# Provincial Carbon Emission Allocation and Efficiency in China Based on Carbon Peak Targets

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**Abstract:** As the world's largest carbon emitter, China is facing great pressure to reduce emissions. With the country's proposed timeline for carbon peaking and carbon neutralization, a new goal has been established for China's low-carbon development. Based on the improved equal proportion allocation method, this paper allocates the overall carbon emission control goal for 2025 among 30 provinces and cities, based on 2015 figures, and measures and studies the country's carbon emission allocation efficiency on this basis. The results show that Beijing, Tianjin, Hebei, Shandong, Zhejiang, Shanghai, Jiangsu, Guangdong and Inner Mongolia need to increase their emission reduction capacity, while Jiangxi, Guizhou, Gansu, Qinghai, Hainan and Guangxi have relatively low emission reduction targets. Based on this allocation scheme, more provinces can reduce carbon emissions by increasing their efficiency with up-to-date technology, and a new vision for national allocation that is more easily accepted by all provinces and regions can be developed. Based on the research results of this paper, each province and region can choose its own low-carbon economic development path within the constraints of China's carbon intensity emission reduction targets, without compromising its own economic development characteristics.

**Keywords:** carbon emissions; DEA; equal proportion distribution method; carbon peak

## 1. Introduction

With the beginning of a new stage of global climate governance, reducing carbon dioxide emissions has become a common goal of global national development. As the country producing the most carbon dioxide emissions in the world, to realize the development of a green, low-carbon economy, China made commitments at the Copenhagen climate conference and the Paris climate conference to reduce the intensity of emissions and to designate a year for peak emissions. To successfully implement the country's goals to reach a carbon peak in 2030 and carbon neutralization in 2060, all the provinces of China should work together. Over the past decade, China has actively promoted energy conservation, emission reduction and climate change initiatives, and it has established a relatively complete low-carbon developmental model and policy system, accumulating rich experience in relation to carbon peaking and carbon neutralization. Presently, China's carbon intensity shows a downwards trend. However, there are still great differences between cities in responsibility, capacity, efficiency and demand related to carbon emission objectives. The period of the 14th Five-Year Plan is when China aims to reach a carbon peak and realize carbon neutralization. All the provinces and cities of China should formulate active and effective distribution plans through scientific research to help China reach its carbon peak on time.

The Five-Year Plan is China's special guidance for the direction of national development; 2015 is the end of the 12th Five-Year Plan, and the National Climate Change Program (2014–2020) of China includes 2015. The 13th Five-Year Plan still highlights the importance

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of carbon emissions. Meanwhile, the overall carbon emission intensity target for the 14th Five-Year Plan is still 18%, and the results for the allocation of total $CO_2$ control targets in 2025 will be discussed in this paper. In context, however, 2014 was a turning point, when a series of air pollution mitigation actions were launched [1,2]. Therefore, this paper used 2015 data to successfully lay out a plan to reach the national carbon emission reduction target. We propose a carbon emission allocation scheme based on the improved equal proportion method, which provides a reference for China in relation to achieving its carbon emission reduction target in 2025.

## 2. Literature Review

As the world's largest carbon emitter, China is facing substantial pressure to reduce its emissions [3]. Shao et al. [4] constructed a provincial decomposition scheme of China's carbon emission quota using the zero-sum gains data envelopment analysis (ZSG-DEA) model, which shows that China's current available space for carbon emissions already presents a deficit. Thus, differentiated emission reduction policies have been implemented for different provinces to ensure that China can successfully achieve its carbon emission reduction target by 2030. Most previous studies on carbon emission reduction are based on national quotas [5–7]. However, in recent years, scholars have begun to study carbon emissions from the perspective of regional and industrial factors. Some scholars have suggested that in future research, we can consider methods other than DEA [8]. Against this background, through a literature review, we find that three other methods are used to examine carbon emission quotas: the index method, the DEA method and other models.

The index method employs rational quota allocation by assigning index weights under different principles and combining allocation principles. When constructing a regional carbon dioxide emission model, Wang [9] selected five indicators, namely per capita GDP, industrial energy efficiency, the no fossil energy utilization ratio and per capita emissions, for research. Some scholars have established a comprehensive index system based on the principles of fairness, efficiency and feasibility to allocate carbon emissions according to regional differences [10]. However, this method ignores the differences among provinces and regions, which may lead to deviations in the distributions of results; moreover, certain difficulties arise in implementing such distribution schemes nationwide [11].

Data envelopment analysis (DEA) is used for decision making, and it is a mathematical programming approach used to evaluate the relative efficiency of emission reduction [12]. The DEA method has been the most widely used for analysis in recent years. It is an effective method for evaluating the efficiency of $CO_2$ emissions [13] because it focuses on efficiency factors. It can be used to evaluate carbon emission performance and analyse the potential for emission reduction. Feng [8], using the DEA common weight method, calculated carbon emission quotas for all the provinces of China, providing a new perspective on the national allocation of carbon quotas that can be accepted by all provinces and regions. Liu and Wang [14] introduced the DEA method, analysed the applicability of distribution methods from the perspective of fairness and efficiency and tested the impact of different distribution methods on the market. Based on the results of an efficiency evaluation, Zhu Weiwei used the DEA method to allocate carbon emission reductions and ultimately provided a new perspective on fair and effective carbon emission reduction allocation [15]. In addition, other scholars [16] have used the DEA method to optimize China's initial carbon emissions allocation scheme. Based on empirical results, Liu and Wang [14] suggested that DEA can be used to improve the fairness of the initial carbon emission rights allocation.

