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Evaluation of Provincial Carbon Neutrality Capacity of China Based on Combined Weight and Improved TOPSIS Model

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Abstract: It will be a huge challenge for China to achieve carbon neutrality by 2060. At present, China needs to understand its own carbon neutrality status and then scientifically plan a path to achieve carbon neutrality. In order to evaluate the carbon neutrality capacity of China's provinces, this paper firstly constructs an evaluation indicator system, which includes 20 indicators at six levels. Then, a combination of subjective and objective weighting methods, as well as an improved technique for order preference by similarity to an ideal solution (TOPSIS) model, are used to calculate evaluation results. On this basis, the reasons for their different carbon neutrality capacities are analyzed. The results show that the use of renewable energy, maintaining ecological environmental quality, and low-carbon technology are important factors affecting China's carbon neutrality capacity, and according to the evaluation results, China's provinces are divided into three categories. Finally, corresponding suggestions for speeding up the pace of carbon neutrality are put forward.

Keywords: carbon neutrality; capability assessment; cloud model; improved TOPSIS model

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1. Introduction

According to The Global Climate Report in 2015–2019, published by the World Meteorological Organization (WMO), with the rising concentration of greenhouse gases in the atmosphere, global temperature is rising continuously, and global problems such as melting glaciers and rising sea levels are becoming increasingly serious, so it is urgent to take effective measures to deal with the greenhouse effect. The main cause of the greenhouse effect is increasing carbon emissions. Currently, China is one of the world's largest carbon emitters [1], which has an impact on the global climate. In response, China has proposed to achieve the goal of carbon neutrality by 2060 [2] and actively participates in global climate governance. Carbon neutrality refers to greenhouse gas emissions that do not cause a net increase in the global greenhouse gas emissions into the atmosphere [3]. Under such circumstances, how to achieve the goal of carbon neutrality in China in the next 40 years and how to plan the carbon neutrality path scientifically are questions worth exploring. At the same time, due to the great differences in regional development in China, it is also urgent to evaluate the carbon neutrality capacity of all the provinces and put forward corresponding strategic suggestions.

In the beginning, most of the published literature focused on the study of the factors influencing carbon emissions [4,5] or on the evaluation of the ability to reduce carbon emissions [6,7]. With the introduction of the concept of carbon neutrality, some scholars began to assess the potential for carbon neutrality. The factors considered in the relevant articles mainly include sewage treatment plants [8], the carbon absorption and carbon emissions of urban forests [9], and the balance between carbon source/sink [10]. Then, based on a full consideration of various influencing factors, Huang (2020) proposed a comprehensive carbon assessment model to assess the carbon neutrality capacity of urban areas in terms of population change, redevelopment, and renewable energy [11]. However, on the basis of a carbon neutrality capacity assessment, it is also very important to formulate an appropriate carbon neutralization path policy. Sannamari et al. (2019) analyzed national and local ways to achieve carbon neutrality from the perspectives of technology, emissions, and resilience [12]. Karna et al., (2018) and Li et al., (2018) further analyzed the necessity of a renewable energy policy and carbon emission capacity for achieving carbon neutrality [13,14]. How to effectively achieve carbon neutrality has become an important issue.

Besides, evaluation methods have been extensively studied. Comprehensive evaluation methods include an objective weighting method, a subjective weighting method, and a combination weighting method. Objective weighting methods include the entropy weight method (EWM) [15], the principal component analysis (PCA) method [16], coefficient of variation [17], etc. Among them, the entropy weight method has the advantage of distinguishing between indicators. Subjective weighting methods include the analytic hierarchy process (AHP) [18], the Delphi method [19], the cloud model [20], etc. Compared with other subjective weighting models, the cloud model has the advantage of uncertainty transformation, which can maximize the retention of the inherent uncertainty in the evaluation process and improve the credibility of the evaluation results. However, a single weighting method has limitations: (1) The objective weighting method only depends on differences between attributes, which easily leads to one-sided results; (2) the subjective weighting method may lead to an unreasonable weight ratio due to a lack of experience. A combination weighting method is the weighted summation of the subjective weighting method and the objective weighting method and can comprehensively consider subjective and objective factors to ensure the rationality of the index weight [21,22].

In terms of decision analysis methods, technique for order preference by similarity to an ideal solution (TOPSIS), the Vikor method (VIKOR), and PROMETHEE-II are traditional analysis methods. The TOPSIS method is easy to understand and flexible in application, and it has been widely used in social economy, engineering technology, and other fields [23]. VIKOR is a typical multicriteria compromise method and requires the determination of a criteria weight coefficient and criteria value, which is difficult to achieve in actual decision making [24]. PROMETHEE-II introduces a dominance function to process the index information of samples, which can reflect the advantages of different samples under a certain index. However, there are also some problems, such as there being no definite index evaluation standard, and the subjectivity of the dominance function is strong [25]. In recent years, multicriteria decision-making methods have been improving. For example, stochastic algorithms such as a particle swarm optimization (PSO) algorithm and simulated annealing algorithm (SAA) have been introduced to evaluate a given scheme, similar to the unknown decision model [26]. The random forest (RF) algorithm optimized by smote method and contribution function was used to evaluate enterprise credit risk [27]. The introduction of these stochastic algorithms can optimize traditional decision-making evaluation methods, while the results are usually unstable.

In summary, recent studies have only researched carbon emissions. However, for the evaluation of carbon neutrality capacity, the evaluation of this aspect alone is not comprehensive enough. In addition, there has been no systematic and in-depth study of carbon neutrality capacity in China; a few studies are limited to small-scale carbon neutrality capacity. Therefore, this paper tries to evaluate the carbon neutrality capacity of provincial regions. In the selection of an evaluation weighting method, the combination weighting method containing the entropy weight method and the cloud model is selected to ensure the rationality of the index weight. At the same time, considering the large amount of data in this paper and the practicability of the decision-making method, the TOPSIS method is selected as the carbon neutrality capacity evaluation method.

The structure of this paper is as follows: In Section 2, this paper constructs a provincial carbon neutrality capacity evaluation system with 20 indicators in six dimensions. In Section 3, this paper introduces the cloud model, entropy weight method, and improved TOPSIS model. In Section 4, this paper calculates the neutrality capacity of each province and analyzes the reasons for the differences. In Section 5, this paper makes corresponding suggestions on how to achieve the 2060 carbon neutrality goal based on the results. The specific provincial carbon neutrality capacity evaluation process in this paper is shown in Figure 1.

