Investigating Low-Carbon City: Empirical Study of Shanghai

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Received: 23 March 2018; Accepted: 30 March 2018; Published: 2 April 2018

Abstract: A low-carbon economy is an inevitable choice for achieving economic and ecological sustainable development. It is of significant importance to analyze a city’s low-carbon economy development level scientifically and reasonably. In order to achieve this goal, we propose an urban low-carbon economic development level evaluation model based on the matter-element extension method. First, we select some indicators from the existing indicator system based on past research and experience. Then, a matter-element model is established on the basis of weight to evaluate the level of a city’s low-carbon, the critical value of each index is determined through the classical domain and the section domain, calculating the correlation degree of a single index and a comprehensive index. Finally, we analyze the low-carbon economy development status and future development trends according to the analysis results. In this study, we select Shanghai as an empirical study—the results show that Shanghai is a city with a low-carbon level and there is a trend of further improvement in Shanghai’s low-carbon economy. But its low carbon construction and low carbon technology investment are relatively low. In summary, this method can provide another angle for evaluating a city’s low-carbon economy.

Keywords: low-carbon economy; entropy weight; matter-element extension model; Shanghai

1. Introduction

The 21st century will be an era of the low-carbon economy. The low-carbon economy was first proposed by the 2003 British White Paper “The Future of Our Energy: Creating a Low-Carbon Economy”. It provides more economic output by reducing the consumption of natural resources and reducing environmental pollution, it is a way and an opportunity to create a higher standard of living and a quality of life and it creates opportunities for the development, application and export of advanced technologies. It also creates new business opportunities and more job opportunities [1,2]. Characteristics of a low carbon economy include reducing greenhouse gas emissions as the goal and building a system of economic development based on low energy consumption and low pollution, including low carbon energy systems, low carbon technology and low carbon industry systems. Climate change is a global challenge, the future development of the city must be a sustainable low-carbon economy [3,4]. In 2017, global carbon disintegration was set as the long-term goal of the Paris Agreement. At present, China, as the world’s second largest economy in terms of carbon emissions has already surpassed the US as the largest country in the world’s carbon emissions [3,5,6]. Facing post-Paris climate challenges, China should develop a bold national strategy for low-carbon economy.

Only by understanding and evaluating the current state of development and future trends can we formulate corresponding measures to better achieve the development of a low-carbon economy.
To support this work, in this paper, the urban low-carbon economic evaluation model is established by using the element extension method. The study calculated the impact of evaluation indicators on the level of low-carbon economic development and their correlation (that is, multi-indicator correlation). We can not only horizontally analyze the low-carbon economy level among cities but also vertically compare the differences between the various indicators. In addition, this model provides a reference value for the evaluation and analysis of the low-carbon economic development level in other cities.

2. Literature Review

On the low carbon level of the city, the research on the theory and practice of urban low carbon is carried out from the perspectives of energy consumption [3,5,6], carbon emissions [5,6] and urban social construction. The construction of evaluation indexes mainly focuses on the energy department, transportation department, industrial department and carbon footprint, and a few scholars construct a comprehensive evaluation index system. “Sustainable Development Indicators: Guiding Principles and Methods” was published by the UN Commission on Sustainable Development (2001), detailing its indicator system and elaborating the concept and methodology of indicators. The index system emphasizes policy-oriented themes to serve policy-making needs. Ultimately, four dimensions of social, environmental, economic and institutional dimensions were identified, with a total of 15 themes and 38 sub-themes. Lynn et al. tracked energy efficiency and emissions reductions through energy use and carbon dioxide emissions and established benchmarks for evaluation [7]. Moriarty et al. proposed to reduce energy consumption and carbon emissions by changing human lifestyles and establishing low-carbon cities [8]. York et al. used the STIRPAT model to study the drivers of carbon dioxide emissions and energy footprints and the human-driven drivers of environmental change [9]. Khanna et al. further defined the meaning of low-carbon cities—they evaluated and analyzed China’s low-carbon pilot city and proposed from the policy, energy and other aspects to enhance low-carbon levels [10]. Urban emphasized the importance of low-carbon technological innovation for the development of a low-carbon economy in China and emphasized that raising the level of the low-carbon economy in China is of great significance to global low-carbon transformation and climate change mitigation [11]. Fankhauser et al. suggested that energy is necessary for economic growth. Low-carbon is the future energy trend and will eventually lead to a low-carbon economy [12]. Eicker et al. used simulation tools to establish the relationship between energy supply and demand efficiency, building geometric building standards and data availability functions [13]. Wang et al. evaluate the low-carbon economy in China, mainly from the assessment of coal consumption [6,14], electricity consumption [15], and put forward corresponding suggestions [3,5].

Menezes et al. constructed a dynamic simulation model and used the (BAU) scenario as a reference to assess the potential for greenhouse gas emissions in São Paulo’s transport department [16]. Ohnishi et al. established a framework for a comprehensive assessment of I/URS by combining material flow analysis (MFA), carbon footprint (CF) and emerge methods [17]. Bai et al. Developed a low carbon practice cooperation framework based on the DEMATEL and NK models to directly assess the dependence of low carbon supply chain participants, providing a new perspective for the study of carbon emissions in China’s supply chain [18]. Geels et al. were based on the comprehensive evaluation model combined with social technology transformation analysis and practice of case-forming assessment chain to assess the city’s low-carbon economy level to help policy decisions [19]. Mei et al. mainly studied the impact of low-carbon awareness on low-carbon behavior and energy emissions, they suggested that to improve the sustainable development of the country, we should not only save energy and reduce emissions but also increase policy [20]. Tan et al. established a low carbon economy evaluation index system based on factors such as economy, energy structure, society and life, carbon and environment, urban mobility, solid waste and water resources, and then synthetically evaluated LCC ranking by using the entropy weight factor method. The framework was used in 10 cities around the world to assess their low-carbon levels. The final study showed that the
assessment of LCC from the economic, social and environmental perspectives has further increased the integrity of the study [21].

