring results and analysis

The measurement results for each regional low-carbon circular economic development subsystem in Sichuan Province are shown in Figure 4.

The measurement results for the LCCE development criterion in Sichuan Province are shown in Figure 5.

Table 3. Evaluation index weight values

Index	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
X_{11}	0.0101	0.0105	0.0114	0.0128	0.0141	0.0154	0.0166	0.0176	0.0198	0.0242	0.0303
X_{12}	0.0278	0.0508	0.0591	0.0576	0.0351	0.0247	0.0211	0.0199	0.0197	0.0203	0.0201
X_{13}	0.0158	0.0201	0.0161	0.0142	0.0148	0.0151	0.0174	0.0187	0.0263	0.0355	0.0425
X_{14}	0.0106	0.0134	0.0125	0.0116	0.0122	0.0129	0.0147	0.0157	0.0206	0.0259	0.0317
X_{21}	0.0100	0.0106	0.0114	0.0124	0.0137	0.0150	0.0166	0.0185	0.0211	0.0249	0.0299
X_{22}	0.0111	0.0115	0.0122	0.0133	0.0147	0.0160	0.0177	0.0197	0.0225	0.0267	0.0332
X_{23}	0.0123	0.0126	0.0132	0.0144	0.0156	0.0178	0.0198	0.0221	0.0253	0.0298	0.0369
X_{24}	0.0073	0.0102	0.0112	0.0084	0.0093	0.0102	0.0112	0.0141	0.0161	0.0161	0.0218
X_{25}	0.0093	0.0108	0.0105	0.0112	0.0275	0.0200	0.0159	0.0278	0.0207	0.0179	0.0144
X_{31}	0.0392	0.0278	0.0200	0.0151	0.0135	0.0162	0.0148	0.0186	0.0148	0.0131	0.0147
X_{32}	0.0096	0.0101	0.0113	0.0128	0.0141	0.0173	0.0182	0.0216	0.0218	0.0238	0.0288
X_{33}	0.0121	0.0136	0.0122	0.0118	0.0175	0.0150	0.0160	0.0354	0.0186	0.0186	0.0162
X_{34}	0.0325	0.0220	0.0156	0.0119	0.0108	0.0121	0.0117	0.0218	0.0214	0.0214	0.0204
X_{35}	0.0309	0.0270	0.0202	0.0171	0.0153	0.0174	0.0153	0.0122	0.0116	0.0109	0.0103
X_{36}	0.0263	0.0201	0.0182	0.0167	0.0149	0.0299	0.0173	0.0123	0.0115	0.0104	0.0100
X_{41}	0.0221	0.0140	0.0128	0.0114	0.0098	0.0087	0.0074	0.0086	0.0096	0.0108	0.0128
X_{42}	0.0096	0.0097	0.0115	0.0137	0.0148	0.0156	0.0158	0.0178	0.0203	0.0239	0.0288
X_{51}	0.0050	0.0072	0.0075	0.0078	0.0080	0.0082	0.0085	0.0088	0.0101	0.0125	0.0150
X_{52}	0.0138	0.0144	0.0148	0.0155	0.0161	0.0170	0.0181	0.0193	0.0208	0.0364	0.0415
X_{53}	0.0254	0.0217	0.0185	0.0156	0.0133	0.0135	0.0132	0.0169	0.0251	0.0303	0.0395
X_{54}	0.0066	0.0077	0.0098	0.0105	0.0116	0.0109	0.0092	0.0115	0.0159	0.0164	0.0199
X_{55}	0.0230	0.0230	0.0230	0.0230	0.0230	0.0689	0.0689	0.0689	0.0689	0.0689	0.0689
X_{61}	0.0385	0.0379	0.0407	0.0371	0.0282	0.0237	0.0196	0.0171	0.0141	0.0136	0.0136
X_{62}	0.0100	0.0102	0.0116	0.0134	0.0153	0.0164	0.0158	0.0149	0.0206	0.0240	0.0301
X_{63}	0.0323	0.0396	0.0205	0.0162	0.0151	0.0136	0.0132	0.0171	0.0187	0.0140	0.0164
X_{64}	0.0455	0.0338	0.0288	0.0202	0.0192	0.0164	0.0173	0.0183	0.0152	0.0155	0.0162
X_{65}	0.0186	0.0244	0.0259	0.0210	0.0201	0.0157	0.0141	0.0121	0.0106	0.0094	0.0086
X_{66}	0.0084	0.0089	0.0109	0.0122	0.0148	0.0146	0.0160	0.0186	0.0198	0.0220	0.0253
X_{67}	0.0275	0.0235	0.0189	0.0182	0.0166	0.0147	0.0138	0.0126	0.0112	0.0095	0.0092
X_{68}	0.0065	0.0081	0.0103	0.0088	0.0103	0.0122	0.0137	0.0138	0.0196	0.0182	0.0184