In addition to the index method and the DEA method, the directional distance function (DDF) model was used to point out that the emission reduction target should be divided into different stages, such that it could be achieved in steps [17]. Feng [8] constructed a regional allocation scheme for carbon emission allocation by improving the technique for order of preference by similarity to an ideal solution (TOPSIS). Cui et al. [18] calculated the radiation effect of carbon emissions across different regions based on the Shapley algorithm. The CGE model, ELC model, Gini coefficient optimization model and other methods have

been applied in relevant research [18]. Francis also used a DEA model to analyse energy efficiency in West African countries. The results show that gross national income and urbanization negatively influence West Africa's energy efficiency [19].

The above literature provides a good overview and reference for the study of carbon emission reduction allocation. The allocation method mainly distributes pollutant quotas from the perspectives of fairness, efficiency, economy or environmental quality, which is reasonable [10,20,21]. The recent research on carbon emission quota allocation has mainly focused on efficiency, fairness and responsibility [19].

There are few studies on the allocation of carbon emission quotas from the perspective of the two constraints of total carbon emissions and intensity; such studies are helpful in achieving the goal of carbon emission reduction [22,23]. In view of this, this study constructs a target allocation index system for total carbon dioxide control based on differences in economic development levels, carbon dioxide emissions and main functional areas across regions and uses the improved equal proportion allocation method to study the governance of provinces, autonomous regions and municipalities directly under the central government. On this basis, the DEA model is used to analyse the distribution results to provide a basis for the distribution of China's overall carbon dioxide throughout various regions.

## 3. Research Methods

### 3.1. Carbon Emission Measurement

To date, no official authority has published standards for measuring $CO_2$ emissions. Therefore, according to Lu [24], the IPCC National Greenhouse Gas Inventory Guide can provide scientific data; the IPCC is regarded as an authority in the international context, and it can provide a scientific basis for government and policy makers.

According to Xiang, Yang, Xie et al. (2022), there are 18 kinds of energy sources for production and living, considering the actual energy use in different regions, but different studies can limit the selection of energy sources based on different situations [25]. Referring to the method used by the Intergovernmental Panel on Climate Change (IPCC, 2006) [26] and combining it with the data from the China Energy Statistical Yearbook, Yan, Wang and Dong (2022) used eight major energy sources to calculate carbon emissions, according to the specific research context [27]. For this paper, the data for calculating carbon emissions are from the China Statistical Yearbook 2015 and include 9 energy sources that are all fossil fuels: raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas and liquefied petroleum gas. The calculation formula for carbon emissions is as follows:

$$G_t = \sum_{j=1}^{9} E_{jt} \times \delta_j \times \eta_j. \tag{1}$$

$$G_t^i = \sum_{j=1}^{9} E_{jt} \times \delta_j \times \eta_j. \tag{2}$$

where $G_t$ and $G_t^i$ represent the carbon emissions of the whole country during year $t$ and the carbon emissions of a particular province during year $t$, respectively. The unit is millions of tonnes. $E_{jt}$ and $E_t^i$ represent the country's conversion coefficient for energy $j$ during year $t$ calculated in standard coal and the province's conversion coefficient for standard coal corresponding to energy $j$ in year $t$, respectively. The unit is millions of tonnes. $\delta_j$ is the standard coal conversion coefficient of energy $j$. $\eta_j$ stands for the carbon emission coefficient of energy $j$.

The standard coal coefficient and coefficient of carbon emissions of each of the 9 energy sources are shown in Table 1.

**Table 1.** Standard coal coefficient and coefficient of carbon emissions of the energy sources.

| Types of Energy | Standard Coal Coefficient | Coefficient of Carbon Emissions |
|---|---|---|
| Raw coal | 0.714 | 0.756 |
| Coke | 0.971 | 0.855 |
| Crude oil | 1.429 | 0.586 |
| Gasoline | 1.472 | 0.554 |
| Kerosene | 1.472 | 0.571 |
| Diesel | 1.457 | 0.5921 |
| Fuel oil | 1.429 | 0.619 |
| Natural gas | 1.330 | 0.448 |
| Liquefied petroleum gas | 1.741 | 0.504 |

For the standard coal coefficient, the unit used for natural gas and liquefied petroleum gas is kg standard coal/cubic metres, and the units used for the other seven energy sources are millions of tonnes of standard coal/millions of tonnes. For the coefficient of carbon emissions, the unit of the nine energy sources is millions of tonnes of carbon/millions of tonnes of standard coal.

### 3.2. Improved Equal Proportion Allocation Method

The improved equal proportion allocation method aims to adjust the reduction proportions appropriately according to the different provinces. It also reflects the differences among the provinces and ensures fairness. Suppose $Q_i$ is the base carbon emissions of region $i$, and $C$ refers to the total target reduction rate in relation to the base period region; then, the target reduction rate of region $i$ is:

$$x_i = \overline{x} \times \alpha_i \tag{3}$$

Formula (3) will be used for the target reduction rate of the region later.