Domestic scholars on China’s urban low-carbon economy development level evaluation system research mainly the low carbon policy, low productivity, low carbon resources and low carbon consumption, paying attention to a selection of indicators. Li et al. conducted systematic dynamic modeling of an urban low-carbon economic development level from three aspects: economy, energy and environment [22]. Wang et al. selected 22 indicators based on the DPSIR (Drivers, Pressures, State, Impact, Response model of intervention) model and constructed a low carbon city evaluation system using principal component analysis [23]. Based on the economic and social development in Nanjing, Wang et al. constructed an indicator measurement system for Nanjing’s low-carbon economy cities, including greenway construction, from three aspects: economic level, environmental level and social development level [24]. Wang et al. adopted the entropy weight -TOPSIS evaluation method and obstacle degree model to measure the low-carbon development level of a low-carbon city pilot in Tianjin [25]. Xie et al. used the DEA (Data envelopment analysis) model and the Malmquist total factor productivity index to build a low-carbon economic development performance evaluation index system. This method was used to evaluate the urban low-carbon economy development level both statically and dynamically [26]. The “Strategic Objectives of China’s Low-carbon Eco-City Development 2009–2020” (ILCC) formulated by the China National Institute of Standardization contains three general indicators of economy, society and environment and nine sub-indicators so that relevant departments can formulate an internal evaluation system.

As mentioned above, there are still some unresolved issues in this area: First, the evaluation model of urban low-carbon economic development level is mainly aimed at the establishment of a city or a certain region, lacking a unified theory and widely applicable index system. Second, scholars’ research on the low-carbon economy mainly focuses on carbon energy, ignoring the impact of economic sustainability, humans and technology. Finally, the quantitative research is relatively weak, mainly using subjectivity to determine the weight.

In view of this, based on the existing research results, this paper constructs an urban low-carbon economic development level evaluation index system based on the PSR (Pressure State Response) framework and proposes an evaluation method of matter-element extension model based on entropy weight. Using PSR as the framework, the influence of human activities is included and the entropy weight method is adopted as the index weighting. Taking Shanghai as an example, the results show that it can overcome the one-sidedness of the evaluation of urban low-carbon economic development and eliminate human factors as much as possible. It provides a new angle for the quantitative evaluation of urban low-carbon economic development.

3. Methods

3.1. Urban Low-Carbon Economic Development Level Evaluation Index System

The PSR model is a frame system that is used to research environment problems by the UNECP (The United Nations Economic Cooperation Program). The model used the logical thinking called “Pressure- State- Response” which reflects the interaction between human beings and the environment [3,5,6,27]. By referring to literature and related materials, we adopt the LCCI (Low-carbon City Indicator) index system established by Tan. It establishes the evaluation system from seven aspects of energy, environmental, economic, social, technological, water and urban transport, in order to evaluate the low carbon economic development level of the city [5,6,21,28]. Domestic scholars mainly adopt the LCCC (Low-Carbon City in China) system established by the Chinese Academy of Social Sciences. We select some indicators in the LCCC system and LCCI system from three aspects. In order to establish a low-carbon economic evaluation system in line with China’s national conditions, the annual average concentration of particulate matter (PM) 2.5 and the good air days ratio proposed
by the “13th Five-year Ecological Environment Protection Planning” are included in the evaluation system [29]. It is shown in Table 1.

1) Energy Economics indicators.

It mainly reflects the city’s economic development level and energy utilization efficiency.

Unit GDP energy consumption: It is directly linked to GDP output, which can directly reflect the overall resource utilization efficiency of the social economy.

Tertiary industry as a share of GDP: Most of the industries in the tertiary industry are zero-pollution, zero-emission or less-polluting and less-emissions industries. At the same time, some industries also have considerable economic added value. Whether the tertiary industry is developed or not is directly related to the development level of the low-carbon economy—the higher the ratio of a city’s tertiary industry, the stronger the economic foundation for the development of a low-carbon economy. Therefore, when we examine the development level of a city’s low-carbon economy, the development of the tertiary industry is an important aspect that must be considered.

Per capita GDP: It can reflect the economic development of a city in the process of low carbonization. It shows that the city is not at the expense of economic development at the same time as it is reducing carbon emissions but it is the coordinated development of low carbon and economy. The higher it shows that the higher the level of economic development, the more secure the people’s lives, the better the foundation for economic transformation and industrial restructuring.

2) Natural and social environmental indicators.

It is mainly divided into social development indicators and natural environment indicators.

The social development index is mainly the Engel’s coefficient of urban residents, which can be used to reflect the people’s living standards.

Natural environment indicators are the annual average concentration of PM 2.5, air good days’ ratio and annual average concentration of sulfur dioxide. The degree of air pollution can directly reflect the degree of carbon emissions in a city.

Low-carbon construction indicators are the urban built-up area to green coverage ratio, the per capita parkland area and forest coverage. Green plants reduce greenhouse gas concentrations in the atmosphere by absorbing carbon dioxide. So, the higher the degree of urban greening, the stronger the carbon sink ability and the stronger the inhibition effect on carbon source.

3) Technology and policy indicators.

Urban sewage treatment rates, industrial solid comprehensive utilization ratio and Research and Development (R&D) to GDP are used to describe low carbon technology levels. The low carbon technology in cities is mainly reflected by the input and the application of low-carbon technologies, R&D to GDP indicates that the company has invested in technological transformation in achieving low-carbon technologies. Urban sewage treatment rates and the industrial solid comprehensive utilization ratio are the effects of low-carbon technologies in the treatment of urban life and industrial pollution, the higher the index value, the higher the level of low carbon technology in the city and the higher the low carbon level.