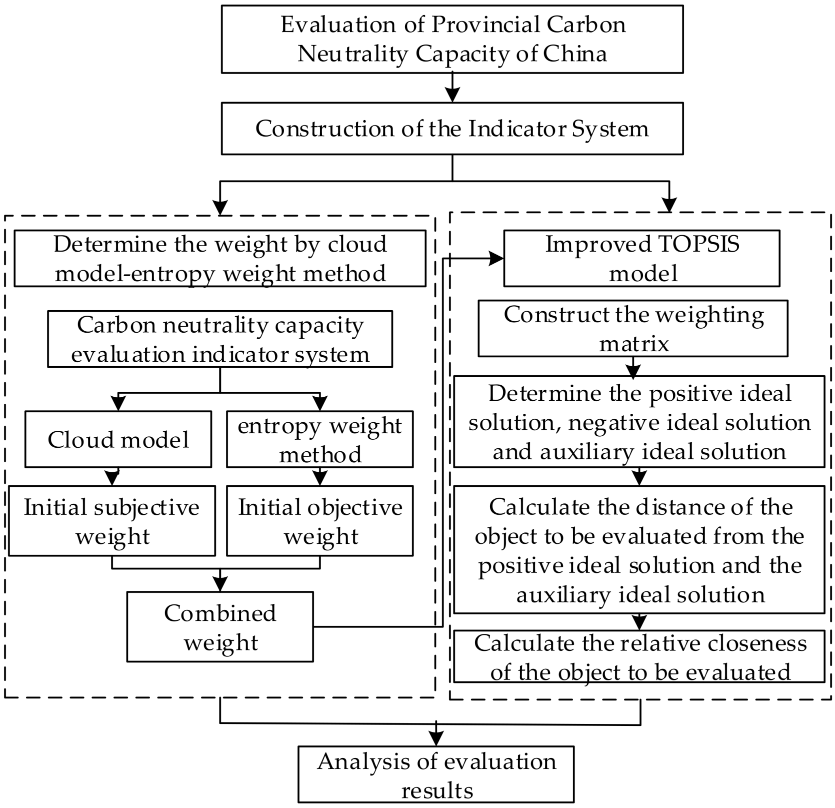

Figure 1. Flowchart of provincial carbon neutrality capacity evaluation of China.

2. Evaluation Indicator System of Carbon Neutrality Capacity

For the evaluation of carbon neutrality capacity, different indicators need to be selected from multiple perspectives to reflect the overall level. In fact, there are two ways to achieve carbon neutrality: carbon absorption and carbon emission reduction. Carbon absorption mainly uses forests and oceans to absorb carbon dioxide for carbon sequestration, so the evaluation of sink capacity is essential. For carbon emission reduction, carbon emission efficiency and technological progress are an important reflection of the emission reduction capacity. Economic growth is the main driving factor of the significant increase in carbon emissions in China in recent decades, so it is necessary to consider the social and economic development of each province. In addition, energy consumption, construction, and traffic are the main sources of carbon emissions. The utilization of renewable energy and the low-carbon development of construction and traffic can accelerate the pace of carbon neutrality in China. Therefore, the indicator system of this paper is composed of relative indicators, including carbon emission efficiency, carbon sink capacity, energy consumption, economic development of society, scientific and technological progress, and construction and traffic.

1. Carbon Emission Efficiency

Carbon efficiency can be reflected by the growth rate of carbon emissions, carbon emission intensity, and per capita carbon emissions [6].

(1) Growth rate of carbon emissions. The higher the growth rate of carbon emissions, the faster the growth of carbon emissions and the more difficult it is to achieve carbon neutrality.

$$Growth\ rate\ of\ carbon\ emissions = \frac{Last\ year's\ carbon\ emissions}{This\ year's\ carbon\ emissions} - 1. \tag{1}$$

(2) Carbon emission intensity. Carbon emission intensity is used to measure the relationship between regional economy and carbon emissions.

$$Carbon\ emissions\ intensity = \frac{Carbon\ emissions}{GDP}. \tag{2}$$

(3) Per capita carbon emissions. Per capita carbon emissions reflect the average level of regional carbon emissions.

$$Per\ capita\ carbon\ emissions = \frac{Carbon\ emissions}{Population}. \tag{3}$$

2. Carbon Sink Capacity

A forest carbon sink is an important way to offset carbon emissions [28]. In this paper, the carbon sink capacity of a region is calculated by four indicators: afforestation area per capita, forest volume, forest coverage rate, and green coverage rate. Afforestation area per capita reflects the intensity and motivation of human afforestation. The other three indicators reflect the carbon absorption capacity of existing terrestrial ecosystems. Forest volume refers to the total volume of tree trunks in a certain forest area. Green coverage rate refers to the ratio of green coverage area and regional area in urban built-up area at the end of the report period.

$$Afforestation\ area\ per\ capita = \frac{Total\ afforestation\ area}{Population}. \tag{4}$$

3. Energy Consumption

Currently, fossil energy plays a leading role in China's energy structure. The reduction in energy intensity and the development of renewable energy will have a significant reduction effect on carbon emissions [29].

(1) Total energy consumption per capita. Currently, the main source of energy is still fossil energy, and higher energy consumption per capita means higher carbon emissions.

$$Total\ energy\ consumption\ per\ capita = \frac{Total\ energy\ consumption}{Population}. \tag{5}$$

(2) Energy consumption intensity. Energy consumption intensity is the reflection of energy utilization efficiency. With the gradual improvement in energy utilization efficiency, society is moving towards low-carbon development.

$$Energy\ consumption\ intensity = \frac{Energy\ consumption}{GDP}. \tag{6}$$

(3) The proportion of renewable energy power generation. The electric power industry is a major consumer of energy, and the proposal of carbon neutrality means that the electric power industry must accelerate the pace of clean energy development.

4. Economic Development of Society

Economic development will inevitably increase energy consumption and carbon emissions [30]. In this paper, the economic development of a region is measured from four indicators: the proportion of secondary industry, per capita GDP, GDP index, and urbanization level.

5. Scientific and Technological Progress

Scientific and technological progress will lead to the application of low-carbon technologies, the improvement in energy utilization efficiency, and the development of green electricity, which is an important way to increase carbon emission reduction and carbon absorption [31]. In this paper, scientific and technological progress is measured via three indicators: number of patents granted per capita, investment in R&D per capita, and waste disposal rate. Progress in technology can improve the efficiency of waste treatment, reduce carbon emissions from waste, and make full use of the biomass in waste to improve energy efficiency.

$$Number\ of\ patents\ granted\ per\ capita = \frac{Number\ of\ patents\ granted}{Population}. \tag{7}$$

6. Construction and Traffic

In recent years, high energy consumption and emissions from the increasingly large-scale construction industry and increasingly congested traffic have been a great hindrance to achieve carbon neutrality [32,33]. In this paper, construction and traffic are measured via three indicators: housing construction area per capita, gross output value of construction industry per capita, and ownership of vehicles per capita.

$$Housing\ construction\ area\ per\ capita = \frac{Housing\ construction\ area}{Population}. \tag{8}$$

In summary, this paper selects 20 specific indicators, and the specific indicator system is shown in Table 1.

Table 1. Provincial carbon neutrality capacity evaluation indicator system in China.

Target Layer	Criterion Layer	Indicator Layer
Evaluation Indicator System of Carbon Neutrality Capacity	Carbon Emission Efficiency	Growth rate of carbon emissions X1 Carbon emission intensity X2 Per capita carbon emissions X3
	Carbon Sink Capacity	Afforestation area per capita X4 Forest volume X5 Forest coverage rate X6 Green coverage rate X7
	Energy Consumption	Energy consumption per capita X8 Energy consumption intensity X9 The proportion of renewable energy power generation X10
	Economic Development of Society	The proportion of secondary industry X11 Per capita GDP X12 GDP index X13 Urbanization level X14
	Scientific and Technological Progress	Number of patents granted per capita X15 Investment in R&D per capita X16 Waste disposal rate X17
	Construction and Traffic	Housing construction area per capita X18 Gross output value of construction industry per capita X19 Ownership of vehicles per capita X20

3. Comprehensive Evaluation Model

3.1. Cloud Model for Subjective Weights

The cloud model was proposed by Li D.Y. [34]. This method refers to the uncertainty transformation model between a qualitative concept and quantitative expression. The cloud model consists of three characteristic numbers of expectation, entropy, and super entropy, which are usually defined as $C(E_x, E_n, H_e)$. The weights can be obtained through the following process.