From the subsystem grade evaluation table (Table 6), the comprehensive Sichuan LCCE development grade table was developed as Table 7.

5.1.1 Analysis of developmental evaluation results. Figure 5 shows that in addition to the slight fluctuations in 2013, the continuous growth in the social progress subsystem and the small economic development subsystem changes resulted in a steady rise in Sichuan's development.

- *Economic development subsystem*. Figure 4 shows that the economic development system was volatile but increased in all 10 years from 0.064 in 2008 to 0.125 in 2018. From 2008 to 2011, the government's vigorous promotion of Sichuan Province's development led to its economy's continued rise. However, from 2012 to 2015, economic growth was somewhat flat and slightly lower than the previous two years. From 2016 to 2018, the economic expansion had an upward trend. Overall, the total financial volume rose, the regional GDP growth rate maintained a high-speed growth of about 8%, and the economic structure was transformed and upgraded.
- *Social progress subsystem*. Figure 4 indicates that the social subsystem score was steadily increasing, from 0.05 in 2008 to 0.136 in 2018, with the evaluation level increasing from "D" in 2008 to "C" in 2015 to "B" in 2017.

The 2008 score of the economic development subsystem was significantly lower than in the other years because of the global financial crisis and the impact of the 2008 Wenchuan earthquake. The main reason for the social progress subsystem increase was a result of the Chinese Government's stated goal that "urbanization was the only way to modernization" in 2012, with the urbanization rate in Sichuan increasing from 37.4% in 2008 to 52.3% in 2018, and greater attention was paid to environmental livability and improving the resident's sense of gain and their disposable incomes. Simultaneously, investment in science and

Year	Economic development	Social progress	Energy consumption	Low carbon emissions	Carbon sink capacity	Environmental carrying capacity	Comprehensive score
2008	0.0643	0.0499	0.1507	0.0317	0.0738	0.1874	0.5578
2009	0.0949	0.0557	0.1206	0.0237	0.0739	0.1864	0.5552
2010	0.0991	0.0585	0.0975	0.0243	0.0736	0.1675	0.5206
2011	0.0961	0.0598	0.0854	0.0251	0.0723	0.1470	0.4858
2012	0.0762	0.0808	0.0862	0.0245	0.0721	0.1397	0.4795
2013	0.0679	0.0791	0.1079	0.0243	0.1186	0.1274	0.5252
2014	0.0697	0.0812	0.0933	0.0232	0.1178	0.1237	0.5089
2015	0.0719	0.1022	0.1219	0.0264	0.1254	0.1246	0.5725
2016	0.0864	0.1057	0.0997	0.0299	0.1408	0.1298	0.5923
2017	0.1058	0.1154	0.0982	0.0347	0.1645	0.1262	0.6448
2018	0.1245	0.1363	0.1005	0.0416	0.1848	0.1377	0.7254

Table 4. Evaluation subsystem score and comprehensive score

Value	Economic development	Social progress	Energy consumption	Low carbon emissions	Carbon sink capacity	Environmental carrying capacity	Comprehensive score
Optimal value	0.1636	0.1496	0.1969	0.0509	0.1848	0.2542	1

Table 5. Optimal evaluation value based on the reference sequence

technology and education gradually increased, resulting in a strong science and technology province.