The amount of carbon cuts in each region is eventually denoted as $\Delta Q_i$:

$$\Delta Q_i = \frac{C \sum_{i=1}^n Q_i}{\sum_{i=1}^n \alpha_i \times Q_i}(\alpha_i \times Q_i) = \frac{C \sum_{i=1}^n Q_i}{\sum_{i=1}^n \left( \frac{\sum_{j=1}^m r_{ij} \times w_j}{\frac{1}{n}\sum_{i=1}^n \sum_{j=1}^m r_{ij} \times w_j} \times Q_i \right)} \times \frac{\sum_{j=1}^m r_{ij} \times w_j}{\frac{1}{n}\sum_{i=1}^n \sum_{j=1}^m r_{ij} \times w_j} \times Q_i \tag{4}$$

In Formula (4), $x_i$ represents the target reduction rate of region $i$; $\overline{x}$ represents the average target reduction rate of all $n$ regions, and $\overline{x} = \frac{C \sum_{i=1}^n Q_i}{\sum_{i=1}^n (\alpha_i \times Q_i)}$; $\alpha_i$ represents the relative reduction factor of region $i$, and $\alpha_i = \frac{\sum_{j=1}^m r_{ij} \times w_j}{\frac{1}{n}\sum_{i=1}^n \sum_{j=1}^m r_{ij} \times w_j}$; $r_{ij}$ represents the normalized value of the $j$ index in region $i$; and $w_j$ represents the weight of index $j$.

### 3.3. DEA Model

At present, the DEA models that are widely used include $C^2R$ and $BC^2$. Among them, the $C^2R$ model is a DEA model with constant returns to scale based on the efficiency index (output–input ratio) of the focal decision-making unit and the efficiency index of all decision-making units (including target decision-making units); however, the $BC^2$ model adds the constraint condition $\sum_{k=1}^N \lambda_k = 1$. Following the literature on carbon emission allocation [19], this paper constructs a $BC^2$ model based on traditional DEA to calculate the corresponding technical efficiency of carbon emission allocation, which is more stable because constraint conditions can take into account more situations and ensure data integrity.

If there are a total of $n$ decision-making units in a production system, every decision-making unit $DMU_i (i = 1, 2, \ldots n)$ has $m$ types of input and $s$ types of output. Moreover, $X_i$ is the input, and $Y_i$ is the output. The $BC^2$ model can be shown as:

$$Min \left[ \theta_{i_0} - \varepsilon \left( e^T s^+ + e^T s^- \right) \right]$$

$$s.t. \begin{cases} \sum\limits_{i=1}^{N} x_i \lambda_i + s^- = \theta_{i_0} x_{i_0} \\ \sum\limits_{i=1}^{N} y_i \lambda_i - s^+ = y_{i_0} \\ \sum\limits_{i=1}^{N} \lambda_i = 1, \lambda_i \geq 0, i = 1, 2, \cdots, n \\ s^+ \geq 0, s^- \geq 0 \end{cases} \tag{5}$$

In Formula (5), $X_i = (x_{1i}, x_{2i}, \cdots, x_{ki})^T$, $Y_i = (y_{1i}, y_{2i}, \cdots, y_{ri})^T$, and $x_i$ and $y_i$ represent the input and output, respectively. When $x_{ki} > 0$, the $DMU_i$ of decision-making unit $i$ has input variables of input type $k$; when $y_{ri} > 0$, the $DMU_i$ of decision-making unit $i$ has output variables of output type $r$. $s^+$ and $s^-$ refer to slack variables, $e^T$ refers to the unit row vector, $\theta_{i_0}$ refers to the relative efficiency value of the decision-making unit, and $\lambda$ is the weight vector. $\theta_{i_0}$ relates to $s^-$ and $s^+$, which decrease strictly monotonically, and $0 \leq \theta_{i_0} \leq 1$. If and only if $\theta_{i_0} = 1$, then $s^- = 0$. If $s^+ = 0$, the decision-making unit is effective. If $\theta_{i_0} < 1$, the decision-making unit is invalid.

## 4. Construction of the Index

### 4.1. Indicator Selection

According to the pathway of "generation, emission reduction, emission" [4], a total carbon dioxide allocation index system should be constructed based on the following three principles: emission responsibility, emission capacity and emission efficiency. Total carbon dioxide reduction rules are determined according to the connotation of each principle and its differential allocation criteria (as shown in Table 2).