Step 1: Quantitative Conversion of Evaluation Language.

In this paper, five uncertain language evaluation scales are set as {I, II, III, IV, V}. The corresponding intervals on the domain [0, 1] are ([0, 0.33], [0.17, 0.5], [0.33, 0.67], [0.5, 0.38], [0.67, 1]). According to the one-dimensional normal cloud approximation representation of uncertain language evaluation scales introduced in [35], the one-dimensional normal cloud corresponding to the uncertainty evaluation in this paper is calculated as shown in Table 2.

Table 2. Language evaluation scales and corresponding cloud model.

Language Evaluation Scales	Cloud Model
I	(0.165, 0.055, 0.0262)
II	(0.335, 0.055, 0.0162)
III	(0.5, 0.567, 0.01)
IV	(0.665, 0.055, 0.0162)
V	(0.835, 0.055, 0.0262)

The composition of clouds satisfies the following equation, where k, l is a constant:

$$\begin{aligned} kC_1 + lC_2 &= k(E_{x_1}, E_{n_1}, H_{e_1}) + l(E_{x_2}, E_{n_2}, H_{e_2}) \\ &= \left(kE_{x_1} + lE_{x_2}, \sqrt{(kE_{n_1})^2 + (lE_{n_2})^2}, \sqrt{(kH_{e_1})^2 + (lH_{e_2})^2}\right) \end{aligned} \tag{9}$$

Step 2: Calculation of Subjective Weights

The initial subjective weights are calculated by converting the evaluation language of each expert on the indicators into a comprehensive cloud model and then using the cloud similarity to determine the subjective weights of each indicator. We suppose that there are s experts $(k = 1, 2, \cdots s)$ who evaluate the importance of the evaluation indicators $A_j (j = 1, 2, \cdots)$. The calculation steps are as follows:

(1) According to Table 2, the expert's language evaluation is transformed into the corresponding cloud model: $Z_j^k = \left(E_x^k, E_n^k, H_e^k\right)$.

(2) Using the cloud composition equation, the comprehensive cloud model of evaluation indicators A_j is constructed with the following equation:

$$Z_j = \frac{1}{s}\sum_{k=1}^{s} Z_j^k. \tag{10}$$

(3) According to the calculation method of cloud similarity in [36], the cloud model Z^* corresponding to language evaluation V is taken as the cloud with an importance value of 1. Then, the similarity $Similar(Z_j, Z^*)$ is calculated.

(4) The initial subjective weights of each evaluation indicator are obtained by normalization processing $Similar(Z_j, Z^*)$. The equation is as follows:

$$r_j = \frac{Similar(Z_j, Z^*)}{\sum\limits_{j=1}^{n} Similar(Z_j, Z^*)}. \tag{11}$$

3.2. Entropy Weight Method for Objective Weights

Entropy was originally a thermodynamic concept. It was first introduced into information theory by Shannon [37]. The basic idea of the entropy weight method is to determine weight according to the amount of information on the indicators. Generally speaking, the lower the information entropy of an indicator, the more information it provides, so the greater the role it can play in the comprehensive evaluation and the greater its weight. The initial objective weights v_j are obtained by normalizing the information entropy E_j according to the steps of the entropy weight method algorithm in [38]. The equation is as follows:

$$v_j = \frac{1 - E_j}{\sum\limits_{j=1}^{n} (1 - E_j)}. \tag{12}$$

Finally, the initial subjective weights calculated by the cloud model are combined with the initial objective weights calculated by the entropy weight method to obtain the comprehensive weights of the indicators. In this paper, the importance of both subjective weights and objective weights are set to 0.5. The equation for calculating the combined weights is as follows:

$$w_j = \frac{1}{2}(r_j + v_j). \tag{13}$$

3.3. Improved TOPSIS Model for Evaluation

The TOPSIS method is an analysis method that is applicable to the comparison of multiple evaluation objects by multi-attribute indicators. This method aims to choose alternatives that simultaneously have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution [39]. However, the traditional TOPSIS analysis method cannot distinguish between the advantages and disadvantages of the sample points in the vertical line of the positive ideal solution and the negative ideal solution. Therefore, this paper introduces an auxiliary negative ideal solution instead of a negative ideal solution to solve the above problems, which can make the evaluation results more convincing [40]. The algorithm of the improved TOPSIS model is to construct an auxiliary negative ideal solution on the basis of a traditional TOPSIS model. The steps are as follows:

Step 1: Constructing a weighted judgment matrix:

$$S = YW = \left\{ \begin{array}{cccc} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{array} \right\} \left\{ \begin{array}{cccc} w_{11} & 0 & \cdots & 0 \\ 0 & w_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{mn} \end{array} \right\} = \left\{ \begin{array}{cccc} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mn} \end{array} \right\} \tag{14}$$

In the above equation, S is the weighted judgment matrix, Y is the judgment matrix, W is the weight matrix; w_{ij} is calculated by Equations (9)–(13).

Step 2: Constructing a positive ideal solution, negative ideal solution, and auxiliary negative ideal solution:

$$S^+ = \left\{ \begin{array}{l} \max\limits_{1 \le i \le m} s_{ij}, j \in J^+ \\ \min\limits_{1 \le i \le m} s_{ij}, j \in J^- \end{array} \right. = \left\{ s_1^+, s_2^+, \cdots, s_n^+ \right\} \tag{15}$$

$$S^- = \left\{ \begin{array}{l} \min\limits_{1 \le i \le m} s_{ij}, j \in J^+ \\ \max\limits_{1 \le i \le m} s_{ij}, j \in J^- \end{array} \right. = \left\{ s_1^-, s_2^-, \cdots, s_n^- \right\} \tag{16}$$

$$S^* = 2S^- - S^+ = \left\{ 2s_1^- - s_1^+, 2s_2^- - s_2^+, \cdots, 2s_n^- - s_n^+ \right\} = \{ s_1^*, s_2^*, \cdots, s_n^* \}. \tag{17}$$

In the above equations, S^+ is the positive ideal solution, S^- is the negative ideal solution, and S^* is the auxiliary negative ideal solution; J^+ is the set of benefit-based indicators, and J^- is the set of cost-based indicators.

Step 3: Calculating the distance of the object to be evaluated to the positive ideal solution and the auxiliary negative ideal solution:

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(s_{ij} - s_j^+\right)^2} \tag{18}$$

$$D_i^* = \sqrt{\sum_{j=1}^{m}\left(s_{ij} - s_j^*\right)^2}. \tag{19}$$

In the above two equations, D_i^+ is the distance from the object to be evaluated to the positive ideal solution and D_i^* is the distance from the object to be evaluated to the auxiliary negative ideal solution.

Step 4: Calculation of relative closeness:

$$C_i = \frac{D_i^*}{D_i^* + D_i^+}. \tag{20}$$

In the above equation, C_i is the closeness degree of the object to be evaluated, and the greater the closeness, the better the evaluation results. Then, the closeness of the evaluated objects is ranked and the advantages and disadvantages are compared.

4. Case Analysis

In this section, this paper evaluates the carbon neutrality capacity of 30 provinces in China (except Tibet, Hong Kong, Macao, and Taiwan) based on the evaluation indicator system in Section 2 and the methods proposed in Section 3. The data were obtained from the National Bureau of Statistics of China, *the China Energy Statistical Yearbook*, and the China Emission Accounts and Datasets (CEADs) in 2017. And Some data are shown in Table A1 in the Appendix A.