5.1.2 Analysis of low carbon evaluation results. Under the combined influence of the energy consumption and low-carbon emissions subsystems, the low-carbon assessment results are shown in Figure 5. The low-carbon emissions subsystem results were relatively stable, and the low-carbon results were similar to the energy consumption trends.

- *Energy consumption subsystem*. Figure 4 shows that the energy consumption system score went through three stages: decreasing from 0.151 in 2008 to 0.086 in 2012, increasing to a peak of 0.122 in 2015 and decreasing to 0.1 in 2018. The main reason for the 2008–2010 system downgrading from "B" to "D" was the eagerness to restore the economy after the earthquake, which meant that the total energy consumption in the industry, construction and transportation sectors rose substantially. The main reason for the 2014–2015 system upgrading from "D" to "C" was that the 18th National Congress emphasized green development, circular development and low-carbon development. However, in 2015, due to robust infrastructure construction in poverty-stricken areas to actively win the "fight against poverty," construction and transportation energy consumption rose, causing the system score to decline again.
- *Low-carbon emissions subsystem*. Figure 4 shows that the low-carbon emissions system was relatively stable. After a slight decline from 0.032 in 2008 to 0.024 in 2009, it rose to 0.042 in 2018. Due to an intensification in human activities and a continuous deterioration in the ecological environment, the total CO_2 emissions increased from 23.815 million tonnes in 2008 to 33.222 million tonnes in 2014. However, when Sichuan Province focused on polluting enterprises and publicized and encouraged low-carbon environmental protection, the CO_2 emissions fell to 28.619 million tonnes in 2017. Furthermore, after introducing the "Ecological Civilization" policy in 2007, the carbon emissions intensity decreased, from 1.89 in 2008 to 0.77 in 2017. Under the combined effect of the two indicators, the low-carbon emissions system was upgraded from "D" to "C" in 2017 to "B" in 2018.

Therefore, energy production and consumption transformations need to be continuously promoted to improve the low-carbon level. Specifically, the industrial energy usage in each link of the resource input-product processing-product output process needs to be assessed, and low-carbon cycle-related technologies implemented to improve resource utilization,

Evaluation level	Economic development	Social progress	Energy consumption	Low carbon emissions
A	[0.1472, 0.1636]	[0.1347, 0.1496]	[0.1772, 0.1969]	[0.0458, 0.0509]
B	[0.1227, 0.1472]	[0.1122, 0.1347]	[0.1477, 0.1772]	[0.0382, 0.0458]
C	[0.0982, 0.1227]	[0.0898, 0.1122]	[0.1181, 0.1477]	[0.0305, 0.0382]
D	[0.0000, 0.0982]	[0.0000, 0.0898]	[0.0000, 0.1181]	[0.0000, 0.0305]
Evaluation level	Carbon sink capacity		Environmental carrying capacity	Comprehensive score
A	[0.1663, 0.1848]		[0.2288, 0.2542]	[0.9000, 1.0000]
B	[0.1386, 0.1663]		[0.1907, 0.2288]	[0.7500, 0.9000]
C	[0.1109, 0.1386]		[0.1525, 0.1907]	[0.6000, 0.7500]
D	[0.0000, 0.1109]		[0.0000, 0.1525]	[0.0000, 0.6000]