**Table 2.** Total carbon emission reduction and distribution indicator system.

| Indicators/ Principles | Index | Regulations | Explanation | Negative/ Positive |
|---|---|---|---|---|
| Responsibility | Carbon dioxide emissions per capita | The higher carbon dioxide emissions per person are, the smaller the cuts are | Everyone has the responsibility to reduce carbon dioxide emissions | Negative |
| Ability | Per GDP | The higher GDP per capita is, the larger the cuts are | Regions with high levels of economic development should shoulder more responsibility for carbon dioxide reduction | Positive |
| Ability | The proportion of environmental protection investment to government revenue | The larger the investments in environmental protection are, the larger the cuts are | The higher the investment in environmental protection is, the greater the regional support for carbon dioxide emission reduction is | Positive |
| Ability | Fiscal revenue | The higher the revenue is, the larger the cuts are | The higher fiscal revenue is, the greater the economic strength of the focal region is and the greater its responsibility to reduce emissions is | Positive |
| Efficiency | Carbon emissions per unit of GDP | The greater the carbon intensity per unit of GDP is, the smaller the cuts are | The higher carbon dioxide emissions per unit of GDP are, the higher the corresponding emission efficiency is and the lower the carbon emissions per unit of GDP are | Negative |

China is a responsible country, and coping with climate change is a common responsibility of society as a whole. Therefore, in the prioritization of indicators, emission responsibility comes first. To successfully achieve China's goal of a carbon peak, everyone has to assume responsibility for carbon dioxide emission reduction. Therefore, we select the indicator "cumulative carbon emissions per capita". The greater the cumulative carbon emissions per capita of a region are, the worse the total carbon emissions of the corresponding province and city are; thus, this is a negative indicator. Required emission

capacities have been established by each province and city, but due to the different development degrees of each region, this emission capacity varies greatly. The indicators "GDP per capita", "environmental protection investment" and "fiscal revenue" represent the emission capacity of each region. The higher the per capita GDP of a region is, the higher its levels of regional economic development and matched total carbon emissions are. The greater a region's investment in environmental protection is, the greater the regional support for emission reduction is. A higher fiscal revenue is accompanied by a greater regional economic strength, a decreased need for emission reduction and a greater responsibility for emission reduction. Therefore, per capita GDP, environmental protection investment and fiscal revenue are positive indicators. Emission efficiency can be improved by reducing per unit carbon emissions. Therefore, carbon emissions per unit of GDP are a negative indicator.

### 4.2. Data Selection

In this paper, 2015 was taken as the base year, and the data were taken from sources that included the "China Environmental Statistical Annual Report" (2016), the "China Environmental Statistical Yearbook" (2016) and the "China Statistical Yearbook" (2016). Missing data were processed using regression analysis.

### 4.3. Data Processing

Since the data of the indicators have different orders of magnitude and dimensions, to eliminate these influences, the indicators should be standardized. The entropy weight method can clearly reflect the utility of the entropy value of index information and prevent the interference of human subjectivity. The index processing and calculation methods for the entropy weight are as follows:

(1) Data are standardized. When the indicator is a positive indicator:

$$r_{ij} = (x_{ij} - x_{min} / (xmin_{max}) \tag{6}$$

When the indicator is a negative indicator:

$$r_{ij} = (xij_{max} / (xmin_{max}) \tag{7}$$

(2) The information value $d_j$ of indicator $j$ is calculated as:

$$d_j = 1 + c \sum_{i=1}^{n} p_{ij} ln \, p_{ij} \tag{8}$$

where $p_{ij} = r_{ij} / \sum_{i=1}^{n} r_{ij}$ and $c = \frac{1}{ln \, n}$.

(3) The weights of the evaluation indicators are confirmed. The weight of indicator $j$ can be calculated as:

$$w_j = d_j / \sum_{j=1}^{m} d_j \tag{9}$$

The five original indicators of overall carbon emission allocation were normalized according to Formulas (8) and (9), and then the entropy weights of each overall $CO_2$ allocation indicator were calculated as shown in Table 3.

**Table 3.** Weight of the carbon total allocation index.

| Index | Per Capita Carbon Emissions | Per GDP | Environmental Input | Fiscal Revenue | Carbon Emissions per Unit of GDP |
|---|---|---|---|---|---|
| $CO_2$ entropy value | 0.27 | 0.16 | 0.10 | 0.16 | 0.32 |