4.1. Determination of Indicator Weights

4.1.1. Determination of Subjective Weights

A qualitative evaluation of the 20 indicators in Table 1 was performed by five experts, which were shown in Table A2 in the Appendix A. And the evaluation was converted into a corresponding cloud model according to Table 2. Then, the comprehensive cloud model of each indicator was calculated according to Equations (10) and (11) to obtain the initial subjective weight. The relevant data of the calculation process are shown in Table 3 ($n = 2000$).

Table 3. Relevant data of the calculation process.

Indicators	Comprehensive Cloud Model	*Similar*(Z_j,Z^*)	Initial Subjective Weight
Growth rate of carbon emissions X1	(3.665, 0.123, 0.046)	0.064	0.059
Carbon emission intensity X2	(4.175, 0.123, 0.059)	0.075	0.070
Per capita carbon emissions X3	(4.005, 0.123, 0.055)	0.072	0.066
Afforestation area per capita X4	(3.495, 0.123, 0.042)	0.060	0.055
Forest volume X5	(2.995, 0.125, 0.031)	0.049	0.045
Forest coverage rate X6	(2.500, 0.125, 0.029)	0.038	0.035
Green coverage rate X7	(2.170, 0.125, 0.029)	0.030	0.028
Energy consumption per capita X8	(3.325, 0.123, 0.036)	0.056	0.052
Energy consumption intensity X9	(3.835, 0.123, 0.051)	0.068	0.062
The proportion of renewable energy power generation X10	(4.005, 0.123, 0.059)	0.072	0.066

Table 3. *Cont.*

Indicators	Comprehensive Cloud Model	$Similar(Z_j, Z^*)$	Initial Subjective Weight
The proportion of secondary industry X11	(4.005, 0.123, 0.055)	0.072	0.066
Per capita GDP X12	(2.665, 0.124, 0.026)	0.041	0.038
GDP index X13	(2.500, 0.127, 0.022)	0.037	0.035
Urbanization level X14	(3.160, 0.124, 0.034)	0.052	0.048
The number of patents granted per capita X15	(2.995, 0.125, 0.031)	0.049	0.045
The investment in R&D per capita X16	(2.995, 0.125, 0.031)	0.049	0.045
Waste disposal rate X17	(2.665, 0.126, 0.026)	0.041	0.038
Housing construction area per capita X18	(3.495, 0.123, 0.042)	0.060	0.055
Gross output value of construction industry per capita X19	(2.830, 0.125, 0.029)	0.045	0.041
Ownership of vehicles per capita X20	(3.325, 0.123, 0.036)	0.056	0.052

4.1.2. Determination of the Combined Weights

Then, the entropy weight method was used to calculate the initial objective weight, and after combining the initial subjective weight and initial objective weight according to Equation (13), the final weight was obtained. The results of the weight calculation are shown in Table 4.

Table 4. Weights of evaluation indicators.

Indicators	Initial Subjective Weight r_j	Initial Objective Weight v_j	Combined Weight w_j
Growth rate of carbon emissions X1	0.0587	0.0110	0.0349
Carbon emission intensity X2	0.0695	0.0160	0.0427
Per capita carbon emissions X3	0.0660	0.0182	0.0421
Afforestation area per capita X4	0.0552	0.1038	0.0795
Forest volume X5	0.0448	0.1379	0.0914
Forest coverage rate X6	0.0346	0.0514	0.0430
Green coverage rate X7	0.0277	0.0263	0.0270
Energy consumption per capita X8	0.0517	0.0177	0.0347
Energy consumption intensity X9	0.0624	0.0202	0.0413
The proportion of renewable energy power generation X10	0.0660	0.1138	0.0899
The proportion of secondary industry X11	0.0663	0.0701	0.0682
Per capita GDP X12	0.0381	0.0277	0.0329
GDP index X13	0.0346	0.0341	0.0343
Urbanization level X14	0.0483	0.0247	0.0365
The number of patents granted per capita X15	0.0450	0.1574	0.1012
The investment in R&D per capita X16	0.0449	0.0987	0.0718
Waste disposal rate X17	0.0379	0.0109	0.0244
Housing construction area per capita X18	0.0553	0.0219	0.0386
Gross output value of construction industry per capita X19	0.0414	0.0181	0.0297
Ownership of vehicles per capita X20	0.0517	0.0200	0.0359

4.2. Comprehensive Evaluation Results

First, we calculated the positive and auxiliary negative ideal solutions according to Equations (14)–(17). Then, we calculated the distance of the object to be evaluated from the positive and auxiliary negative ideal solutions according to Equations (18)–(19). Finally, the relative closeness of each province was calculated by Equation (20). The results are shown in Table 5.

Table 5. Calculation results of relative closeness of each province.

Object to Be Evaluated	D_i^+	D_i^*	C_i	Ranking
Sichuan	0.0521	0.1932	0.7876	1
Yunnan	0.0546	0.1923	0.7789	2
Qinghai	0.0654	0.1856	0.7394	3
Inner Mongolia	0.0626	0.1772	0.7390	4
Guizhou	0.0660	0.1678	0.7175	5
Heilongjiang	0.0735	0.1731	0.7020	6
Hubei	0.0704	0.1630	0.6984	7
Hunan	0.0704	0.1627	0.6978	8
Gansu	0.0713	0.1642	0.6972	9
Jilin	0.0723	0.1631	0.6929	10
Guangxi	0.0734	0.1625	0.6889	11
Fujian	0.0725	0.1585	0.6862	12
Chongqing	0.0757	0.1575	0.6754	13
Shaanxi	0.0769	0.1573	0.6716	14
Jiangxi	0.0781	0.1564	0.6670	15
Guangdong	0.0804	0.1573	0.6617	16
Xinjiang	0.0803	0.1500	0.6512	17
Hebei	0.0850	0.1512	0.6401	18
Liaoning	0.0853	0.1484	0.6351	19
Anhui	0.0876	0.1491	0.6299	20
Henan	0.0887	0.1507	0.6295	21
Shandong	0.0887	0.1505	0.6290	22
Hainan	0.0904	0.1499	0.6239	23
Shanxi	0.0874	0.1446	0.6232	24
Zhejiang	0.0896	0.1478	0.6226	25
Beijing	0.0920	0.1501	0.6200	26
Tianjin	0.0916	0.1482	0.6179	27
Shanghai	0.0920	0.1482	0.6171	28
Jiangsu	0.0921	0.1461	0.6134	29
Ningxia	0.0934	0.1383	0.5971	30

4.3. Analysis of Carbon Neutrality Capacity Evaluation Results

4.3.1. Analysis of Evaluation Results

The subjective weight is $0.5r_j$ and the objective weight is $0.5v_j$ in Figure 2. As can be seen from Figure 2, the six indicators that have the greatest impact on the evaluation of carbon neutrality capacity are forest volume, afforestation area per capita, proportion of renewable energy power generation, proportion of secondary industry, number of patents granted per capita, and investment in R&D per capita. Forest volume and afforestation area per capita are indicators of carbon sequestration capacity. It shows that natural carbon sequestration plays a key role in carbon neutrality. The number of patents granted per capita and the investment in R&D per capita are indicators of scientific and technological progress It shows that attention needs to be paid to the development of low-carbon technologies. In addition, accelerating the development of clean energy and controlling the energy consumption of high energy-consuming industries are also the key to accelerating the movement towards carbon neutrality. The objective weights of these six indicators are also the highest among all indicators, indicating that the differences among provinces are the greatest in these four aspects.

