Inter-provincial responsibility allocation of carbon emission in China to coordinate regional development

Feng Wang 1 · Xing Ge 1

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Abstract
To establish the carbon emission trading scheme and achieve the carbon emission reduction goals in China, it is critical to allocate the carbon emission allowance (CEA). Using the entropy method and the modified fixed cost allocation model (MFCAM), we calculated the CEA and the carbon emission intensity (CEI) reduction targets of 30 Chinese provinces in 2030, from four principles (equity-efficiency-feasibility-sustainability) and three dimensions (economy-society-environment). The results are shown as follows. First, China’s total carbon emissions in 2030 calculated in this paper are 17567.9 Mt. Second, on the whole, CEA in China’s southeast half of the Hu line is higher than that in the northwest half. Eastern China has a larger final CEA than western China and central China. Third, Henan, Guangdong, Shandong, and Jiangsu are the four provinces with the most CEA, while Gansu, Qinghai, Ningxia, and Hainan are the four regions with the least carbon allowances. Fourth, the regions of Shanxi, Shaanxi, Xinjiang, Ningxia, Inner Mongolia, Guizhou, and Anhui will take on greater responsibility for carbon reduction in the future. On the contrary, the zones of Tianjin, Qinghai, Guangxi, Jilin, Yunnan, and Beijing will be able to sell CEA in the future. Fifth, provinces are divided into three categories from the perspective of CEI reduction. Finally, we put forward relevant policy recommendations based on the conclusions.

Keywords Carbon emission allowance · Entropy method · Modified fixed cost allocation model · Carbon emission intensity

Introduction
The sustainable development of contemporary human beings is facing the severe challenge of global warming. To cope with this challenge, countries around the world have made persistent efforts and implemented many mitigation and adaptation measures. As the second-largest economy and the largest carbon emitter in the world, China is facing huge pressure to reduce emissions (Zhang and Cheng 2009). The Chinese government has put forward a series of emission reduction policies and regarded energy conservation and emission reduction as a long-term national policy. In the Copenhagen Climate Change Conference, China promised it would reduce its CEI by 40–45% in 2020 compared to the level of 2005 (Cui et al. 2014). It marks that China has entered the era of quantitative control of carbon emission reduction. Furthermore, China pledges to peak CO2 emissions by around 2030 and strives to achieve it as soon as possible and by 2030 reduce CO2 per unit of GDP by 60–65% over the 2005 level (Qin et al. 2017).
Carbon markets and total carbon emission rights control are the main quantitative regulatory policy tools used by the Chinese government to promote low-carbon transition and achieve domestic environmental governance. The construction of the carbon market includes total amount design, sector coverage, the initial allocation of carbon emission rights, and the selection of trading targets. Among them, the initial carbon quota allocation is the core of the carbon market, which is the key to determining the effectiveness of the market and the emission reduction effect. Carbon emission allowance is free allocation dominated. China successively established carbon emission trading pilots in seven provinces and cities from 2013. In 2017, the national carbon market was officially

1 School of Economics and Finance, Xi’an Jiaotong University, Xi’an 710061, China

1 “Carbon Emission Trading Management Measures (Implementation)” released by the ministry of ecology and environment on December 31, 2020
launched, and the “baseline method” was proposed as the basis for carbon quota allocation. However, the allocation based on historical carbon emissions is likely to result in “whip the fast and hard working-unfair punishment” and reduce the efficiency of emission reduction (Feng and Lu 2016). By setting different baseline standards for each industrial process and technology type, the baseline approach overcomes the results of “whipping the cow” but can cause companies to stagnate at low levels of technology (Han et al. 2017). There is still room for improvement in the current way of allocating carbon allocations due to problems such as inefficiency and uncontrollable totals (Zhou et al. 2018).

China’s economy has stepped into the “new normal” phase. When China aims to achieve energy conservation and reduce emissions in coping with the problems in energy and environment, it also needs to address poverty, unemployment, and regional development gaps by promoting its economic growth. The green economy accompanied by energy-saving and emission reduction is a major opportunity and represents the direction of the future. It will not only drive high-quality economic development, but also has the potential to become a new source of economic growth.

Therefore, when formulating the CEA allocation scheme, we have to consider the constraint objectives comprehensively. It includes total greenhouse gas control, optimal carbon emission input-output efficiency, economic growth, energy structure upgrading, and industrial structure adjusting. Considering the diversity of objectives in reality, we integrate the “principles-dimensions” multi-criteria indicators, entropy method, and fixed cost allocation model (FCAM) to explore the CEA allocation method suitable for China’s national conditions.

First, we construct the indicator system from four principles and three dimensions. Concretely, the principles include equity, efficiency, feasibility, and sustainability. Dimensions include economic, social, and environmental. Then, we evaluate the “principles-dimensions” multi-criteria indicators using the entropy method. Finally, we embed the comprehensive value of the “principles-dimensions” multi-criteria indicators into the FCAM to obtain the MFCAM.

Thus, the MFCAM model can not only control the total amount of greenhouse gases but also achieve the optimal input-output efficiency of carbon emissions. It can also take into account economic growth, energy structure upgrading, and industrial structure adjustment, which is conducive to the implementation of the new development idea.