The ratio of environmental protection expenditure to GDP is used to describe the government’s concern for a low-carbon economy. The higher the value, the more adequate the requirements of the government and the society in the region for the construction of a low-carbon economy.
Table 1. Index System.

| Target Layer                                   | Feature Layer                                                   | Indicator Layer | Unit                        | Value of Shanghai (2016) |
|------------------------------------------------|----------------------------------------------------------------|----------------|-----------------------------|---------------------------|
| Urban Low-Carbon Economic Development Level    | Energy Economics indicators (press)                             | unit GDP energy consumption $C_1$ | Ton standard coal/ten thousand yuan | 0.43                      |
|                                                |                                                                | tertiary industry as a share of GDP $C_2$ | % | 69.80                      |
|                                                |                                                                | per capita GDP $C_3$ | yuan | 116,562.00                 |
|                                                | natural and social environmental indicators (state)            | Annual average concentration of PM 2.5 $C_4$ | ug/m$^3$ | 45.00                     |
|                                                |                                                                | air good days ratio $C_5$ | % | 75.40                      |
|                                                | technology and policy indicators (reflect)                     | annual average concentration of sulfur dioxide $C_6$ | ug/m$^3$ | 15.00                     |
|                                                |                                                                | Engel’s coefficient of urban residents $C_7$ | % | 25.13                      |
|                                                |                                                                | urban built-up to area to green coverage ratio $C_8$ | % | 38.80                      |
|                                                |                                                                | the per capita parkland area $C_9$ | m$^3$/people | 7.82                      |
|                                                |                                                                | forest coverage $C_{10}$ | % | 15.60                      |
|                                                |                                                                | urban sewage treatment rate $C_{11}$ | % | 93.00                      |
|                                                |                                                                | industrial solid comprehensive utilization ratio $C_{12}$ | % | 95.68                      |
|                                                |                                                                | R&D to GDP $C_{13}$ | % | 3.72                       |
|                                                |                                                                | the ratio of environment protection expenditure to GDP $C_{14}$ | % | 3.01                       |

3.2. Weight Determination by the Entropy Weight

In information theory, information is a measure of the degree of systematic order, Entropy is a measure of the degree of disorder in a system. If the index’s entropy is smaller, it can provide more information, the more it plays a role in the overall evaluation, the higher the weight should be. On the contrary, if the index’s entropy is bigger, it can provide less information, the less its contribution to the overall evaluation and the lower its weight process of weight determination. The entropy method has been applied in many fields such as water quality measurement, risk assessment, network security assessment and so on and it is mainly used for index screening, processing and weight determination [30–35]. Delgado used integrated gray clustering and the entropy weight method to analyze the environmental conflicts in the northern Peru mine project. Finally, it was proved that the main factors affecting the environmental conflict can be effectively determined by using the entropy weight method [30]. Radkowski used the entropy method for fault monitoring and identification in vibrational acoustic signals [33]. Yazdi optimized the water quality monitoring network of an urban drainage system based on entropy theory and designed water quality monitoring points less than before [35].

Therefore, the impact of various indicators on the level of an urban low-carbon economy can not only avoid the subjective influence but also can be quantitatively determined.

This paper uses the index data on China’s 2012–2016 statistics and the key green cities statistics, which are sourced from the 2013 to 2017 China Statistical Yearbook, The Bulletin on the State of China’s Environment and the Statistical Yearbook for Urban and Rural Areas and so on [36,37].

Process of weight determination:
Make the index with the same degree of quantification.
For positive indicators:

$$x'_{ij} = \frac{x_{ij} - \min\{x_j\}}{\max\{x_j\} - \min\{x_j\}}$$ (1)
For negative indicators:

\[ x'_{ij} = \frac{\max_i \{x_j\} - x_{ij}}{\max_i \{x_j\} - \min_i \{x_j\}} \]  

(2)

In these formulas, \( x_{ij} \) is the \( j^{th} \) index of the \( i^{th} \) year of the original data; \( x'_{ij} \) is the index after processing. Table 2 presents these processed data.

Calculate the proportion of the \( j^{th} \) index in the \( i^{th} \) year.

\[ Y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \]  

(3)

Calculate the index information entropy.

\[ e_j = -k \sum_{i=1}^{m} (Y_{ij} \ln Y_{ij}) (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \]  

(4)

\[ e'_j = -k \sum_{i=1}^{m} (f_{ij} \ln f_{ij}) (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \]  

(5)

In these formulas, if \( Y_{ij} = 1 \) then \( Y_{ij} \ln Y_{ij} = 0 \), if \( Y_{ij} = 0 \) then \( Y_{ij} \ln Y_{ij} = 0 \). But it does not meet the actual meaning. So, we make \( f_{ij} = \frac{1+Y_{ij}}{\sum_{i=1}^{m}(1+Y_{ij})} \), \( k = 1/ \ln m \).

Calculate the information entropy’s degree of redundancy.

\[ d_j = 1 - e'_j \]  

(6)

In the formula, the bigger the \( d_j \), the more important the index.

Calculate the weight of index.

\[ w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} (j = 1, 2, \ldots, n) \]  

(7)

Table 2. The data of national average.

| Index | 2012 | 2013 | 2014 | 2015 | 2016 |
|-------|------|------|------|------|------|
| C_1   | 0.82 | 0.79 | 0.75 | 0.71 | 0.66 |
| C_2   | 45.3 | 46.7 | 47.8 | 50.2 | 51.6 |
| C_3   | 40007| 43852| 47203| 49992| 53980|
| C_4   | 83   | 72   | 62   | 53   | 47   |
| C_5   | 70   | 60.5 | 78.21| 76.7 | 78.8 |
| C_6   | 50   | 40   | 35   | 25   | 22   |
| C_7   | 36.2 | 35   | 34.2 | 34.8 | 29.3012|
| C_8   | 39.59| 39.7 | 40.22| 40.12| 40.3 |
| C_9   | 12.26| 12.64| 13.08| 13.35| 13.7 |
| C_10  | 20.36| 21.63| 21.63| 21.63| 21.63|
| C_11  | 87.3 | 89.34 | 90.18 | 91.9 | 93.44 |
| C_12  | 60.9 | 62.3 | 62.13| 60.8 | 59.5 |
| C_13  | 1.91 | 1.99 | 2.02 | 2.06 | 2.11 |
| C_14  | 1.53 | 1.52 | 1.49 | 1.28 | 1.24 |