On the other hand, it is worth noting that the indicators with greater subjective weights are concentrated in two areas: carbon emission efficiency and energy consumption. Currently, fossil fuel consumption is the largest source of carbon emissions. Reducing the proportion of fossil energy, developing clean energy, and improving carbon emission efficiency are the main ways to improve carbon neutrality at this stage. Therefore, the importance of these two aspects cannot be ignored.

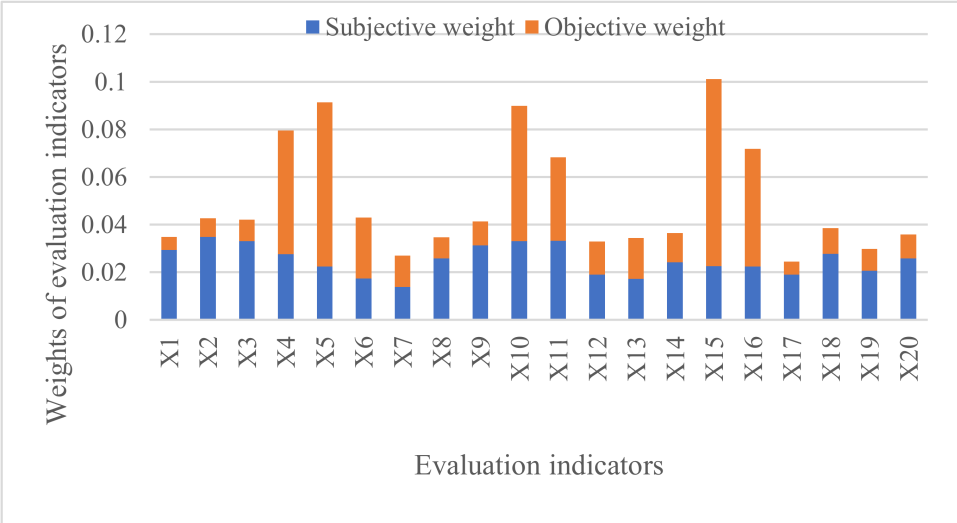

Figure 2. Weights of evaluation indicators.

In Figure 3, the 30 provinces can be divided into three categories. The first category has a carbon neutrality capacity value of 0.7 or higher and includes six provinces. The second category has carbon neutrality capacity values between 0.623 and 0.7 and includes 18 provinces. The third category has a carbon neutrality of less than 0.623 and includes six provinces. It can be seen that carbon neutrality capacity in the first category is mainly in some economically underdeveloped areas, for the following reasons. Firstly, the levels of transportation, construction, and energy consumption in economically developed areas are much higher than those in economically underdeveloped areas. Secondly, some provinces are rich in renewable energy, and the proportion of renewable energy power generation is very high, which makes the carbon emission level of the power industry very low. For example, the clean energy power generation of Qinghai Province and Yunnan Province accounts for more than 80%. Thirdly, the forest ecosystem of some provinces has a high greening level and strong carbon absorption capacity. For example, the forest volume and forest coverage of Sichuan Province, Yunnan Province, and Heilongjiang Province are at the top level in China.

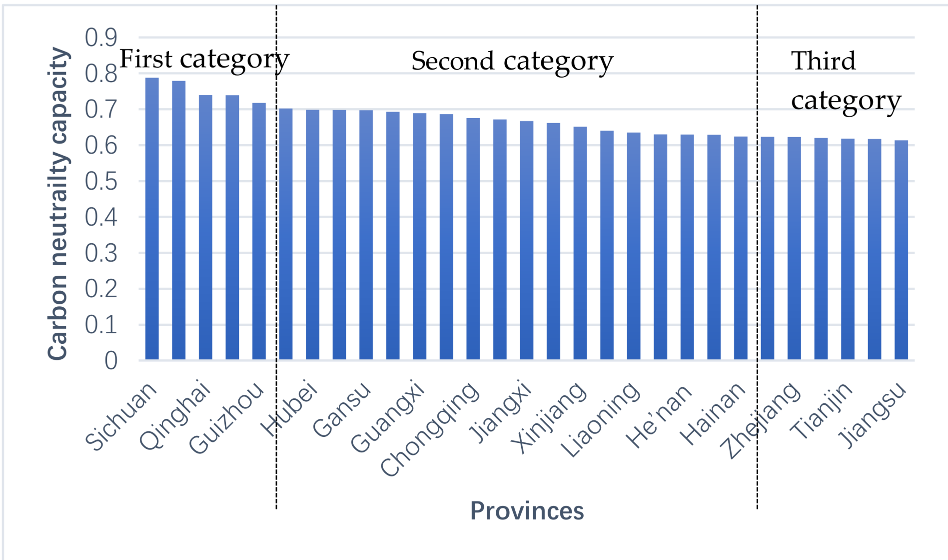

Figure 3. Carbon neutrality capacity of each province.

In order to further analyze the characteristics of provinces in different categories, the indicator data were first normalized, followed by further processing of the normalized values by the following equation:

$$\bar{u_{ij}} = \frac{1}{t_j}\sum_{i=1}^{t_j} u_{ij}(t). \tag{21}$$

In the above equation, i indicates the indicator, j indicates the category, t_j indicates the number of provinces belonging to category j, t indicates the province, $u_{i,j}$ (t) indicates the value of indicator i in province t, and $\bar{u_{ij}}$ indicates the average level of indicator i of provinces belonging to category j, where the higher the value of $\bar{u_{ij}}$, the higher the level.

As can be seen in Figure 4, the high level of the first category is mainly reflected in three aspects: economic development of the society, construction and traffic, and the proportion of renewable energy generation. This shows that most of the provinces in this category have good environmental quality and a high utilization rate of renewable energy, but their economic and social development is relatively backward. Therefore, for these provinces, the first thing is to maintain the advantage of renewable energy as the main energy consumption structure and a stable ecosystem. Future economic development should focus on a circular economy, developing green buildings and transportation, and avoiding weakening the capacity of these aspects in the process of development. The second group of provinces are relatively balanced in all aspects and have no outstanding advantages. This category of provinces should focus on their own strengths for development. The third category of provinces are mainly economically developed provinces. The advantages of these provinces lie in the level of scientific and technological progress. Therefore, they should first continue to develop carbon emission technology to further improve efficiency. After that, efforts should be made to make up for the shortcomings in the energy structure, optimize the industrial structure, and control the high carbon emissions of construction and transportation. In addition, there is little difference in carbon emission efficiency among the three categories of provinces, so China's overall carbon emission capacity needs to be improved. It is worth noting that Ningxia is in last place in the third category but does not have the general characteristics of the third category provinces. Most of its indicators are weaker than those of other provinces.