## 5. Results Analysis

### 5.1. Analysis of Total Carbon Dioxide Distribution

Based on the proportional distribution, the 30 cities are presented in Figure 1. From the distribution results regarding overall $CO_2$ control, it can be seen that in terms of the actual target of reducing China's overall carbon emission intensity by 18%, there are obvious differences in the $CO_2$ reduction rates across the regions. After adjusting the adjustment coefficient, we find that there are obvious differences across the carbon intensity reduction targets allocated by the provinces. As shown in Table 4, Jiangsu has the highest reduction rate, 31.40%, and this region is followed by Guangdong and Inner Mongolia, which have rates of 31.15% and 28.23%, respectively. There are nine provinces with carbon emission intensity reduction rates that are higher than the general national target. These provinces are Beijing, Tianjin, Hebei, Shandong, Zhejiang, Shanghai, Jiangsu, Guangdong and Inner Mongolia. The reduction rates of these provinces, 21.19%, 20.67%, 18.73%, 21.91%, 20.33%, 23.51%, 31.40%, 31.15% and 28.23%, respectively, are higher than the general national target. Among these regions, Beijing, Tianjin, Zhejiang, Shanghai and Guangdong have high levels of economic development, and their per capita GDP and levels of environmental protection investment are also higher than those of the other regions. Therefore, they play a prominent role in emission reduction capacity. Hebei and Inner Mongolia, as important provinces in the production of China's heavy industry and energy for transmission, have high per capita cumulative carbon emissions and great emission reduction responsibilities. The ratio of environmental protection investment to financial expenditures in these regions is also high, and their carbon emissions per unit of GDP are low. Therefore, based on their high emission reduction potential and low emission reduction costs, the allocated reduction targets of these regions are also relatively high.
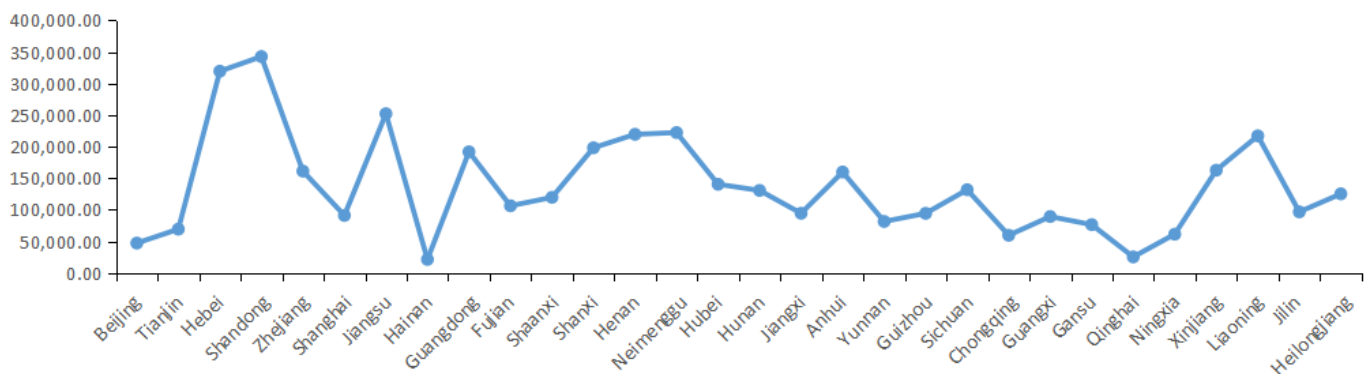


**Figure 1.** Proportionally distributed quantity/(million t) of 30 cities.

**Table 4.** Allocation of total $CO_2$ control targets in China, 2025.

| City | Reduction Rate/% | National Reduction Rate/% | Distribution Difference/% |
|------|------|------|------|
| Beijing | 21.19 | 20.50 | 0.69 |
| Tianjin | 20.67 | 20.50 | 0.17 |
| Hebei | 18.73 | 19.00 | −0.27 |
| Shandong | 21.91 | 20.50 | 1.41 |
| Zhejiang | 20.33 | 20.50 | −0.17 |
| Shanghai | 23.51 | 20.50 | 3.01 |
| Jiangsu | 31.40 | 20.50 | 10.9 |
| Hainan | 3.85 | 12.00 | −8.15 |
| Guangdong | 31.15 | 20.50 | 10.65 |
| Fujian | 13.18 | 19.50 | −6.32 |
| Shaanxi | 12.73 | 18.00 | −5.27 |

**Table 4.** *Cont.*

| City | Reduction Rate/% | National Reduction Rate/% | Distribution Difference/% |
|---|---|---|---|
| Shanxi | 11.79 | 18.00 | −6.21 |
| Henan | 13.49 | 19.50 | −6.01 |
| Neimenggu | 28.23 | 17.00 | 11.23 |
| Hubei | 13.47 | 19.5 | −6.03 |
| Hunan | 12.13 | 18.00 | −5.87 |
| Jiangxi | 7.70 | 19.50 | −11.8 |
| Anhui | 10.03 | 18.00 | −7.97 |
| Yunnan | 8.97 | 18.00 | −9.03 |
| Guizhou | 6.91 | 18.00 | −11.09 |
| Sichuan | 13.80 | 19.50 | −5.70 |
| Chongqing | 12.49 | 19.50 | −7.01 |
| Guangxi | 7.36 | 17.00 | −9.64 |
| Gansu | 5.77 | 17.00 | −11.23 |
| Qinghai | 8.77 | 12.00 | −3.23 |
| Ningxia | 17.63 | 17.00 | 0.63 |
| Xinjiang | 13.97 | 12.00 | 1.97 |
| Liaoning | 16.57 | 18.00 | −1.43 |
| Jilin | 11.28 | 18.00 | −6.72 |
| Heilongjiang | 10.97 | 17.00 | −6.03 |

Most of the areas with low reduction rates are underdeveloped; these include Jiangxi, Guizhou, Gansu and Qinghai, which have reduction rates of 7.70%, 6.91%, 5.77% and 8.77%, respectively. These regions are located in southwestern or northwestern China and have a low per capita GDP, low fiscal expenditures and environmental protection investments that are lower than the national average, along with a low emission reduction capacity. Therefore, their reduction rates are also low. The reduction rates of Hainan and Guangxi are 3.85% and 7.36%, respectively, because their per capita carbon dioxide emissions, per capita GDP, proportion of environmental protection investment to fiscal expenditures and carbon emissions per unit of GDP are low; thus, their allocated reduction rates are also low. Although the reduction rates of the other regions are not higher than the national target, they are at an intermediate level compared with the lower-level regions. For example, the reduction rates of Fujian, Shaanxi, Shanxi, Henan, Hubei, Hunan, Chongqing, Ningxia, Xinjiang, Liaoning and Jilin are 13.18%, 12.73%, 11.79%, 13.49%, 13.47%, 12.13%, 12.49%, 17.63%, 13.97%, 16.57% and 11.28%, respectively. By adjusting their industrial and energy structures, these regions can improve their emission reduction capacity and achieve their allocated reduction targets through future development.