3.3. Matter-Element Extension Model

Cai Wen, a Chinese scholar, founded the matter-element extension theory in the 1980s, which regards incompatible questions as a research center for seeking the internal mechanism of contradictions [38]. Matter element analysis is a multi-index comprehensive evaluation method,
which mainly includes the matter-element model, extension set and correlation function [39]. The model is applied to many research areas. Zhang Feng et al. established a water scarcity index measurement model using matter-element extension theory and a correlation function [40]. Peng et al. introduced the matter-element extension method with using sequence relations of groups to carry out comprehensive power evaluation on the economic and safe operation evaluation model of a power system that consists of key indicators during the operation process [41]. Li et al. effectively solved the problem of incompatible conflicts based on a matter-element extension model for the comprehensive evaluation of energy sustainability [42].

Urban Low-Carbon Economic Development Level Evaluation is a complex system of engineering. So, using the matter-element extension model to objectively analyze it can make the evaluation method and the result more reasonable and scientific.

3.3.1. Build the Matter-Element Extension Model

(1) Determine the classic domain

There are some evaluation indexes for the development level of an urban low-carbon economy, that is, $C_1, C_2, \ldots, C_n$. According to the relevant national standards and the data in the relevant statistical yearbook, the urban low-carbon economy is divided into $m$ levels $N_1, N_2, \ldots, N_m$, the corresponding matter element $R_i$ established is as follows:

$$R_i = (N_i, C_j, X_{ij}) = \begin{bmatrix} N_i & C_1 & X_{i1} \\ C_2 & X_{i2} \\ \vdots & \vdots & \vdots \\ C_n & X_{in} \end{bmatrix}$$

In this formula, $X_{ij} = (a_{ij}, b_{ij})$ is the Urban low-carbon economy development level evaluation rating—$N_i(i = 1, 2, \ldots, m)$—about the range of magnitudes for index—$C_j(j = 1, 2, \ldots, n)$.

(2) Determine the section domain

$$R_p = (N_p, C_j, X_{pj}) = \begin{bmatrix} N_p & C_1 & X_{p1} \\ C_2 & X_{p2} \\ \vdots & \vdots & \vdots \\ C_n & X_{pn} \end{bmatrix}$$

In this formula, $N_p$ represents all the evaluation levels of Urban Low-Carbon Economic Development Level; $X_{pj}$ represents the range of evaluation index $C_j$ (The range is from the minimum value to the maximum value), In the classical domain, $X_{ij} \in X_{pj}$.

(3) Determine the matter-element to be evaluated

$$R_0 = (P_0, C_j, x_j) = \begin{bmatrix} P_0 & C_1 & X_1 \\ C_2 & X_2 \\ \vdots & \vdots & \vdots \\ C_n & X_n \end{bmatrix}$$

In this formula, $P_0$ represents the city to be evaluated, $X_j$ represents the city to be evaluated the $j^{th}$ index of the measured data.

3.3.2. Construct the Correlation Function

The correlation function is used to measure the approximate degree between each evaluation index of cities to be evaluated and each rank.
(1) Calculate the Distance.

\[ \rho(x_j, X_{ij}) = \left| x_j - \frac{1}{2}(a_{ij} + b_{ij}) \right| - \frac{1}{2}(b_{ij} - a_{ij}) \]

\[ \rho(x_j, X_{pj}) = \left| x_j - \frac{1}{2}(a_{pj} + b_{pj}) \right| - \frac{1}{2}(b_{pj} - a_{pj}) \]

\[ i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \]  

(11)

(2) Calculate the correlation function.

\[ K_i(x_j) = \begin{cases} \frac{-\rho(x_j, X_{ij})}{b_{ij} - a_{ij}} & x_j \in X_{ij} \\ \frac{\rho(x_j, X_{pj}) - \rho(x_j, X_{ij})}{\rho(x_j, X_{pj}) - \rho(x_j, X_{ij})} & x_j \notin X_{ij} \end{cases} \]  

K_i(x_j) reflects the approximate degree between jth evaluation index of cities to be evaluated and ith rank.

3.3.3. Comprehensive Evaluation and Determine The grade

\[ K_i(P) = \sum_{j=1}^{n} w_j K_i(x_j) (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n) \]  

(13)

According to 11th and 12th formula, when \( K_m(x_j) = \max K_i(x_j), m = (1, 2, \cdots, i) \), the index \( x_j \) in the matter-element to be evaluated, \( N_0 \), is the evaluation grade of \( N_m \). when \( K_m(P) = \max K_i(P) \), \( m = (1, 2, \cdots, i) \), the level of development of low-carbon economy in the assessed cities belongs to the evaluation level \( N_m \).

4. Empirical Study: Shanghai

Over the past thirty years, China has witnessed rapid economic growth. However, pollution of the air, soil and water resources has become increasingly serious. In recent years, the level of sustainable development has also gradually improved and China has issued low-carbon cities, low-carbon emissions and other standards [43]. In recent years, Shanghai, as the country’s resource-saving and environment-friendly society comprehensive reform pilot city center area, gradually promotes low-carbon urban construction and the development of low-carbon measures and has achieved some success [44]. There are also many problems. Therefore, objectively evaluating the development level of Shanghai’s low-carbon economy and further revealing its advantages and disadvantages is an effective way to break the bottleneck of development and provide the direction and policy-making basis for further raising the level of development of the low-carbon economy.

4.1. Grade Division and Determining Weight Coefficient

The classification of urban low-carbon economy development level is mainly determined through the following processes:

(1) According to the target value put forward by the “2009–2020 Chinese low-carbon eco-city development strategy” this paper determines the upper limit of the grade.