Table 6. Evaluation rating table

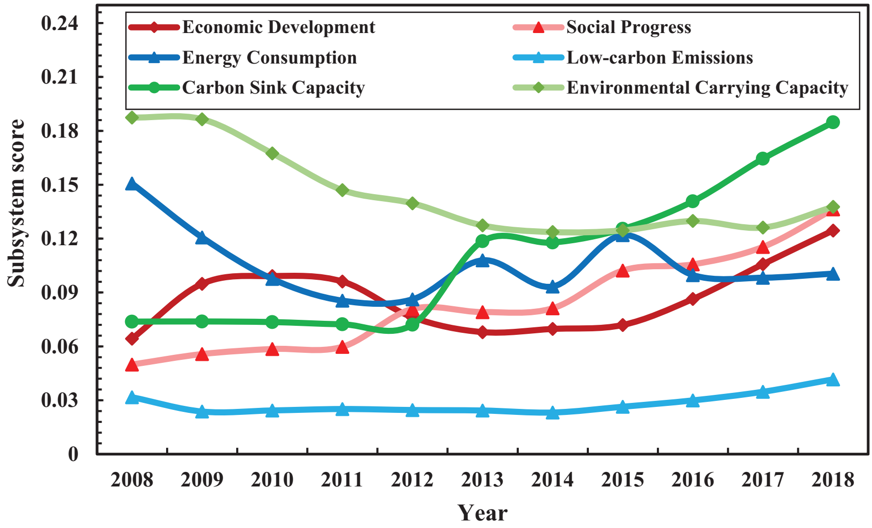

Figure 4.
Sichuan province low-carbon circular economic development system scores

waste recycling and resource treatment rates. Construction technology innovation and optimization are needed, low-carbon recyclable building materials used and mechanical equipment energy consumption strictly controlled. Urban transportation route planning and functional area divisions need to be optimized and low-carbon transportation networks are built and promoted to reduce the energy consumption of the transportation sector.

In addition, traditional industrial structure transformation needs to be better promoted. High energy consumption, emissions and pollution in conventional industries should be strictly controlled (Chandio *et al.*, 2021). Therefore, high-tech sectors should be encouraged, integrating high-tech sectors, such as artificial intelligence, blockchain, the Internet of Things, cloud computing and big data, with traditional sectors' accelerated informatization

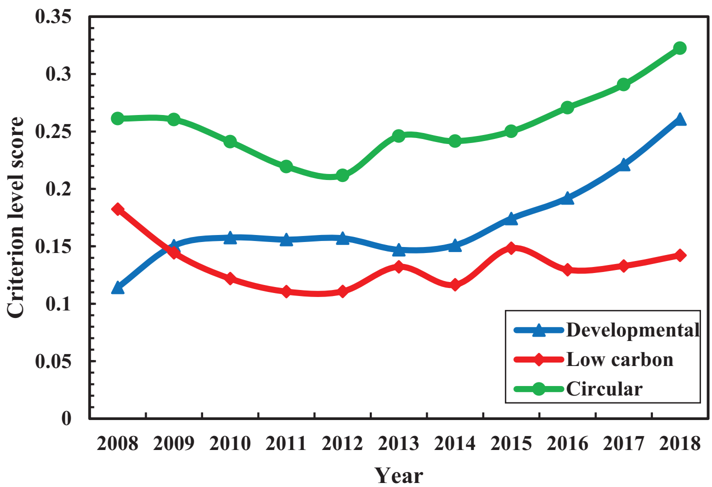

Figure 5.
Measurement results for the three criterion layers

capabilities industries enhanced. Simultaneously, representative innovative low-carbon recycling industries must be established to realize a highly efficient low-carbon recycling industry chain. Thus, the transformation and upgrading of traditional industries, the development of high-tech industries and the rise of intelligent low-carbon industries can jointly promote a reduction in resource consumption and environmental pollution and ultimately achieve environmentally friendly, sustainable development that reduces production costs and increases output efficiencies.