CEA is a scarce resource, how to effectively and rationally allocate inter-provincial CEA under the constraint of energy conservation, emission reduction, and economic growth? To answer this question is not only a practical problem that needs to be solved urgently in China’s practice of tackling climate change, but also a theoretical problem that needs to be settled in the climate change economics with Chinese characteristics. The CEA allocation approach explored in this paper has the following four main implications.

First, when China’s overall carbon emissions are approaching a peak, it is facing pressures from the control of overall carbon emissions and the upcoming absolute carbon emission reduction. Considering the negative externality of greenhouse gas emissions, the accomplishment of China’s emission reduction targets requires joint efforts from provinces, cities, and firms. Therefore, the allocation of inter-provincial CEA is an important measure to achieve emission reduction targets (Feng and Lu 2016).

Second, as the largest developing country, development is an absolute priority for China. Whereas there are significant differences among provinces in resource endowment, population distribution, economic development, input-output efficiency, and carbon efficiency, thus, reasonable and effective allocation of inter-provincial carbon emission rights is conducive to reduce the regional gap and promote sustainable development.

Third, the rational allocation of inter-provincial CEA urges regions to choose between increasing R&D investment and purchasing carbon emission rights. Carbon emission rights are scarce resources, and the increasing purchase on it will increase its price and finally pushes regions to focus on technological innovation for the maximum of their benefits.

Fourth, inter-provincial CEA can lay a fundamental role in establishing a perfect carbon trading market. From 2011 till now, China has opened the prelude of managing climate change with the participation in carbon trading market; to effectively control carbon emission, China has placed local pilots of carbon emission trading and constructed and improved the national carbon market. According to the Coase theorem, the initial allocation of carbon emission rights affects its trading efficiency, and the trading framework of CEA is an effective tool to stimulate and achieve energy conservation and emission reduction (Han et al. 2017). Therefore, a reasonable and effective inter-provincial CEA is conducive to improving the efficiency of carbon emission trading, which is the key to establish and improve China’s carbon emission trading market and realize the 2030 carbon emission reduction target (Zhou et al. 2018; Zhang et al. 2014).

This paper considers the multi-objective CEA allocation approach, which provides guidance and reference for the Ministry of Ecology and Environment to determine the total carbon emissions and develop allocation schemes. The method also guides provincial ecological and environmental authorities to allocate CEA in the region. In addition, the CEA allocation approach proposed in this paper is universal and can be applied to the responsibility allocation of emission reduction for other classes of pollutants, and it can also be extended to different allocation dimensions such as international, inter-municipal, sectoral, and enterprise.
The remainder of this paper is as follows. The “Literature review” section reviews the relevant literature. The “Methodology and data” section introduces the research model and data used in this paper. The “Results and discussion” section provides the empirical results and discussion. The “Conclusions and policy suggestions” section presents the conclusions with policy suggestions.

Literature review

The carbon emission right was originally defined by Dales as the right of a permit holder to emit pollutants to the environment within legally defined limits. Scholars have proposed many allocation principles of CEA, such as the principle of equity, the principle of efficiency, the principle of feasibility, and the principle of sustainability, where equity and efficiency principles are more common. They also introduced some main methods of CEA which include indicator method, game theory method, data envelopment analysis (DEA) method, and synthesis method.

The research on CEA based on equity perspective is earlier. The criteria of equity allocation include the principles of grandfathering, egalitarianism, the ability to pay, etc. Different criteria correspond to different indicators, but with the continuous development of research, different understandings of equity produced new criteria and indicators of equity distribution.

Rose regards equity as the equal right of all people to pollute and not to be polluted. Schmidt and Heitzig (2014) research CEA from the perspective of historical carbon emission. By comparing the distribution of inter-provincial CEA under the principle of grandfathering, egalitarianism, and the ability to pay, Wu et al. (2010) believed that ability to pay was a more appropriate standard. Zhou et al. (2013) concluded that population and historical carbon emission better reflect the principle of equity by comparing energy consumption, GDP, population, GDP per unit of capital, and historical carbon emission.

However, some scholars indicated that the allocation based on historical carbon emission will lead to insufficient incentives (Cui et al. 2014; Zhou et al. 2017; Zhou and Wang 2016). Pan et al. (2014) believe that carbon emission per unit of capital accumulation is a more appropriate indicator of CEA. Zhou and Wang (2016) calculate the CEA according to the GDP share of each region, which reflects the imbalance of regional development. Han et al. (2017) obtain CEA in the Beijing-Tianjin-Hebei region by constructing comprehensive evaluation indicators. Scholars hold different views on the pros and cons of the criteria and indicators of equity distribution. Although the principle of equity plays a vital role in CEA, absolute equity will discourage other provinces.