(2) According to the Chinese Academy of Social Sciences, “a low-carbon capacity of more than 20% of the national average is identified as low-carbon.” This paper studies the 2012–2016 national average of urban indicators (shown in Table 2)—the average of the five-year data is taken as the normal economic level and then plus and minus 20%, divided into five grades.

(3) According to the frequency distribution of indicators in 78 key cities in China’s statistical yearbook, we divide them into five grades. According to the actual situation and considering the relatively long-time span, we adjust the upper limit of the second step to determine the final evaluation level.
By the above established evaluation index system, the Urban Low-Carbon Economic Development Level evaluation in Shanghai contains 14 evaluation indexes, \( n = 14 \). At the same time, the urban low-carbon economic development level is divided into five grades. In Table 2, \( N_1 \) represents grade I (the stronger), \( N_2 \) represents grade II (strong), \( N_3 \) represents grade III (general), \( N_4 \) represents grade IV (weak), \( N_5 \) represents grade V (weaker). As shown in Table 3. The measured value data of low-carbon economic development level in Shanghai come from the Shanghai statistical yearbook 2017.

| Index | \( N_1 \) | \( N_2 \) | \( N_3 \) | \( N_4 \) | \( N_5 \) | The Data of Shanghai (2016) |
|-------|-------|-------|-------|-------|-------|-----------------------------|
| \( C_1 \) | 0.45  | 0.5   | 0.9   | 1.2   | 1.5   | 0.43                        |
| \( C_2 \) | 75    | 65    | 55    | 45    | 35    | 69.80                       |
| \( C_3 \) | 95,000| 75,000| 60,000| 45,000| 25,000| 116,362.00                  |
| \( C_4 \) | 25    | 55    | 65    | 75    | 95    | 45.00                       |
| \( C_5 \) | 95    | 85    | 71    | 57    | 45    | 75.40                       |
| \( C_6 \) | 25    | 33    | 42    | 50    | 60    | 15.00                       |
| \( C_7 \) | 28    | 32    | 35    | 38    | 42    | 25.13                       |
| \( C_8 \) | 45    | 40    | 35    | 32    | 24    | 38.80                       |
| \( C_9 \) | 20    | 15    | 13    | 10    | 7     | 7.82                        |
| \( C_{10} \) | 35    | 30    | 25    | 20    | 13    | 15.60                       |
| \( C_{11} \) | 99    | 98    | 95    | 92    | 80    | 93.00                       |
| \( C_{12} \) | 99    | 95    | 90    | 85    | 75    | 95.68                       |
| \( C_{13} \) | 8     | 5     | 3     | 2.5   | 1.5   | 3.72                        |
| \( C_{14} \) | 4     | 3     | 2.5   | 1.5   | 0.8   | 3.01                        |

We use the entropy method to obtain the weights for the national average of the indicators for the five years from 2012 to 2016, as shown in Table 4.

| Index | \( C_1 \) | \( C_2 \) | \( C_3 \) | \( C_4 \) | \( C_5 \) | \( C_6 \) | \( C_7 \) | \( C_8 \) | \( C_9 \) | \( C_{10} \) | \( C_{11} \) | \( C_{12} \) | \( C_{13} \) | \( C_{14} \) |
|-------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|-----------|-----------|-----------|
| The weight | 0.0849 | 0.0833 | 0.0692 | 0.0639 | 0.047 | 0.0623 | 0.1473 | 0.077 | 0.068 | 0.0379 | 0.0661 | 0.0577 | 0.0571 | 0.0785 |

4.2. The Evaluation Processes

Step 1 Standardized processing

Due to the low carbon economy development level evaluation of different diameters and dimensions of the index data, such as Unit GDP energy consumption, annual average concentration of PM 2.5, annual average concentration of sulfur dioxide and Engel’s coefficient of urban residents. Four indexes belong to a negative index—the smaller the data, the better—the other 10 indicators are positive indicators—the greater the value, the more superior—so it is necessary to standardize the evaluation index data processing. According to the standardized grading standard, data are shown in Table 5.

For positive indicators:

\[
y_i = 1 - \frac{(d_i - d_5)}{d_1}
\]

(14)

For negative indicators:

\[
y_i = \frac{d_i}{d_5}
\]

(15)

In these formulas, \( y_i \) is the standardized standard value after standardization, \( d_i \) is the standard value and measured value before standardization (\( i = 1, 2, 3, 4, 5 \)).
Table 5. Urban Low-Carbon Economic Development Level.

| Index Number | \( N_1 \) | \( N_2 \) | \( N_3 \) | \( N_4 \) | \( N_5 \) | Shanghai Data |
|--------------|-----------|-----------|-----------|-----------|-----------|---------------|
| \( C_1 \)    | 0.3000    | 0.3333    | 0.6000    | 0.8000    | 1.0000    | 0.2847        |
| \( C_2 \)    | 0.4667    | 0.6000    | 0.7333    | 0.8667    | 1.0000    | 0.5360        |
| \( C_3 \)    | 0.2632    | 0.4737    | 0.6316    | 0.7895    | 1.0000    | 0.0362        |
| \( C_4 \)    | 0.2632    | 0.5789    | 0.6842    | 0.7895    | 1.0000    | 0.4737        |
| \( C_5 \)    | 0.4737    | 0.5789    | 0.7263    | 0.8737    | 1.0000    | 0.6800        |
| \( C_6 \)    | 0.4167    | 0.5500    | 0.7000    | 0.8333    | 1.0000    | 0.2500        |
| \( C_7 \)    | 0.6667    | 0.7619    | 0.8333    | 0.9048    | 1.0000    | 0.5983        |
| \( C_8 \)    | 0.5333    | 0.6444    | 0.7556    | 0.8222    | 1.0000    | 0.6711        |
| \( C_9 \)    | 0.3500    | 0.6000    | 0.7000    | 0.8500    | 1.0000    | 0.9590        |
| \( C_{10} \) | 0.3714    | 0.5143    | 0.6571    | 0.8000    | 1.0000    | 0.9257        |
| \( C_{11} \) | 0.8081    | 0.8182    | 0.8485    | 0.8788    | 1.0000    | 0.8687        |
| \( C_{12} \) | 0.7576    | 0.7980    | 0.8485    | 0.8990    | 1.0000    | 0.7911        |
| \( C_{13} \) | 0.1875    | 0.5625    | 0.8125    | 0.8750    | 1.0000    | 0.7225        |
| \( C_{14} \) | 0.2000    | 0.4500    | 0.5750    | 0.8250    | 1.0000    | 0.4475        |