5.1.3 Analysis of circular evaluation results. Figure 5 shows that under the combined effect of carbon sink capacity and the environmental carrying capacity subsystem's decline from 2008 to 2012, Sichuan Province's economic cycle assessment was the lowest in 2012. However, after 2012, the cyclical evaluation steadily increased because of the continuous improvements in carbon sink capacity and the environmental carrying capacity:

- *Carbon sink capacity subsystem.* Figure 4 shows that the carbon sink capacity system increased from 0.074 in 2008 to 0.185 in 2018. From 2012 to 2018, the wetlands increased from 961,700 to 1,744,800 hectares. The remaining indicators grew steadily or fluctuated within a relatively small range over the decade. From 2008 to 2018, the forest coverage rate increased from 30.79% to 38.03% and the forest stock volume also steadily increased. Therefore, the carbon sink capacity subsystem moved from a "D" in 2008 to an "A" in 2018, which indicated that the policy implementation had been effective.
- *Environmental carrying capacity subsystem.* Figure 4 shows that while the environmental carrying capacity system first decreased and then increased, the overall level decreased. As the industrial solid waste comprehensive utilization rate continued to decline, the environmental carrying capacity system dropped from 0.187 in 2008 to 0.124 in 2014. After the announcement of the CE Development Strategy and Immediate Action Plan by the State Council in 2013, the environmental carrying capacity subsystem improved to 0.138 in 2018. However, the environmental carrying capacity score since 2011 was at "D".

Therefore, to increase low-carbon economic development, improvements are need in the environmental carrying capacity subsystem. Resource inputs should be reduced, resource recycling should increase and waste recycling schemes should be implemented. Therefore, industrial solid waste management needs to be strengthened to increase comprehensive industrial solid waste utilization. Further, enterprises should adopt

Year	Economic development	Social progress	Energy consumption	Low carbon emissions	Carbon sink capacity	Environmental carrying capacity
2008	D	D	B	C	D	C
2009	D	D	C	D	D	C
2010	C	D	D	D	D	C
2011	D	D	D	D	D	D
2012	D	D	D	D	D	D
2013	D	D	D	D	C	D
2014	D	D	D	D	C	D
2015	D	C	C	D	C	D
2016	D	C	D	D	B	D
2017	C	B	D	C	B	D
2018	C	B	D	B	A	D

Table 7. System layer level table

advanced cleaner production technologies to reduce hazardous waste generation at the source. Strict sewage discharge assessment systems are also required. Assessment indicators, such as annual forest volume, afforestation area, grassland degradation area, the number of fires in various regions are needed. A complete evaluation index system from planting to protection to destruction is assigned to protect and expand carbon sinks (Chandio *et al.*, 2020). Besides, forestry science management, pest control, forestry construction technology and restoration technologies are needed to drive the technological innovations required to ensure healthy forestry development.

5.2 Comprehensive results and analysis

The comprehensive regional LCCE development in Sichuan Province is shown in Figure 6.

Based on the comprehensive results and the grade evaluation table (Table 6), the comprehensive LCCE development in Sichuan Province is shown in Table 8.

Figure 6 shows that from 2008 to 2018, Sichuan's overall LCCE development level decreased from 0.558 in 2008 to 0.48 in 2012 and then expanded to 0.725 in 2018. This was because the low-carbon and development levels continued to fall from 2008 to 2012, resulting in Sichuan's LCCE development reaching its lowest value in 2012. However, after 2012, Sichuan's comprehensive LCCE development level continued to rise steadily because of the combined effects of the low-carbon level fluctuations and the steady rise in the development and circular levels.

The analysis of each subsystem's evaluation results indicated that the main reason for the continuous decline in the overall score before 2012 was decreased energy consumption subsystem, the environmental carrying capacity subsystem and the carbon sink capacity subsystem. Specifically, the total energy consumption in the manufacturing, construction