The principle of efficiency emphasizes the reduction of potential carbon emissions. In the case of the same carbon emission, regions with high carbon emission efficiency can achieve greater output (Ma et al. 2017). The input-output model is used to evaluate the efficiency of carbon emission, and the DEA model is a widely recognized method to evaluate the efficiency of multi-input and multi-output. Lins et al. established the zero-sum game DEA (ZSG-DEA) model based on the DEA model and combined with the idea of Zero-sum game. This method is suitable for a fixed amount of input variables. Comes and Lins (2008) study the CEA of countries related to the Kyoto Protocol based on the ZSG-DEA model. Zeng et al. (2016) use the ZSG-DEA model to optimize the CEA efficiency of China’s 30 provinces and cities, based on the premise of fixed overall carbon emissions and non-fossil energy consumption. Zhang and Hao (2017) evaluate the carbon emission efficiency of China’s 39 industrial sectors in 2020 by using the ZSG-DEA model.

However, the CEA will affect regional economic development. If we are only based on the principle of efficiency, it would bring negative effects on the future development of underdeveloped regions which is unfair.

Scholars are more and more concerned with the multi-principle of CEA for the multi-dimensional of the realistic target. CEA with the multi-principle can avoid the extreme results that may occur under a single principle. Yang et al. (2012) discuss the carbon emission reduction potential of different regions regarding the principles of equity and efficiency, based on the cluster analysis. Zhao et al. (2017) integrate the principles of equity and efficiency with the comprehensive indicator method to analyze the CEA of 41 sectors in China. Zhou et al. (2018) obtain the CEA of 71 Chinese cities by applying the DEA model to construct the comprehensive allocation coefficient. Zhou et al. (2018) calculate China’s 71 cities CEA by applying the DEA model to construct the comprehensive allocation coefficient. Li et al. (2018) study the CEA of the Pearl River Delta region by using population, GDP, and historical carbon emission to represent the principles of equity, efficiency, and feasibility, respectively. Although these scholars consider multiple principles of CEA, most of them adopt the proportional distribution or ZSG-DEA model in their methods. Wang and Li (2013) calculate China’s province CEA in 2010 by introducing population indicators in the fixed cost allocation model (FCAM). Fang et al. (2018) built an indicator system of equity, efficiency, feasibility, and sustainability, used factor analysis to calculate the weight of each province, and then found the CEA of China’s 31 provinces from 2016 to 2030. In a word, there is no consensus on the principles and indicators of CEA under the overall amount constraint.
Through the summary of the existing research, (1) we find that principles of equity, efficiency, feasibility and sustainability are relatively comprehensive at present. (2) The comprehensive indexes have been used widely, which can integrate different principles. (3) The ZSG-DEA model is used more extensively in CEA compared with the FCAM model. By comparing FACM and ZSG-DEA, both of them can allocate the overall fixed cost. The difference lies in that ZSG-DEA considers the efficiency of each decision-making unit (DMU) and makes all DMUs relatively effective through iteration, but FCAM regards the element with a fixed amount as new input, and its first two steps can be used to find countless solutions that make the decision unit reach the frontier. The solution iterated by the ZSG-DEA model many times is only one of the countless solutions of the FCAM model. The third step of FCAM selects the CEA that best meets the constraint conditions conforms. Theoretical analysis shows that the FCAM method has more advantages than the ZSG-DEA model.

Scholars have many differences in measuring principles and specific research methods and obtained different CEA due to different national backgrounds. Therefore, it is very important to explore a specific CEA method under China’s national conditions. China’s extensive development model in the past has led to high emissions, environmental damage, and regional imbalances. Green development is a key solution to saving energy, reducing emissions, increasing economic growth, and narrowing the imbalance. Since the 19th communist party of China’s national congress, coordinated regional development has become a national strategy, the core of which is to narrow the regional gap and pay attention to efficiency. Addressing climate change is an important opportunity for China to adjust its economic structure, transform its development mode, and accelerate a new round of industrial revolution. At this moment, any single-principle allocation of carbon emission rights will be biased, while the multi-criterion allocation of carbon emission is more conducive to promoting regional coordinated development. Also, because the integrated analysis uses a variety of methods or models, it can gather the advantages of a variety of methods, so problem analysis will be more comprehensive and systematic. Therefore, we combine the indicator method with the FCAM model as an integrated analysis.

To sum up, we take China’s 30 provinces as research objects and calculate the interval value of CEA of each province in China on the premise of achieving the maximum average value of carbon emission efficiency of each province in China. Then, we modify the FCAM model. We construct an indicator system that includes the four principles (equity-efficiency-feasibility-sustainability) and three dimensions (economy-society-environment). We use the entropy method to get the comprehensive value and embed the comprehensive value into the objective function of the third step of the FCAM. We get the Chinese province’s final CEA in 2030. Next, we calculated the Chinese province’s CEI in 2030 and the CEI reduction compared to 2015. Then, we compare the CEA in this paper with the results of CEA in reality for analysis. Finally, we divide regions into three categories according to CEI reduction.