Step 2 Establish the classical domain

\[
R_1 = \begin{bmatrix}
N_1 & C_1 (0, 0.3000) \\
C_2 (0, 0.4667) & C_3 (0, 0.2632) \\
C_4 (0, 0.2632) & C_5 (0, 0.4737) \\
C_6 (0, 0.4167) & C_7 (0, 0.6667) \\
C_8 (0, 0.5333) & C_9 (0, 0.3500) \\
C_{10} (0, 0.3714) & C_{11} (0, 0.8081) \\
C_{12} (0, 0.7576) & C_{13} (0, 0.1875) \\
C_{14} (0, 0.2000)
\end{bmatrix}
\]

\( R_2, R_3, R_4, R_5 \) can be obtained in the same way.

Step 3 Establish the section domain

\[
R_p = \begin{bmatrix}
N_p & C_1 (0, 1) \\
C_2 (0, 1) & C_3 (0, 1) \\
C_4 (0, 1) & C_5 (0, 1) \\
C_6 (0, 1) & C_7 (0, 1) \\
C_8 (0, 1) & C_9 (0, 1) \\
C_{10} (0, 1) & C_{11} (0, 1) \\
C_{12} (0, 1) & C_{13} (0, 1) \\
C_{14} (0, 1)
\end{bmatrix}
\]
Step 4 Establish the matter-element to be evaluated

\[
R_0 = \begin{bmatrix}
N_0 & C_1 & 0.2847 \\
C_2 & 0.5360 \\
C_3 & 0.0362 \\
C_4 & 0.4737 \\
C_5 & 0.6800 \\
C_6 & 0.2500 \\
C_7 & 0.5983 \\
C_8 & 0.6711 \\
C_9 & 0.9590 \\
C_{10} & 0.9257 \\
C_{11} & 0.8687 \\
C_{12} & 0.7911 \\
C_{13} & 0.7225 \\
C_{14} & 0.4475 \\
\end{bmatrix}
\]

Step 5 Calculate comprehensive relevance and evaluation

The calculated result is in Table 6.

| Index | \( N_1 \) | \( N_2 \) | \( N_3 \) | \( N_4 \) | \( N_5 \) | Level |
|-------|-------|-------|-------|-------|-------|-------|
| \( C_1 \) | 0.0511 | -0.0511 | -0.1460 | -0.5256 | -0.6442 | I     |
| \( C_2 \) | -0.1300 | 0.4800 | -0.1212 | -0.2984 | -0.4161 | II    |
| \( C_3 \) | 0.1375 | -0.8625 | -0.9236 | -0.9427 | -0.9542 | I     |
| \( C_4 \) | -0.3077 | 0.3333 | -0.1818 | -0.3077 | -0.4000 | II    |
| \( C_5 \) | -0.3920 | -0.2400 | 0.3143 | -0.1264 | -0.3770 | III   |
| \( C_6 \) | 0.4000 | -0.4000 | -0.5455 | -0.6429 | -0.7000 | I     |
| \( C_7 \) | 0.1026 | -0.1455 | -0.2894 | -0.3691 | -0.4328 | I     |
| \( C_8 \) | -0.2952 | -0.50 | 0.2400 | -0.2043 | -0.3148 | III   |
| \( C_9 \) | -0.9369 | -0.8975 | -0.8633 | -0.7267 | 0.2733 | V     |
| \( C_{10} \) | -0.8818 | -0.8471 | -0.7833 | -0.6286 | 0.3714 | V     |
| \( C_{11} \) | -0.3158 | -0.2778 | -0.1333 | 0.3333 | -0.0714 | IV    |
| \( C_{12} \) | -0.1383 | 0.1700 | -0.0318 | -0.2155 | -0.3406 | II    |
| \( C_{13} \) | -0.6585 | -0.3657 | 0.3600 | -0.2449 | -0.3547 | III   |
| \( C_{14} \) | -0.3561 | 0.0100 | -0.0056 | -0.2217 | -0.4576 | II    |

4.3. Analysis Results

(1) Single index correlation analysis

According to \( K_m(x_i) = \max K_i(x_i) \), this paper determines the single index of the low-carbon level. From the correlation degree of Table 4 indicators, we can draw the following conclusions:

(i) \( C_1, C_3, C_6 \) and \( C_7 \) are the grade I; \( C_2, C_4, C_{12} \) and \( C_{14} \) are the grade II; \( C_5, C_8 \) and \( C_{13} \) are the grade III; \( C_{11} \) are the grade IV; \( C_9 \) and \( C_{10} \) are the grade V. There are eleven indexes that are generally higher than the average level. Shanghai has four indicators at a high level, that is, unit GDP energy consumption, per capita GDP, annual average concentration of sulfur dioxide and Engel’s coefficient of urban residents. Thus, it can be seen that Shanghai has done a better job of economic construction, industrial structure optimization and energy conservation and emission reduction.

(ii) However, the per capita parkland area and forest coverage should be taken seriously. Urban sewage treatment rates and the R&D to GDP are also below average levels. Therefore, Shanghai should increase its support for environmental protection technology enterprises in the future. Meanwhile, it can be seen that, in terms of low-carbon construction in Shanghai, the population is relatively high,
the per capita green space is relatively small and the capacity of urban carbon sinks is insufficient. Therefore, in future city construction, Shanghai should rationally plan green spaces and increase the volume of forest carbon sinks.