To date, the provincial carbon emission allocation targets have not all been announced (only Hebei has announced a target of 19%), but the overall carbon emission intensity target of the 14th Five-Year Plan is still 18%, which is the same as that of the 13th Five-Year Plan. Therefore, the provincial reduction targets shown in the table are analysed with reference to the 13th Five-Year Plan. They are 20.5%, 19.5%, 18%, 17% and 12%, respectively. The specific objectives of each province are shown in Table 3. By comparing the reduction targets of various provinces according to the improved equal proportion allocation method, we find that the reduction targets of Beijing, Tianjin, Shandong, Shanghai, Jiangsu, Guangdong, Inner Mongolia, Ningxia and Xinjiang are higher than the national distribution targets, and the reduction targets of the other 21 provinces are lower than the national distribution targets. Among them, Inner Mongolia exceeded its national distribution target by the widest margin. On the one hand, this reflects the fairness of China's rational distribution. Due to the difficulties faced in achieving rapid low-carbon transformation in Inner Mongolia, the national distribution plan gives this region a target of only 17%. On the other hand, according to data from 2015, Inner Mongolia's per capita carbon dioxide emissions, environmental protection investment and carbon emissions per unit GDP are among the highest in the country, which indicates that Inner Mongolia needs to bear more responsibility for emission reduction in the process of economic development. The 28.23%

target assigned to this region in this paper can better urge Inner Mongolia to adjust its industrial structure and energy structure, which would be more conducive to the overall progress of national carbon emission reduction and the improvement of economic benefits. Gansu falls the farthest below the national distribution target, with a distribution target of 5.77% and a national distribution target of 17%. This reflects the country's full trust in this region's emission reduction capacity. However, based on 2015 data, Gansu's carbon emissions per unit of GDP are high, and its investment in environmental protection is not substantial, which means that Gansu's emission reduction potential is limited and that pursuing such a reduction may result in high economic costs. From the perspective of the overall economic interests of the country, it is not recommended to increase regional emission reduction targets. Appropriate targets can encourage provinces and cities to increase their emission reduction capacity and reach emission reduction targets faster.

In general, it is possible for the carbon dioxide allocation levels of all the provinces and cities of China to reach the national allocation level by 2025. Under the constraints of carbon intensity emission reduction targets, provinces and cities can improve relevant emission reduction technologies through reasonable resource allocation, promote the adjustment and optimization of their industrial structures and energy structures and lay a solid foundation for achieving a carbon peak. The carbon emissions of some regions are declining because these regions are able to make rational and effective use of invested resources and environmental factors, which also shows that the corresponding technical efficiency of China's overall carbon dioxide emission reduction capacity has increased. This increase in technical efficiency means that indicators of China's total carbon emissions do not exist or that little resource investment is wasted at the existing technical level. Therefore, measuring and analysing the technical efficiency of China's carbon emission reduction is of great significance in terms of reducing the carbon emission indicators in provincial administrative regions and realizing these regions' potential for carbon dioxide emission reduction.

### 5.2. Analysis of the DEA Model

DEAP 2.1 software was used to settle the technical and scale efficiency, according to Wang [28]. Therefore, with the help of DEAP 2.1, the DEA model analysis results obtained in this study are shown in Figure 2.
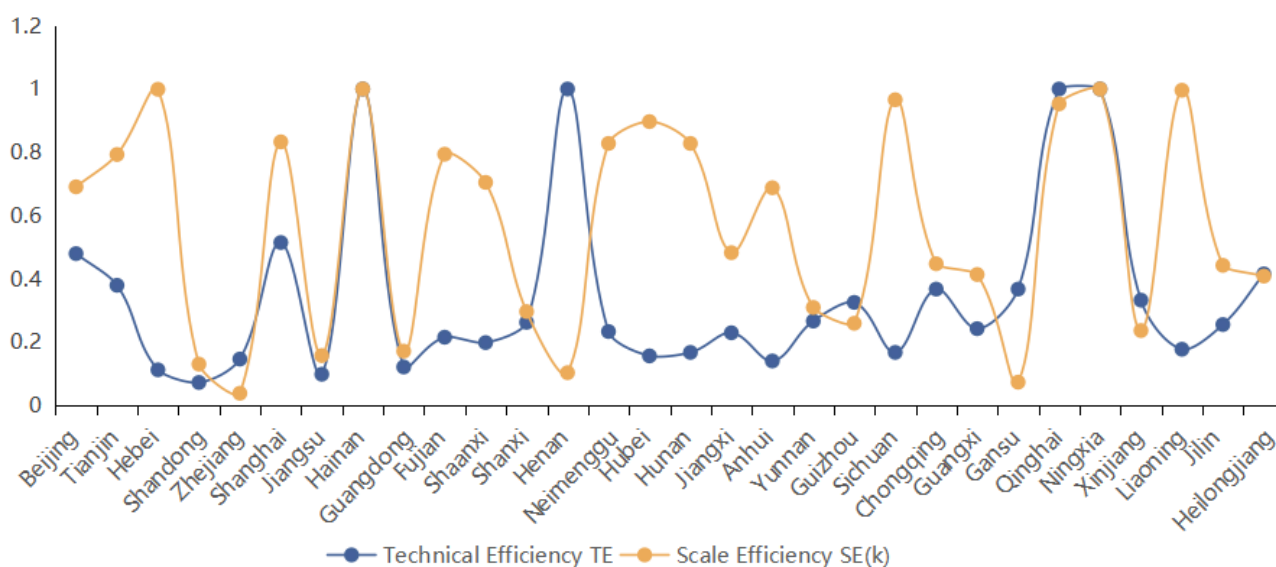