The existing literature provides a reference for the further study of this paper. The innovations of this paper are as follows: (1) we construct 12 indicators from the four principles (equity-efficiency-feasibility-sustainability) and three dimensions (economy-society-environment). The indicator system constructed in this paper is more comprehensive than the existing research. (2) We modified the FCAM model by embedding multi-criteria principles and indicators into the original FCAM model. Through the literature review, we find that there are few studies of CEA based on the four principles of equity, efficiency, feasibility, and sustainability. Beasley (2003) FCAM first realizes the optimal of all the average efficiency of DMUs. Second, the fixed total cost is allocated through the proportion of proportional convergence, but the proportional convergence idea will expand regional differences. To solve this problem, we innovatively embed the “principle-dimension” multi-criteria index weighted by the entropy method into the objective function. Therefore, under the premise that all provinces reach the frontier, the results of CEA are closer to fairness, efficiency, feasibility, and sustainability. (3) By comparing the CEA in this paper with the actual CEA, we explore a CEA allocation approach, which is more conducive to coordinating regional development, providing a reference for subsequent research, and serving as a guide for the Ministry of Ecology and Environment to determine the overall carbon emissions and develop allocation schemes.

Methodology and data

Modified fixed cost allocation model

Beasley designed FCAM and divided it into three steps. FCAM takes the total fixed cost as input and aims to maximize the average efficiency of all DMUs. Based on the idea of proportional convergence, the overall fixed cost is distributed to all DMUs (Beasley 2003).

By reviewing the literature, we find that scholars made similar choices for input-output variables, but different treatments for carbon emission. There are two main ways. The first one adheres to the economic production process and treats carbon emission as an undesired output. The other one regarded overall carbon emissions as a limited
resource, so CEA is an input variable (Gomes and Lins 2008). Here we choose the second treatment method. In the FCAM model, the input variable is CEA, and the output variables are GDP, population, energy consumption, and capital stock, respectively. The implication is that regions with higher GDP, population size, energy consumption, and capital stock are more efficient under the same CEA.

In step 1, we take overall carbon emissions as fixed costs to be allocated. Therefore, the input variable of FCAM is the CEA. GDP, population, energy consumption, and capital stock are output variables. China has fixed overall carbon emissions. We use Equation (1) to determine the max average value of the input-output efficiency of China’s province.

\[
\max \sum_{p=1}^{N} \frac{E_p}{n} \left( \frac{\sum_{i=1}^{s} \alpha_i y_{ip}}{\sum_{j=1}^{t} \beta_j x_{jp} + f_p} \right) = e_p
\]

\[
0 \leq e_p \leq 1 \\
\sum_{p=1}^{N} f_p = F \\
f_p = F_p \quad \forall p \in S \\
f_p \geq 0 \quad p = 1, 2, \ldots, n \\
\alpha_i \geq \epsilon \quad i = 1, 2, \ldots, s \\
\beta_j \geq \epsilon \quad j = 1, 2, \ldots, t
\]

Among them, \( e_p \) is the efficiency value of DMU \( p \) \((p=1, 2, \ldots, n)\). In this paper, DMU refers to provinces. \( N \) is equal to 30, representing 30 provinces. Each DMU has \( t \) input variables and \( s \) output variables. We take \( t=1 \), that is, the input variable is the carbon emission allowance. We take \( s=4 \), that is, the output variables are GDP, population, energy consumption, and capital stock, respectively. \( y_{ip} \) stands for output \( i \) \((i=1, 2, \ldots, s)\) of DMU \( p \), \( x_{jp} \) refers to input \( j \) \((j=1, 2, \ldots, t)\) of DMU \( j \). \( \alpha_i \) is the weight of output \( i \), and \( \beta_j \) is the weight of input \( j \). The set \( S \) contains all DMUs assigned. \( F \) is China’s total carbon emission rights for 2030 to be allocated to provinces, and \( f_p \) is the carbon emission rights allocated to the province \( p \). \( F_p \) is the result of the allocation of the DMU \( p \) in the set \( S \), and \( \epsilon \) is Archimedean infinitely decimal, with a general value of \( 10^{-6} \). We set the optimal solution of the objective function in Equation (1) which is \( \frac{\sum_{p=1}^{N} E_p}{N} = E^* \).

In step 2, we use the optimal solution of Equation (1) as a constraint in the subsequent optimization process to ensure that the average efficiency value of each province in China does not decrease. Then, we use Equation (2) to solve the \( \max f_p \) and the \( \min f_p \) of the province \( p \)’s CEA.

\[
\max f_p \left( \min f_p \right)
\]

\[
\left( \frac{\sum_{i=1}^{s} \alpha_i y_{ip}}{\sum_{j=1}^{t} \beta_j x_{jp} + f_p} \right) = e_p
\]

\[
0 \leq e_p \leq 1 \\
f_p = F_p \quad \forall p \in S \\
\sum_{p=1}^{N} f_p = F \\
f_p \geq 0 \quad p = 1, 2, \ldots, n \\
\alpha_i \geq \epsilon \quad i = 1, 2, \ldots, s \\
\beta_j \geq \epsilon \quad j = 1, 2, \ldots, t
\]

In the optimal solution of the objective function in Equation (2), the abbreviated minimum optimal solution is \( L_p \), and the maximum optimal solution is \( U_p \). So DMUs have \( L_p \leq f_p \leq U_p \). Since the optimization of Equation (2) tends to maximize the efficiency of each DMU, that is, \( f_p \) tends to \( L_p \), the result is that China’s overall carbon emission rights \( F \) cannot be allocated completely. To solve this problem, Beasley proposes the idea of proportional convergence, that is, the ratio of \( f_p \) is as the same as possible in \([L_p, U_p]\).