In summary, these conditions are basically in line with Shanghai’s economic level and mode of development. Shanghai, as China’s financial center, has less heavy industry and chemical industry, so its environment and economy are higher. Meanwhile, it is clear that the Shanghai government attaches importance to the development of the low-carbon economy, however, the per capita parkland area and forest coverage are not ideal.

(2) Multi-index correlation analysis

(i) According to \( K_m(P) = \max K_i(P) \), the comprehensive correlation of Shanghai is “−0.1879” and “−0.2093” is the second largest number—the second level data is very close to the first level data. This shows that the overall development level of a low carbon economy in Shanghai is between the first and second level.

(ii) Most of the low-carbon indicators are higher than the average level, which shows that its overall development level is good and there is big development potential.

5. Conclusions

The Evaluation Model of Urban Low-Carbon Economic Development Level based on entropy weight extension combines matter-element extension theory with entropy weight theory. The quantitative evaluation of the urban low-carbon economic development level provides a new method, which benefits the monitoring, analysis and evaluation of the city’s low-carbon economy.

(1) Based on the PSR framework, the Urban Low-Carbon Economic Development Level Evaluation Index System is constructed. It better reflects the interrelationship and role between social, natural, human activities and the low-carbon economy. The structure is clear, simple and concise. It establishes a basic framework for the evaluation index system of an urban low-carbon economy development level and expands the comprehensive assessment of the urban low-carbon economy development level.

(2) The model uses the entropy method for weighting and is suitable for the comprehensive evaluation of multiple indicators. The result is not easily affected by the subjective factors and improves the scientificity and rationality of the weights.

(3) The low-carbon indicators are quantified through the matter-element extension model. Each indicator has data support, which can not only measure the level of individual indicators and the impact on the whole but also measure the comprehensive level, which can be applied more flexibly and improve the practicability of the model. At the same time, we can make an approximate comparison between the numerical values and also analyze the constraints of the present city to some extent, which is conducive to the government formulating corresponding measures and predicting the development trend of the city’s low-carbon economy.

(4) The reliability of the model is verified by data from Shanghai and the current situation and development trend of Shanghai’s evaluation are presented. Shanghai is a city with a low-carbon level and there is a trend of further improvement in Shanghai’s low-carbon economy. But its low carbon construction and low carbon technology investment are relatively low.

Acknowledgments: The current work is supported by the Shandong Provincial Natural Science Foundation, China (ZR2018MG016), the Fundamental Research Funds for the Central Universities (17CX05015B) and the Recruitment Talent Fund of China University of Petroleum (East China) (YJ2016002). We have received the grants in support of our research work.