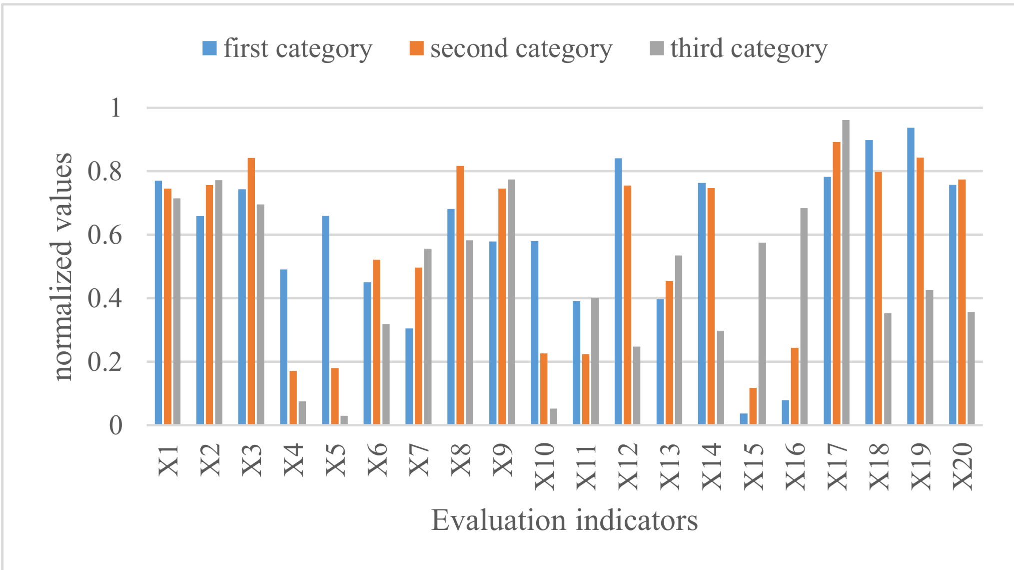

Figure 4. Average level of carbon neutrality indicators for each category.

4.3.2. Comparison of Evaluation Results

(1) Comparison between TOPSIS method and improved TOPSIS method

The TOPSIS method was compared with the improved TOPSIS method, as shown in Table 6. The two methods adopt the same weighting method, but the difference lies in the negative ideal solution. It can be seen from the table that the evaluation results of the two methods are similar, and the changes are basically in the same category. The main difference is that Liaoning and Anhui move up three places, while Henan moves down five places. Comparing the normalized indicator data of three provinces with the average level of the second category indicators, it can be seen that half of the indicators of Henan, including the five indicators with the largest weight, are lower than the average level. Most of the indicators with a high weight in Liaoning and Anhui are above the average level. Therefore, the change in ranking is reasonable. This shows that the improved TOPSIS method is effective.

Table 6. Comparison of evaluation results of different methods.

Ranking	Improved TOPSIS	TOPSIS	Weighted RSR
1	Sichuan	Sichuan	Sichuan
2	Yunnan	Yunnan	Hunan
3	Qinghai	Qinghai	Yunnan
4	Inner Mongolia	Inner Mongolia	Qinghai
5	Guizhou	Heilongjiang	Inner Mongolia
6	Heilongjiang	Guizhou	Guangxi
7	Hubei	Hubei	Jiangxi
8	Hunan	Hunan	Fujian
9	Gansu	Jilin	Hubei
10	Jilin	Gansu	Heilongjiang
11	Guangxi	Guangxi	Chongqing
12	Fujian	Fujian	Guizhou
13	Chongqing	Chongqing	Beijing
14	Shaanxi	Guangdong	Shaanxi
15	Jiangxi	Shaanxi	Jilin
16	Guangdong	Jiangxi	Guangdong
17	Xinjiang	Henan	Anhui
18	Hebei	Xinjiang	Hainan
19	Liaoning	Hebei	Gansu
20	Anhui	Shandong	Liaoning
21	Henan	Hainan	Henan
22	Shandong	Liaoning	Hebei
23	Hainan	Anhui	Shanxi
24	Shanxi	Shanxi	Shandong
25	Zhejiang	Zhejiang	Zhejiang
26	Beijing	Beijing	Xinjiang
27	Tianjin	Shanghai	Jiangsu
28	Shanghai	Jiangsu	Tianjin
29	Jiangsu	Tianjin	Ningxia
30	Ningxia	Ningxia	Shanghai

(2) Comparison between weighted RSR method and improved TOPSIS method

In order to further analyze the accuracy of the improved TOPSIS method, this paper used the weighted rank-sum ratio (RSR) method [41] to evaluate carbon neutrality capacity and compared it with the improved TOPSIS method. The RSR method is an effective multi-index evaluation method which has the characteristics of simple calculation, no special requirements for data, and easy promotion [42]. The weight of weighted RSR is the same as the improved TOPSIS. The evaluation results are shown in Table 6. There are some differences between the evaluation results of the two methods. It is inevitable that the evaluation results of different methods are inconsistent. Through a careful comparison, it can be seen that the top provinces ranked by weighted RSR method are mainly economically underdeveloped with rich forest resources and a high proportion of renewable energy power generation. The provinces at the bottom are mainly economically developed with outstanding advantages in scientific and technological progress. This is consistent with the evaluation results of the improved TOPSIS method on the macro level.

5. Conclusions

China has a long way to go to achieve the goal of carbon neutrality by 2060. Under such circumstances, this paper constructs the first carbon neutrality capacity evaluation indicator system. Furthermore, the carbon neutrality capacity of 30 provinces in China is comprehensively evaluated by the combined weighting and improved TOPSIS model. The main conclusions are as follows:

(1) The evaluation indicator system and comprehensive evaluation method established in this paper can effectively evaluate the carbon neutrality of a region.
(2) The development of low-carbon and carbon sequestration technologies, energy clean-up in the power industry, and ecological improvements have the greatest impact on carbon neutrality.
(3) The results in this paper are helpful to understand the carbon neutrality status of each region and can provide some information for the government to formulate a carbon neutrality strategy.

In addition, based on the evaluation results and the analysis of indicator weights, this paper puts forward some corresponding suggestions for a future carbon neutrality realization path.

(1) It is necessary to improve the environment. The government should increase afforestation efforts, improve forest ecosystems and urban greening programs, and protect marine ecosystems so as to reduce net carbon emissions.
(2) The path to carbon neutrality after 2030 is mainly to reduce carbon emissions and develop artificial carbon sinks. A rapid reduction in carbon emissions with the goal of renewable energy becoming the mainstay of energy consumption will require the large-scale application of energy storage systems to reduce energy waste. Furthermore, we must vigorously develop Carbon Capture, Utilization, and Storage (CCUS).
(3) Developing carbon-neutral demonstration areas is helpful to accumulate carbon neutral experiences. Achieving net carbon emissions close to zero in a small area requires low-carbon-intensive economic industries as the driving factor of economic growth. Energy consumption should be based on electricity generated from renewable energy sources and supplied in combination with energy storage systems. The construction and traffic demand should be met by intelligent low-carbon technology.

However, there are some shortcomings to this paper. The indicator system is constructed on the basis of data accessibility and provincial comparability, so the indicator system can be further improved. At the level of technological progress, indicators will be more relevant if based on energy storage costs, renewable energy generation costs, etc. As for carbon sink capacity, the carbon trading market is also an important way of achieving carbon neutrality which is not considered in this paper because the carbon market is currently in a pilot project stage in China. In addition, the development of vehicles relying on new energy sources has gained momentum in recent years, and their contribution to carbon emission reductions in transportation is also a positive driving factor of carbon neutrality.

Further research should be carried out in the following areas in the future:

(1) We can study China's carbon neutrality-related policies to analyze whether the current policy system can reach the carbon neutrality target on time, as well as how we can improve the existing shortcomings.
(2) It is necessary to study the costs of carbon capture technology and analyze how it can be made economical.