In step 3, fixed costs are allocated based on the idea of proportional convergence, according to the results of the first two steps. Define \( Q_{\text{max}} \) and \( Q_{\text{min}} \) as the maximum/minimum proportion, over and above its minimum fixed cost \( L_p \), paid by any DMU \( q \) within its acceptable range \([L_p, U_p]\).

\[
\min (Q_{\text{max}} - Q_{\text{min}})
\]

\[
\frac{Q_{\text{max}} \geq \left( f_p - L_p \right) \left( U_p - L_p \right)}{Q_{\text{min}} \geq \left( f_p - L_p \right) \left( U_p - L_p \right)} \\
\frac{\sum_{i=1}^{s} \alpha_i y_{ip}}{\sum_{j=1}^{t} \beta_j x_{jp} + f_p} = e_p
\]

\[
0 \leq e_p \leq 1 \\
\sum_{p=1}^{N} f_p = F \\
f_p \geq 0 \quad p = 1, 2, \ldots, n \\
\alpha_i \geq \epsilon \quad i = 1, 2, \ldots, s \\
\beta_j \geq \epsilon \quad j = 1, 2, \ldots, t
\]

However, the distribution result obtained by Equation (3) based on the idea of proportional convergence will widen the gap between high-performance DMUs and low-performance DMUs (Elzen et al. 2005). To solve this problem, based on FCAM, Wang and Li (2013) replaced the idea of proportional convergence with the principle of per capita convergence, to
make the final distribution result as fair as possible. However, this constraint only reflects the principle of equity, but it fails to consider the principles of feasibility and sustainability.

Based on the approach of Wang and Li, we further modify the third step of the FCAM model. Equation (4) is the third step of the MFCAM model, which considers the four principles (equity-efficiency-feasibility-sustainability) and three dimensions (economy-society-environment) as comprehensive indicators into the objective function. It makes the ultimate carbon emission allowance for China’s province that becomes more reasonable.

Among them, \( \delta_p = c'_p / F \), and \( c'_p \) is the CEA of province \( p \) that uses the entropy method to weight the “principle-dimension” multi-criteria. The objective function of Equation (4) \( \min \sum_{p=1}^{n} \frac{f_p}{F} \delta_p \) ensures that the CEA is as close as possible to the principles of equity, efficiency, feasibility, and sustainability on the premise of achieving the optimal average value of overall efficiency.

“Principle-dimension” multi-criteria indicator system

Compared with a single-standard CEA scheme, multi-standard indicators can systematically reflect common but differentiated responsibilities. Referring to the existing literature (Fang et al. 2018; Fang et al. 2019; Yi et al. 2011; Feng et al. 2018; Han et al. 2016), we allocated the inter-provincial CEA from the perspective of four principles (equity-efficiency-feasibility-sustainability) and three dimensions (economy-society-environment). The explanation is as follows.

The principle of equity includes three aspects. First, from a regional economic development standpoint, there are differences in the economic level between developed and underdeveloped areas. Therefore, the developed regions should be given more CEA to keep production consistent. Second, in terms of human needs, everyone has the same rights to products and services. Thus, the populous province should be assigned more CEA. Third, from the perspective of grandfathering, CEA allocation should avoid the impact of substantial emission reductions on development. In summary, we choose GDP, population, and historical carbon emission to represent the economic, social, and environmental dimensions of the equity principle, respectively.

The principle of efficiency means that greater output can be achieved under the same CEA. The essence of the efficiency principle is that CEA flow from low-efficiency areas to high-efficiency areas (Ma et al. 2017). So, we need to consider the differences in energy efficiency, technical level, and energy consumption structure among provinces. For example, the lower the energy efficiency, the greater the potential for emission reduction under the current technological level, and emission reduction can be prioritized. Hence, we choose energy efficiency, the number of patent applications granted, and the proportion of coal consumption to represent the economic, social, and environmental dimensions of the efficiency principle, respectively.

The principle of feasibility means that the distribution of carbon emission rights should take the actual conditions of each region into account; it can ensure that the production, ecology, and life of each DMUs are not affected. Meanwhile, it refers to the issue of emission reduction costs and adaptability. For example, when we are considering factors such as economic driving methods, financial payment capacity, and ecological environment quality, the allocation of carbon emission rights should be within a tolerable range. We choose energy consumption elasticity, general public budget revenue, and carbon emission carrying capacity to represent the economic, social, and environmental dimensions of the feasibility principle, respectively. Among them, the smaller the elasticity coefficient of energy consumption, the stronger the adaptability of regional emission reduction. The greater the fiscal revenue, the greater the ability of the region to undertake the task of emission reduction. The greater the carbon carrying capacity, the greater the ability of the province to absorb CO2.