Author Contributions: Rongrong Li conceived and designed the experiments and wrote the paper; Xuan Yang performed the experiments, and analyzed the data. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.
References
1. Chu, S.; Majumdar, A. Opportunities and challenges for a sustainable energy future. *Nature* 2012, 488, 294–303. [CrossRef] [PubMed]
2. Stahel, W.R. The circular economy. *Nature* 2016, 531, 435–438. [CrossRef] [PubMed]
3. Wang, Q.; Chen, X. Energy policies for managing China’s carbon emission. *Renew. Sustain. Energy Rev.* 2015, 50, 470–479. [CrossRef]
4. Nader, S. Paths to a low-carbon economy—The masdar example. *Energy Procedia* 2009, 1, 3951–3958. [CrossRef]
5. Wang, Q.; Chen, X. China’s electricity market-oriented reform: From an absolute to a relative monopoly. *Energy Policy* 2012, 51, 143–148. [CrossRef]
6. Wang, Q.; Li, R. Journey to burning half of global coal: Trajectory and drivers of China’s coal use. *Renew. Sustain. Energy Rev.* 2016, 58, 341–346. [CrossRef]
7. Lynn, P.; Zhou, N.; David, E; Ohshita, S.; Lu, H.; Zheng, N.; Fino-Chen, C. Development of a low-carbon indicator system for china. *Habit. Int.* 2013, 37, 4–21.
8. Mioriarty, P.; Wang, S.J. Low-carbon cities: Lifestyle changes are necessary. *Energy Procedia* 2014, 61, 2289–2292. [CrossRef]
9. York, R.; Rosa, E.A.; Dietz, T. Stirpat, ipat and impact: Analytic tools for unpacking the driving forces of environmental impacts. *Ecol. Econ.* 2004, 46, 351–365. [CrossRef]
10. Khanna, N.; Fridley, D.; Hong, L. China’s pilot low-carbon city initiative: A comparative assessment of national goals and local plans. *Sustain. Cities Soc.* 2014, 12, 110–121. [CrossRef]
11. Urban, F. Chin’s rise: Challenging the north-south technology transfer paradigm for climate change mitigation and low carbon energy. *Energy Policy* 2018, 113, 320–330. [CrossRef]
12. Fankhauser, S.; Jotzo, F. Economic growth and development with low-carbon energy. *Wiley Interdiscip. Rev. Clim. Chang.* 2017, 9, e495. [CrossRef]
13. Eicker, U.; Monien, D.; Duminil, É.; Nouvel, R. Energy performance assessment in urban planning competitions. *Appl. Energy* 2015, 155, 323–333. [CrossRef]
14. Wang, Q.; Li, R. Decline in China’s coal consumption: An evidence of peak coal or a temporary blip? *Energy Policy* 2017, 108, 696–701. [CrossRef]
15. Wang, Q.; Jiang, X.-T.; Li, R. Comparative decoupling analysis of energy-related carbon emission from electric output of electricity sector in Shandong Province, China. *Energy* 2017, 127, 78–88. [CrossRef]
16. Menezes, E.; Maia, A.G.; Carvalho, C.S.D. Effectiveness of low-carbon development strategies: Evaluation of policy scenarios for the urban transport sector in a brazilian megacity. *Technol. Forecast. Soc. Chang.* 2016, 114, 226–241. [CrossRef]
17. Ohnishi, S.; Dong, H.; Geng, Y.; Fujii, M.; Fujita, T. A comprehensive evaluation on industrial & urban symbiosis by combining MFA, carbon footprint and emergy methods—Case of Kawasaki, Japan. *Ecol. Indic.* 2017, 73, 513–524.
18. Bai, C.; Sarkis, J.; Dou, Y. Constructing a process model for low-carbon supply chain cooperation practices based on the DEMATEL and the NK model. *Suppl. Chain Manag.* 2017, 22. [CrossRef]
19. Geels, F.W.; Berkhout, F.; Vuurpen, D.P.V. Bridging analytical approaches for low-carbon transitions. *Nat. Clim. Chang.* 2016, 6, 576–583. [CrossRef]
20. Mei, N.S.; Wai, C.W.; Ahamad, R.B. Differential environmental psychological factors in determining low carbon behaviour among urban and suburban residents through responsible environmental behaviour model. *Sustain. Cities Soc.* 2017, 31, 225–233.
21. Tan, S.; Yang, J.; Yan, J.; Lee, C.; Hashim, H.; Chen, B. A holistic low carbon city indicator framework for sustainable development. *Appl. Energy* 2016, 185, 1919–1930. [CrossRef]
22. Li, H.; Zhang, J. System dynamics simulation of urban low-carbon economic development path. *J. Jilin Norm. Univ. Nat. Sci. Ed.* 2017, 38, 108–112.
23. Wang, J.; Wang, K.; Zhao, J.; Liu, X.; Zhou, J.; Li, Z. Preliminary study on the development of low carbon city in harbin based on dpsir model. *Nat. Sci. J. Harbin Norm. Univ.* 2017, 33, 92–97.
24. Wang, X.; Zhao, H.; Ji, C. Research on low-carbon economy urban construction based on greenway network—Taking nanjing city as an example. *Eco-Econ. Chin. Vers.* 2017, 33, 60–67.
25. Wang, L.; Zhou, Y.; Zhang, Y. Evaluation and obstacle analysis of low-carbon city development based on entropy-topsis method—Tianjin as an example. *Sci. Technol. Manag. Res.* **2017**, *239*-245. [CrossRef]
26. Xie, Z.; Qin, C.; Shen, W.; Rong, P. China’s low-carbon economy development performance evaluation and influential factors. *Econ. Geogr.* **2017**, *37*, 1–9.
27. Wang, Q.; Chen, X.; Jha, A.N.; Rogers, H. Natural gas from shale formation—The evolution, evidences and challenges of shale gas revolution in United States. *Renew. Sustain. Energy Rev.* **2014**, *30*, 1–28. [CrossRef]
28. Tan, S.; Yang, J.; Yan, J. Development of the low-carbon city indicator (LCCI) framework. *Energy Procedia* **2015**, *75*, 2516–2522. [CrossRef]
29. Zhang, Y. 13th five-year ecological environment protection planning. *Environ. Econ.* **2016**, *37*, 12.
30. Delgado, A.; Romero, I. Environmental conflict analysis using an integrated grey clustering and entropy-weight method. *Environ. Model. Softw.* **2016**, *77*, 108–121. [CrossRef]
31. Hafezalkotob, A.; Hafezalkotob, A. Extended multimoora method based on shannon entropy weight for materials selection. *J. Ind. Eng. Int.* **2016**, *12*, 1–13. [CrossRef]
32. Hamid, T.; Aljumeily, D.; Mustafina, J. Evaluation of the dynamic cybersecurity risk using the entropy weight method. In *Technology for Smart Futures*; Springer: Berlin, Germany, 2018; pp. 271–287.
33. Radkowski, S.; Jasiński, M.; Gumiński, R.; Gałęzia, A.; Radkowski, S.; Jasiński, M.; Gumiński, R.; Gałęzia, A. Using of entropy method in failure diagnostics. In *Advances in Condition Monitoring of Machinery in Non-Stationary Operations*; Springer: Berlin, Germany, 2018.
34. Sahoo, M.M.; Patra, K.C.; Swain, J.B.; Khatua, K.K. Evaluation of water quality with application of bayes’ rule and entropy weight method. *Rev. Française De Génie Civ.* **2016**, *21*, 730–752. [CrossRef]
35. Yazdi, J. Optimization of hydrometric monitoring network in urban drainage systems using information theory. *Water Sci. Technol. A J. Int. Assoc. Water Pollut. Res.* **2017**, *76*, 1603. [CrossRef] [PubMed]
36. Ministry of Environmental Proection of the People’s Republic of China. *The bulletin on the state of china’s environment (2012–2016)*; China Environmental Science Press: Beijing, China, 2013–2017.
37. National Bureau of Statistics of China. *China statistical yearbook (2012–2016)*; China Statistic Press: Beijing, China, 2013–2017.
38. Cai, W. Extension theory and its application. *Chin. Sci. Bull.* **1999**, *44*, 1538–1548. [CrossRef]
39. Huber, P.J. Projection pursuit (with discussion). *Ann. Stat.* **1985**, *13*, 435–525. [CrossRef]
40. Zhang, F.; Xue, H.; Luo, T. Construction of water shortage index in guangdong province and its driving factors—Based on matter-element theory and correlation function. *J. Beijing Inst. Technol.* **2018**, *20*, 52–61.
41. Peng, D.; Zhang, X.; Dan, L.I.; Pan, G.; Tan, Z. Evaluation model for economic and safe operation of electricity system based on matter-element extension method used sequence relations of groups. *Electr. Power Constr.* **2016**, *17*, 35–39.
42. Li, S.; Li, R. Energy Sustainability Evaluation Model Based on the Matter-Element Extension Method: A Case Study of Shandong Province, China. *Sustainability* **2017**, *9*, 2128. [CrossRef]
43. Mathews, J.A.; Hu, M.C.; Tan, H. *Toward Low Carbon Cities: The Chinese Experience*; Springer: Berlin, Germany, 2017.
44. Wang, Q. China should aim for a total cap on emissions. *Nature* **2014**, *512*, 115. [CrossRef] [PubMed]