**Figure 2.** Technical efficiency and scale efficiency of 30 cities.

Technical benefits reflect the efficiency brought by technical factors. Values equal to 1 indicate the rational use of elements. Values less than 1 indicate that there is still room to improve technical efficiency in the use of elements. As shown in Figure 2, the

technical benefits of Hainan, Henan, Qinghai and Ningxia indicate reasonable use, while the technical benefits of Shandong, Jiangsu, Sichuan and Liaoning are low, indicating that their technical efficiency needs to be improved. Although the technical benefit values of Beijing, Tianjin and Shanghai have not reached 1, these regions can quickly develop rational use through appropriate adjustments. Although when used as the target city, Beijing did not present technical benefits, when considering the margins for data error and practical experience, Beijing has made contributions to carbon emissions.

　　Economies of scale reflect the efficiency brought by scale. Values equal to 1 indicate that the corresponding returns of scale are unchanged (optimal state). Values less than 1 indicate that the returns of scale have increased (if the scale is too small, it can be expanded to increase benefits). Values greater than 1 indicate that the returns of scale have decreased (if the scale is too large, it can be reduced to increase benefits). As shown in Figure 2, the scaled return values of Hainan and Ningxia have reached the optimal state. The scaled income values of Hebei, Hubei, Sichuan, Qinghai and Liaoning are 0.999, 0.897, 0.966, 0.953 and 0.966, respectively; these values are very close to 1, so the optimal state can be quickly achieved by appropriately adjusting the scale. The other regions need to strive to expand their scale and achieve the optimal state.

　　Return to scale analysis is used to study returns to scale according to returns to a scale coefficient (lambda value). If a return to scale coefficient is equal to 1, the corresponding return to scale remains unchanged (optimal state); if a return to scale coefficient is less than 1, the return to scale is increasing (if the scale is too small, it can be expanded to increase benefits); and if a return to scale coefficient is greater than 1, the return to scale is decreasing (if the scale is too large, it can be reduced to increase benefits). According to Figure 3, the scale returns of Hainan and Ningxia have reached the optimal state. Although the values of Hebei and Henan are 1.005 and 1.034, respectively, little control can be implemented to maintain the optimal state. The values of Hubei, Sichuan and Liaoning are 0.897, 0.966 and 0.967, respectively, indicating that these three regions are close to the optimal state, so a slight expansion of the scale can help them reach this state.
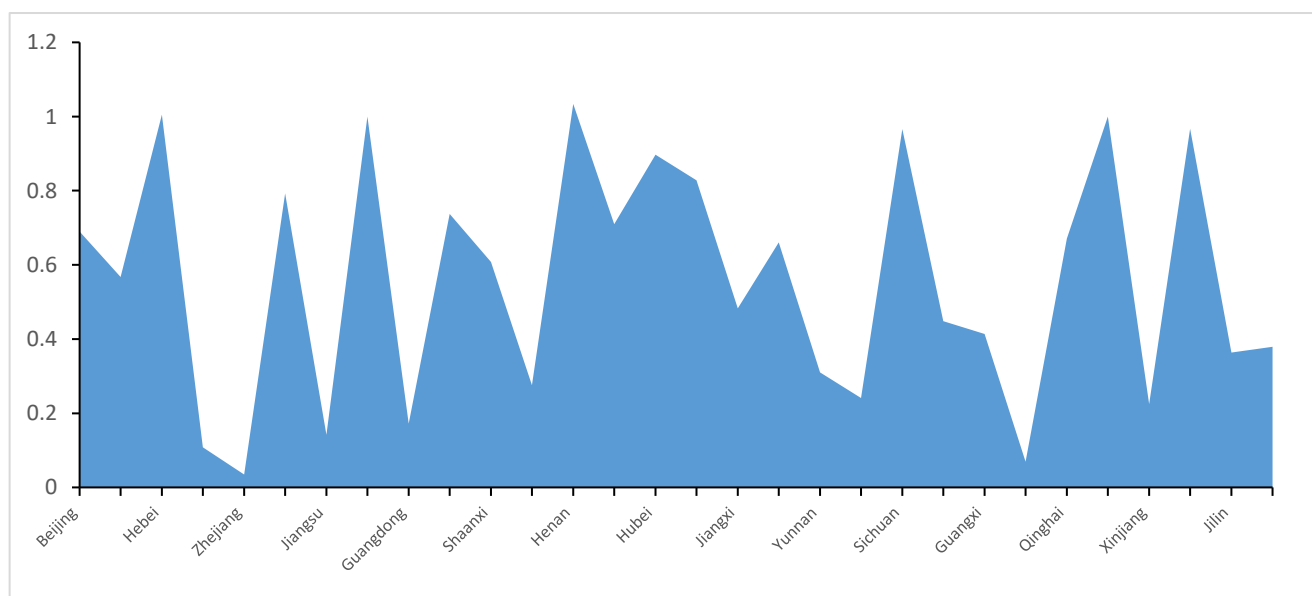