The principle of sustainability refers to the ability of an ecosystem to maintain its productivity even after a shock, taking into account whether the economic, social, and environmental conditions of the abatement costs can bear the cost of abatement and achieve sustainable development. We choose the advanced stage of industry structure, urbanization rate, and investment in anti-pollution projects as a percentage of GDP to denote the economic, social, and environmental dimensions of the sustainability principle, accordingly, in which the advanced stage of industry structure reflects the transformation of industrial structure, and the research results have shown that the upgrading of industrial structure helps to achieve sustainable development. Cities are places where resources are used efficiently, and the increase of urbanization
rate helps to achieve sustainable development goals. The proportion of investment in anti-pollution projects as a percentage of GDP reflects the importance of environmental protection in different provinces.

In summary, we selected 12 indicators under the four principles, three dimensions, and multiple criteria to build a multi-criteria indicator system for the CEA (see Table 1).

The entropy method

The entropy method can evaluate the influence of multiple factors comprehensively. Its principle is as follows. The greater the entropy of the index, the more information it carries, and thus the weight in the comprehensive evaluation is greater. The weighting process of the entropy method is relatively objective, so the result has more reference value (Shannon 1949). The specific steps of this method are as follows.

The first step is to standardize the raw data. Due to the dimension difference of the original data, we use Equation (5) to standardize the original data and make it become dimensionless standardized data.

\[
y_{pq} = \begin{cases} 
\frac{x_{pq} - \min(x_q)}{\max(x_q) - \min(x_q)}, & \text{for the positive indicator} \\
\frac{\max(x_q) - x_{pq}}{\max(x_q) - \min(x_q)}, & \text{for the positive indicator}
\end{cases} \tag{5}
\]

Among them, \(x_{pq}\) (\(p=1, 2, \ldots, n; q=1, 2, \ldots, m\)) is the original data, \(n\) is the number of samples, and \(m\) is the number of indicators. We take \(n\) as 30, representing 30 provinces. We take \(m\) as 12, representing 12 indicators. \(\max(x_q)\) and \(\min(x_q)\) are the maximum and minimum values of the \(q^{th}\) indicator, respectively, and \(y_{pq}\) is the standardized data.

The second step is to calculate the information entropy value \(e_q\) of each indicator by Equation (6) and (7).

\[
u_{pq} = \frac{y_{pq}}{\sum_{p=1}^{n} y_{pq}} \tag{6}
\]

\[
e_q = \frac{\sum_{p=1}^{n} u_{pq} \ln u_{pq}}{\ln(n)} \tag{7}
\]

The third step is to calculate the weight \(w_q\) of each indicator by Equation (8).

\[
w_q = \frac{1-e_q}{m-\sum_{q=1}^{m} e_q} \tag{8}
\]

The fourth step is to calculate the comprehensive score \(h_p\) of each province by Equation (9).

\[h_p = \sum_{q=1}^{m} w_q y_{pq} \tag{9}\]

Data

GDP

China’s GDP growth rate in 2019 was 6.1%, as China’s economy entered a new normal. The potential economic growth rate will slow down because of the decline in the total fertility rate and the aging population will supply-side factors (Li et al. 2020a). Drawing on their estimated results of China’s potential GDP growth rate from 2020 to 2030\(^2\), we predict China’s provincial GDP in 2030, assuming that the potential GDP growth rate of each province is equal to China’s potential GDP growth rate. The data comes from the National Bureau of Statistics of China.

Population

The methods of predicting population mainly include the exponential model, logistic population growth model, Leslie matrix economic model, and cohort-component method. The cohort-component method uses a specific year as the base year and calculates the population size and structure of the next year through fertility rate, death rate, and emigration rate (a small proportion) by age groups recursively. Referring to the practice of Shang et al. (2016), we use the cohort-component method to predict population. This method has four steps. First, estimate the future surplus of the age-specific population. Second, calculate the number of births. Then, calculate the future margin of the birth population. Finally, calculate the number of people in the coming years. The data comes from the National Bureau of Statistics of China. Besides, we refer to the 2013 China Population and Development Research Center’s “National Survey of Fertility Willingness” in 29 provinces.

Energy consumption

The Energy Production and Consumption Revolution Strategy (2016–2030) proposes to limit China’s total energy consumption to less than 6 billion tons of standard coal by 2030, assuming that China’s total energy consumption in 2030 is 6 billion tons of standard coal, and the energy consumption proportion of China’s province in 2030 is equal to the average value of the 2013–2017 proportion. We estimate the energy consumption of China’s province

\(^2\) The predicted values of China’s potential economic growth rate from 2020 to 2030 are 5.7%, 5.83%, 5.58%, 5.42%, 5.33%, 5.21%, 5.13%, 4.94%, 4.78%, 4.74%, and 4.62%.
in 2030. The data comes from the *China Energy Statistical Yearbook (2014–2018).*

**Capital stock**

Regarding the measurement of capital stock, the more recognized method is the perpetual inventory method initiated by Goldsmith. The principle is that capital stock is the weighted sum of past investments, assuming that the relative efficiency of capital goods is geometrically decreasing, and the replacement rate is equal to the depreciation rate. We use Equation (10) to estimate the capital stock.

\[ K_t = I_t + (1 - \delta_t)K_{t-1} \quad (10) \]

Among them, \( K_t \) and \( K_{t-1} \) represent the capital stock in year \( t \) and \( t-1 \), respectively. It is the new investment in year \( t \), and \( \delta_t \) represents the capital depreciation rate in year \( t \). Shan (2008) estimated the capital stock of China’s province from 1952 to 2006. On this basis, we used Equation (10) to calculate the capital stock of China’s province from 2007 to 2017 and converted it into a constant price in 2000. The total fixed capital formation and fixed asset formation price index were obtained from the National Bureau of Statistics of China. Finally, we use the GM (1,1) model to predict the capital stock of China’s province from 2018 to 2030.