(3) Against the backdrop of peak carbon and carbon neutrality, how a decarbonization road map of China's power system could be designed is a problem worthy of study.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

EWM	Entropy weight method
CV	Coefficient of variation
Delphi method	Delphi method
Cloud model	Cloud model
PROMETHEE-II	PROMETHEE-II
RF	Random forest
RSR	Rank-sum ratio
WMO	World Meteorological Organization
PCA	Principal component analysis
AHP	Analytic hierarchy process
TOPSIS	Technique for order preference by similarity to an ideal solution
VIKOR	Vikor method
PSO	Particle swarm optimization
SAA	Simulated annealing algorithm
CCUS	Carbon capture, Utilization and Storage

Appendix A

Table A1. Some raw data of provincial carbon neutrality capacity evaluation indicators.

Provinces	Growth Rate of Carbon Emissions (%)	Carbon Emission Intensity (Mt CO_2/Yuan)	Per Capita Carbon Emissions (Mt CO_2/Person)	Per Capita Area of Afforestation (Thousand Hectares/Person)	Forest Volume Billion (Cubic Meters)	Forest Coverage (%)	Green Coverage Rate (%)
Beijing	−0.0449	0.0030	0.0392	0.0187	0.1400	35.8000	48.4000
Tianjin	0.0408	0.0076	0.0906	0.0078	0.0400	9.9000	36.8000
Hebei	−0.0294	0.0213	0.0965	0.0634	1.0800	23.4000	41.8000
Shanxi	0.0869	0.0314	0.1318	0.0837	0.9700	18.0000	40.6000
Inner Mongolia	0.0831	0.0397	0.2527	0.2679	13.4500	21.0000	40.2000
Liaoning	0.0481	0.0205	0.1096	0.0331	2.5000	38.2000	40.7000
Jilin	0.0149	0.0137	0.0751	0.0569	9.2300	40.4000	35.8000
Heilongjiang	0.0000	0.0169	0.0710	0.0260	16.4500	43.2000	35.5000
Shanghai	0.0106	0.0062	0.0786	0.0011	0.0200	10.7000	39.1000
Jiangsu	0.0166	0.0086	0.0917	0.0045	0.6500	15.8000	43.0000
Zhejiang	0.0269	0.0074	0.0675	0.0075	2.1700	59.1000	40.4000
Anhui	0.0249	0.0137	0.0593	0.0228	1.8100	27.5000	42.1000
Fujian	0.0798	0.0071	0.0588	0.0588	6.0800	66.0000	43.7000
Jiangxi	0.0516	0.0112	0.0485	0.0605	4.0800	60.0000	45.2000
Shandong	−0.0324	0.0111	0.0806	0.0141	0.8900	16.7000	42.1000

Table A1. *Cont.*

Provinces	Growth Rate of Carbon Emissions (%)	Carbon Emission Intensity (Mt CO_2/Yuan)	Per Capita Carbon Emissions (Mt CO_2/Person)	Per Capita Area of Afforestation (Thousand Hectares/Person)	Forest Volume Billion (Cubic Meters)	Forest Coverage (%)	Green Coverage Rate (%)
Henan	−0.0370	0.0111	0.0517	0.0188	1.7100	21.5000	39.4000
Hubei	0.0450	0.0092	0.0551	0.0676	2.8700	38.4000	38.4000
Hunan	0.0544	0.0091	0.0452	0.0801	3.3100	47.8000	41.2000
Guangdong	0.0463	0.0060	0.0485	0.0235	3.5700	51.3000	43.5000
Guangxi	0.0474	0.0119	0.0452	0.0355	5.0900	56.5000	39.1000
Hainan	0.0500	0.0094	0.0454	0.0136	0.8900	55.4000	40.1000
Chongqing	0.0260	0.0081	0.0514	0.0730	1.4700	38.4000	40.3000
Sichuan	−0.0032	0.0084	0.0372	0.0786	16.8000	35.2000	40.0000
Guizhou	0.0241	0.0188	0.0712	0.1872	3.0100	37.1000	37.0000
Yunnan	0.0833	0.0119	0.0406	0.0797	16.9300	50.0000	38.9000
Shaanxi	−0.0113	0.0120	0.0683	0.0864	3.9600	41.4000	39.9000
Gansu	−0.0066	0.0202	0.0575	0.1229	2.1500	11.3000	33.3000
Qinghai	−0.05369	0.0202	0.0886	0.3271	0.4300	5.6000	32.5000
Ningxia	0.2774	0.0508	0.2566	0.1126	0.0700	11.9000	40.4000
Xinjiang	0.0919	0.0371	0.1652	0.1119	3.3700	4.2000	40.0000

Table A2. Evaluation of the importance of each indicator by five experts.

Indicators.	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Growth rate of carbon emissions X1	IV	IV	V	V	IV
Carbon emission intensity X2	V	V	V	V	V
Per capita carbon emissions X3	V	V	IV	V	V
Afforestation area per capita X4	IV	IV	IV	IV	V
Forest volume X5	IV	III	III	IV	IV
Forest coverage rate X6	III	II	IV	III	III
Green coverage rate X7	II	II	III	III	III
Energy consumption per capita X8	IV	IV	IV	IV	IV
Energy consumption intensity X9	IV	V	IV	V	V
The proportion of renewable energy power generation X10	V	V	V	IV	V
The proportion of secondary industry X11	V	V	V	IV	V
Per capita GDP X12	III	III	III	III	III
GDP index X13	III	III	III	III	III
Urbanization level X14	IV	III	IV	IV	IV
The number of patents granted per capita X15	III	III	IV	IV	IV
The investment in R&D per capita X16	III	IV	IV	III	IV
Waste disposal rate X17	II	III	III	III	III
Housing construction area per capita X18	IV	IV	IV	V	IV
Gross output value of construction industry per capita X19	III	IV	III	III	IV
Ownership of vehicles per capita X20	IV	IV	IV	IV	IV

References

1. Zhou, D. China is one of the world's largest carbon emitters. *Sino-Glob. Energy* **2015**, *20*, 56.
2. Xu, S.F. Embrace carbon neutrality and help build a low-carbon sustainable future for the grid. *Electr. Eng.* **2020**, *21*, 7–8.
3. Deng, M.J.; Luo, W.B.; Yin, L.J. A review of the development of carbon neutral theory and practice abroad. *Resour. Sci.* **2013**, *35*, 1084–1094.
4. Wang, Q.W.; Chiu, Y.H.; Chiu, C.R. Driving factors behind carbon dioxide emissions in China: A modified production-theoretical decomposition analysis. *Energy Econ.* **2015**, *51*, 252–260. [CrossRef]
5. Wang, Z.H.; Yin, F.C.; Zhang, Y.C. An empirical research on the influencing factors of regional CO_2 emissions: Evidence from Beijing city, China. *Appl. Energy* **2012**, *100*, 277–284. [CrossRef]
6. Sun, J.J. Research on the Decoupling Status and Mitigation Potential of China's CO_2 Emissions at Provincial Level. Master's Thesis, China University of Mining and Technology, Beijing, China, 2020.
7. Li, F.F.; Qian, W.D.; Xu, Z.S. Analysis of carbon emission reduction potential index and emission reduction policy at provincial and municipal levels in China from the perspective of efficiency and fairness. *J. Hunan Univ. Technol.* **2020**, *34*, 47–55. [CrossRef]
8. Hao, X.D.; Liu, R.B.; Huang, X. Evaluation of the potential for operating carbon neutral WWTPs in China. *Water Res.* **2015**, *87*, 424–431. [CrossRef] [PubMed]