**Figure 3.** Return to scale analysis.

## 6. Conclusions

　　Based on 2015 data, this paper calculates the distribution of the 2025 carbon emission reduction targets of 30 provinces in China. A comprehensive comparison of the two examined allocation schemes shows that the DEA method mainly considers differences in regional environmental status and energy resource endowment between provinces. On

the other hand, the improved equal proportion allocation method takes the improvement of carbon emissions based on regional total carbon dioxide control as the standard and pays more attention to optimizing the overall relationship between regional economies and carbon emissions; moreover, this allocation scheme is relatively easy to implement. On the basis of fairness and efficiency, the improvement ratio method takes into account the development trends and carbon control policy guidance in different provinces and cities, which is different from the decomposition logic and margin focus of the original DEA method. The improvement ratio method can meet the carbon emission target decomposition requirements of provinces with different development characteristics. In addition, the data from the basis year are real data from the government, which is consistent with China's Five-Year Plan, and it shows the carbon emission reduction effect of real data. Therefore, a combination of these two methods can be used to better realize the sustainable development of a low-carbon economy.

According to the results of the equal proportion allocation method, Beijing, Tianjin, Hebei, Shandong, Zhejiang, Shanghai, Jiangsu, Guangdong and Inner Mongolia need to increase their emission reduction capacity, while Jiangxi, Guizhou, Gansu, Qinghai, Hainan and Guangxi have relatively low emission reduction targets. Recent research [14] has stated that Jiangsu and Zhejiang should actively promote and develop energy-saving and emissions reduction technologies to ease the pressure of $CO_2$ emissions reduction nationally.

According to the DEA distribution results, the technical benefits of Hainan, Henan, Qinghai and Ningxia are at a reasonable level, while those of Shandong, Jiangsu, Sichuan and Liaoning are relatively low; this indicates that the technical efficiency of these regions needs to be improved. Although the technical benefit values of Beijing, Tianjin and Shanghai are less than 1, the technical benefits of these regions could be developed to reach a reasonable level quickly through appropriate adjustments. As shown in Lu's (2022) research, resource allocation should be adjusted among different regions [24]. Therefore, even though all 30 provinces and cities have good comprehensive benefits, different countries should make adjustments based on their individual situation.

In contrast to those of previous studies [29,30], the total carbon allocation index of this paper covers social and economic indicators as well as environmental protection indicators. In addition to considering per capita cumulative carbon emissions, per capita GDP and carbon emissions per unit of GDP, this paper includes environmental protection input and fiscal revenue to ensure the rationality and comprehensiveness of the results. In summary, to ensure the realization of a carbon peak, China's 30 provinces and cities should strengthen their technological innovation according to the development conditions of their individual regions and promote rational energy, environmental and economic planning and integration. The goal of a carbon peak can be realized smoothly through a multidimensional system. For example, green investment, green financial planning and the establishment of a green economic growth mechanism should be supported.

*Policy Recommendations*

1.  Measures for local conditions should be adjusted, and resource endowments should be comprehensively considered. Reasonable carbon emission intensity indicators should be utilized, and the total carbon emissions of cities that exceed the overall national carbon emission intensity target should be controlled. The industrial transformation of cities that fail to meet the overall national carbon emission intensity target should be strengthened, and their industrial structure should be upgraded and adjusted. Such cities should be helped to achieve their expected goals as quickly as possible. The market orientation of green technology innovation systems should be actively established, the relevant basic theory and application research should be strengthened and support and guidance for the use of low-carbon technology should be provided.
2.  The carbon emission trading mechanism should be gradually improved, and regional collaborative emission reduction should be realized with the help of cross-provincial authority trading. A coordinated development plan is needed with attention to re-

gional differences and synergies in relation to a carbon peak. All regions should achieve the goal of a carbon peak in an orderly manner according to their own economic development levels, industrial structure and technical conditions. For example, the emission reduction targets and responsibilities for common progress based on the current coordinated development of Beijing, Tianjin and Hebei are mentioned.

3. A dynamic evaluation mechanism should be established. Although the targets of 30 provinces and cities have been reasonably assigned, dynamically adjusting the distribution model is conducive to ensuring the long-term sustainable development of carbon emission reductions. These carbon emission targets should be adjusted in a timely manner according to the regional development progress.

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