**Initial carbon emission allocation**

According to the IPCC guidelines, the historical carbon emission calculation of fossil fuel combustion is shown in Equation (11).

\[ CE_{ij} = AD_{ij} \times NCV_i \times CC_i \times O_{ij} \quad (11) \]

Among them, \( CE_{ij} \) refers to the carbon emission of sector \( j \) burning fossil fuel \( i \), and \( AD_{ij} \) represents the consumption of sector \( j \) burning fossil fuel \( i \). \( NCV_i \) refers to the calorific value per unit of fossil fuel \( i \) combustion. \( CC_i \) refers to the carbon emission contained in each net calorific value produced by fossil fuel \( i \). \( O_{ij} \) refers to the oxidation efficiency from fossil fuel \( i \) burned in sector \( j \). We refer to the research of Shan et al. (2018) about carbon emission from fuel combustion. It included 47 sectors and 26 types of fossil fuels. The fossil fuel loss during transportation and conversion and non-energy use of fossil fuel as raw material were removed from the total fossil fuel consumption to avoid double counting. Our historical carbon emission data comes from China Emission Accounts & Datasets[^3]. In 2015, the Chinese government proposed a goal of reducing CEI by 60–65% compared to 2005 (Qin et al. 2017). Regarding the initial value of carbon emission in 2030, any fixed allocation value of the total amount of

[^3]: [http://ceads.net](http://ceads.net)
carbon emission rights can be selected. Here, we take another approach, assuming that the proportion of the initial carbon emission of China’s province in 2030 is consistent with the average of the proportion from 2011 to 2015, and the China’s province CEA in 2030 is calculated as the initial value of the optimization function.

China’s overall carbon emission forecast in 2030

The Chinese government proposed to achieve peak carbon emission no later than 2030 and lower CEI by 60–65% compared to that in 2005. The determination of overall carbon emission reduction targets in 2030 is a prerequisite for the CEA of China’s province. Referring to Li et al.’s paper (2020b), we set a 65% reduction target in CEI. Then, the CEI reduction target is converted to the overall carbon emissions target. We calculate the overall carbon emissions by Equations (12) and (13):

\[
CEI_{2005} = \frac{CEA_{2005}}{GDP_{2005}} \quad (12)
\]

\[
CEA_{2030} = CEI_{2005} \times GDP_{2030} \times (1-65\%) \quad (13)
\]

where \(CEI_{2005}\) represents the CEI in 2005. \(CEA\) and \(GDP\) represent overall carbon emissions and gross domestic product in the year \(t=2015\) to 2030, respectively.

First, according to Equation (12), we calculated that China’s CEI in 2005 was 2.92 t/10 thousand yuan. Secondly, under the goal of achieving a 65% reduction in CEI by 2030, the target for China’s CEI in 2030 is calculated to be 1.02 t/10 thousand yuan. We refer to the latest results of the Macroeconomic Research Center of the Chinese Academy of Social Sciences and calculate that China’s GDP in 2030 is 171911.55 billion yuan. Finally, we use Equation (13) to calculate China’s overall carbon emissions in 2030 which is 17567.9 Mt.

“Principles-dimensions” multi-criteria indicators

Table 2 shows the data sources for the multi-criteria indicators. We select the average value of each indicator from 2011 to 2015 and apply the entropy method to calculate the multi-criteria CEA of China’s province.

The forecast results of input-output indicators of MFCAM

Through the above calculations, we get the input and output variables value of the MFCAM model. Table 4 shows the forecast results of GDP, population, energy consumption, capital stock, and initial carbon emission of Chinese provinces in 2030.

Results and discussion

Inter-provincial CEA under the “principles-dimensions” multi-criteria

We calculate China’s province CEA from the four principles (equity-efficiency-feasibility-sustainability) and three...
dimensions (economy-society-environment). As can be seen from Fig. 1, overall, CEA in the southeast half of the Hu line\textsuperscript{4} is higher than that in the northwest half under the "principles-dimensions" multi-criteria.\textsuperscript{5}

**Final CEA of China’s province under the MFCAM model**

We calculate the final CEA of China’s province by using the MFCAM model. This model can be divided into three steps. In the first step, we calculated the optimal average efficiency of all China’s province which is $E^* = 1$ through Equation (1). In the second step, we calculated the $L_p$ and $U_p$ of China’s province CEA under the constraint of the optimal average efficiency value of Equation (2) (see Fig. 2). In the third step, we calculated the final CEA using the MFCAM model embedded with “principles-dimensions” multi-criteria. First, we take $L_p$ and $U_p$ of China’s province CEA calculated by Equation (2) as the constraints of Equation (4). Secondly, we embed the “principle-dimension” multi-criterion CEA of China’s province into the objective function of Equation (4). Finally, we obtained the final CEA of China’s province in 2030 (see Fig. 2).