9. Lee, J.H.; Lee, G.G. Carbon-Neutrality Assessment of Local Government's Area Based on Forest Carbon Storage Capacity. *J. Korea Plan. Assoc.* **2012**, *47*, 203–213.
10. Cao, S.Y.; Huo, T.T.; Wang, L.; Chen, Q.; Liu, S.C.; Ma, L.P.; Gao, W.; Zhang, R.X. The potential of carbon neutrality for rural household energy system. *China Popul. Resour. Environ.* **2014**, *24*, 301–303.
11. Huang, B.; Xing, K.; Stephen, P. Exploring carbon neutral potential in urban densification: A precinct perspective and scenario analysis. *Sustainability* **2020**, *12*, 4814. [CrossRef]
12. Sannamari, P.; Vahid, A.; Jani, M. Analyzing National and Local Pathways to Carbon-Neutrality from Technology, Emissions, and Resilience Perspectives—Case of Finland. *Energies* **2019**, *12*, 949. [CrossRef]
13. Karna, D.; Sirkku, J.; Jari, N. The role of renewable energy policies for carbon neutrality in Helsinki Metropolitan area. *Sustain. Cities Soc.* **2018**, *40*, 222–232. [CrossRef]
14. Li, Q.W.; Long, R.Y.; Chen, H. Measurements and Factors That Influence the Carbon Capability of Urban Residents. *Sustainability* **2018**, *10*, 1292. [CrossRef]
15. Li, Y.; Zhang, Q.; Wang, L. Regional environmental efficiency in China: An empirical analysis based on entropy weight method and non-parametric models. *J. Clean. Prod.* **2020**, *276*, 124147. [CrossRef]
16. Jung, S.J.; Kim, Y.S.; Kim, T.H. Risk Evaluation of Slope Using Principal Component Analysis (PCA). *J. Korean Geotech. Soc.* **2010**, *26*, 69–79.
17. Wu, K.; Peng, B.; Xie, H. A Coefficient of Variation Method to Measure the Extents of Decentralization for Bitcoin and Ethereum Networks. *Int. J. Netw. Secur.* **2020**, *22*, 191–200. [CrossRef]
18. Unver, S.; Ergenc, I. Safety risk identification and prioritize of forest logging activities using analytic hierarchy process (AHP). *Alex. Eng. J.* **2021**, *60*, 1591–1599. [CrossRef]
19. Pei, J.; Liu, W.; Han, L. Research on Evaluation Index System of Chinese City Safety Resilience Based on Delphi Method and Cloud Model. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3802. [CrossRef] [PubMed]
20. Gu, B.; Zhang, T.; Meng, H. Short-term forecasting and uncertainty analysis of wind power based on long short-term memory, cloud model and non-parametric kernel density estimation. *Renew. Energy* **2021**, *50*, 687–708. [CrossRef]
21. Huang, T.C.; Ye, L.H.; Zhang, Y.J. Comprehensive evaluation on electricity consumption reliability of power distribution network based on AHP-entropy weight method. *Guangdong Electr. Power* **2018**, *31*, 44–50. [CrossRef]
22. Zhang, Y.L.; Yu, J.; Niu, D.X.; Li, S.; Dai, S.Y. Comprehensive evaluation of the financial efficiency of power sales companies of grid companies. *Friends Account.* **2019**, 63–67. [CrossRef]
23. Serafim, O.; Tzeng, G. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [CrossRef]
24. San, C. Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. *Renew. Energy* **2010**, *36*, 498–502. [CrossRef]
25. Yang, Y.; Zhao, Y. Modified PROMETHEEII for venture capital investment selection decision-making towards SMEs. *J. Interdiscip. Math.* **2020**, *21*, 1017–1029. [CrossRef]
26. Kizielewicz, B.; Salabun, W. A New Approach to Identifying a Multi-Criteria Decision Model Based on Stochastic Optimization Techniques. *Multidiscip. Sci.* **2020**, *12*, 1551. [CrossRef]
27. Wang, Z.Y. Research on Enterprise Credit Risk Evaluation Based on Optimized Random Forest Method. Master's Thesis, Jinan University, Guangzhou, Guangdong, China, 2020.
28. Zhou, J.; Xiao, R.B.; Zhuang, C.W.; Deng, Y.R. The carbon sink of urban forests and efficacy on offsetting energy carbon emissions from city in Guangzhou. *Acta Ecol. Sin.* **2013**, *33*, 5865–5873. [CrossRef]
29. Zhang, Y.J.; Da, Y.B. The decomposition of energy-related carbon emission and its decoupling with economic growth in China. *Renew. Sustain. Energy Rev.* **2015**, *41*, 1255–1266. [CrossRef]
30. Wang, C.J.; Wang, F.; Zhang, X.L. Analysis of influence mechanism of energy-related carbon emissions in Guangdong: Evidence from regional China based on the input-output and structural decomposition analysis. *Environ. Sci. Pollut. Res.* **2017**, *24*, 25190–25203. [CrossRef] [PubMed]
31. Yang, L.S.; Zhu, J.P.; Jia, Z.J. Influencing factors and current challenges of CO_2 emission reduction in China: A perspective based on technological progress. *Econ. Res. J.* **2019**, *54*, 118–132.
32. Wang, Y. Whole Life Cycle Carbon Emissions Research of Industrialized Precast Construction. Ph.D. Thesis, Southeast University, Nanjing, Jiangsu, China, 2016.
33. Li, B.H. Study on Urban Spatial Layout Mode and Optimization Strategy under the Guidance of Low Carbon Transportation—A Case Study of Zhengzhou. Ph.D. Thesis, Xi'an University of Architecture and Technology, Xi'an, Shaanxi, China, 2013.
34. Liu, K.; Yang, L.; Li, M. Application of Cloud Model and Bayesian Network to Piracy Risk Assessment. *Math. Probl. Eng.* **2021**, *2021*. [CrossRef]
35. Ren, J. Linguistic-stochastic multi-criterion decision-making method based on cloud model. *Comput. Integr. Manuf. Syst.* **2012**, *18*, 2792–2797. [CrossRef]
36. Cai, S.B.; Fang, W.; Zhao, J.; Zhao, Y.L.; Gao, Z.G. Research of interval-based cloud similarity comparison algorithm. *J. Chin. Comput. Syst.* **2011**, *32*, 2456–2460.
37. Cui, W.H.; Ye, J. Improved Symmetry Measures of Simplified Neutrosophic Sets and Their Decision-Making Method Based on a Sine Entropy Weight Model. *Symmetry* **2018**, *10*, 225. [CrossRef]

38. Wei, M.; Li, S.H. Study on the measurement of economic high-quality development level in China in the new era. *J. Quant. Tech. Econ.* **2018**, *35*, 3–20. [CrossRef]
39. Melih, Y.; Suleyman, M.; Faruk, S. An Integrated Best-Worst and Interval Type-2 Fuzzy TOPSIS Methodology for Green Supplier Selection. *Mathematics* **2019**, *7*, 182. [CrossRef]
40. Zheng, S.Y.; Li, S.Q. Improved TOPSIS decision method for optimizing mixed indexes supporting schemes for foundation pit. *China Saf. Sci. J.* **2014**, *24*, 98–103. [CrossRef]
41. Fu, X.Q.; Chen, H.Y. Comprehensive power quality evaluation based on weighted rank sum ration method. *Electr. Power Autom. Equip.* **2015**, *35*, 128–132. [CrossRef]
42. Wang, Z.; Dang, S.; Xing, Y. Applying Rank Sum Ratio (RSR) to the evaluation of feeding practices behaviors, and its associations with infant health risk in rural Lhasa, Tibet. *Int. J. Environ. Res. Public Health* **2015**, *12*, 15173–15181. [CrossRef] [PubMed]