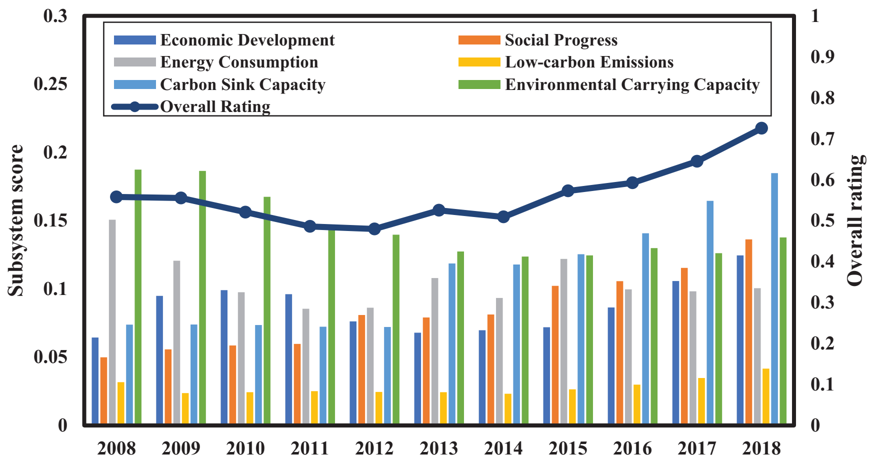

Figure 6.
Comprehensive LCCE development

Table 8.
Comprehensive score grade table

Years	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Overall ratings	D	D	D	D	D	D	D	D	D	C	C

and transportation sectors continued to increase (Shahbaz *et al.*, 2013) and the total industrial solid waste utilization rate and the afforestation area continued to decrease. The comprehensive ranking in Table 8 shows that the LCE development in Sichuan reached a "C" for the first time in 2017, which was a direct result of the government's raising of the ecological crisis awareness and their "Opinions on Accelerating the Construction of Ecological Civilization" in 2015, which again stressed the need to adhere to the development of a LCCE. It also indicated that the relevant low-carbon circular policies positively affected environmental protection and economic development (Yu, 2014). Sichuan's economic development was still mainly dependent on the secondary industry before 2012. However, after the Chinese Government adopted the CE and LCE as a strategic transformation development mode in 2012, Sichuan Province's low-carbon economic development improved slightly until 2015, when it increased significantly.

6. Conclusions

In recent years, the adverse effects of global climate change on human production and life have become more and more prominent, and coping with climate change has become one of the most severe challenges facing human society. Climate change appears to be an environmental issue, but in essence, it is a development issue. Therefore, transforming the traditional economic development model to a circular, low-carbon sustainable economic development path has become inevitable.

Recent reviews about LCCE show that, despite the growing interest of researchers and practitioners towards the LC or CE paradigm, research about indicators and methodologies for measuring the development level of LCCE is still in its earliest phase, particularly on the regional level. This paper tries to fill this gap, proposing an evaluation index system with 30 indexes under six subsystems: economic development, social progress, energy consumption, low carbon emissions, carbon sink capacity and environmental carrying capacity. After which, the objectivity of the entropy weight method and the convenience of grey correlation have been combined in an entropy weight-grey correlation evaluation method, which is then used to evaluate LCCE development in Sichuan Province, China, from 2008 to 2018.

The results show that the LCCE development in Sichuan Province has shown a downward trend in 2008–2012 and a steady upward trend in 2012–2018. The comprehensive evaluation grade of LCCE development from 2008 to 2016 is "D," and from 2017 to 2018, it is "C." The main reason for the continuous decline in the overall score before 2012 is the decline in the scores of the energy consumption subsystem, the carbon sink capacity subsystem and the environmental carrying capacity subsystem. Specifically, the total energy consumption caused by energy consumption in industry, construction and transportation continues to rise; the comprehensive utilization rate of industrial solid waste continues to decrease, and the afforestation area continues to decline. After 2012, the development level of the LCCE showed a fluctuating upward trend. However, due to the large fluctuations in the low-carbon development level and the relatively low score of the development level, the overall level was only maintained at the "C" level. Therefore, it is necessary to improve the energy consumption policy system, conduct intense supervision and promote recycling-related technologies. Intensify efforts to transform traditional industrial structures and strictly control conventional industries with high energy consumption, high emissions and high pollution. Promote the development of high-tech industries, accelerate the integration of high-tech industries, such as artificial intelligence, blockchain, Internet of Things, cloud computing and big data with traditional industries and enhance the informatization capabilities of conventional industries.

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