The position of the triangle in Fig. 2 represents the final CEA of China’s province in 2030. As can be seen from Fig. 2, Henan, Guangdong, Shandong, and Jiangsu are the four provinces with the most final CEA in 2030, all exceeding 1000 Mt. Similar to the conclusion of Kong et al. (2019). We conclude that the CEA of Guangdong province accounts for 7.4% of China’s overall carbon emissions, which is about 1299 Mt, because Guangdong province has an advanced economic development model, a large population (about 8% of China’s population), and high energy efficiency. Gansu, Qinghai, Ningxia, and Hainan are the four regions with the least final CEA in 2030. Among them, Hainan has the smallest CEA, accounting for 0.7% of China’s overall carbon emissions, which is about 123 Mt, because the population of Hainan accounts for only 0.66% of China’s population, and its carbon emission capacity is relatively weak.

We calculated the proportion of the final CEA for eastern, central, and western China under the MFCAM model in 2030. Among them, eastern China received the most final CEA, about 8537 Mt, accounting for 48.6% of China’s overall carbon emissions. Western China received the second-highest final CEA, about 4933 Mt, accounting for 28.1% of China’s overall carbon emissions. Central China received the least final CEA, about 4098 Mt, accounting for 23.3% of China’s overall carbon emissions.

**Comparison between the CEA based on historical emissions in reality and the carbon allowance results in this paper**

Nowadays, the carbon market uses historical carbon emissions as the main allocation basis. To compare the actual CEA with the CEA in this paper, we calculate the results of CEA for each province in 2030 based on the average of historical carbon emissions from 2011 to 2015 (see Fig. 3).

Theoretically, the MFCAM model has advantages over others. The reasons are as follows. Most methods directly calculate the specific value of CEA. However, the MFCAM model first calculates the interval value of CEA for each province that achieves the optimal control of total carbon emissions and input-output efficiency. Then, in the interval value of each province’s CEA, we use the “principle-dimension” multi-criteria comprehensive value to constrain the final CEA result, which is more fair, efficient, feasible, and sustainable.

On a practical level, we use data to verify four aspects, including equity, efficiency, feasibility, and sustainability. From the perspective of fairness, we calculated the standard deviation and Gini coefficient of the two distributions. First, the standard deviation of the CEA by historical emissions is 431.97, and that of the CEA in this paper is 319.23. Second, the Gini coefficient of CEA by historical emissions is 0.38, and that of CEA in this paper is 0.29. The results of both indicators show that the inter-provincial CEA inequality in this paper is lower than the CEA by historical emissions. We

\textsuperscript{4} Also known as the Heihe-Tengchong line, proposed by Hu Huanyong in 1935

\textsuperscript{5} The map is based on the standard map of GS (2016) 2885 downloaded from the standard map service website of the National Bureau of Surveying, Mapping, and Geographic Information, and the bottom map is not modified. Among them, the data of Tibet, Hong Kong, Macao, and Taiwan are missing. The same below.
can see that the fairness of this paper’s CEA is better than that of the CEA by historical emissions.

In terms of efficiency, we use the ZSG-DEA model to calculate the efficiency values of CEA by historical emissions for China’s province in 2030 and this paper’s CEA respectively (see Fig. 4). The average efficiency of CEA by historical emissions for provinces in China is 0.79, and that of CEA for China’s provinces in this paper is 1. We find that the efficiency of the CEA in this paper is better than that of the CEA by historical emissions.

In terms of feasibility, under the historical emission standard, the highest provincial CEA is 1934.87Mt, and the lowest provincial CEA is 89.66Mt. The highest CEA is about 22 times the lowest CEA, and this allocation may be difficult to implement. The CEA of the highest province in this paper is 1363.76Mt, and the lowest value is 123.08Mt; the highest CEA is about 11 times the lowest. Since the 19th National Congress, the regional coordinated development has been elevated to a national strategy, and the core of the strategy is to focus on efficiency while reducing regional disparities. Therefore, the reality of CEA, which is based on historical emissions as a division, is biased in feasibility.

From the viewpoint of sustainability, the per capita CEA of each province by historical emissions in 2030 is 0.134, and its average CEI is 0.015. At the same time, the per capita CEA of each province derived in this paper is 0.129, and the corresponding average CEI is 0.014. Through the above calculation results, the average values of per capita CEA and CEI divided by historical emissions are greater than those calculated in this paper. In terms of the average value for each province, the average value of CEA per unit of GDP for each province is smaller and that of CEA per capita for each province is also

| Province  | GDP (100 million yuan) | Population (10 thousand persons) | Energy consumption (10 thousand tons of SCE) | Capital stock (100 million yuan) | Initial value of carbon emission (Mt) |
|-----------|------------------------|----------------------------------|--------------------------------------------|---------------------------------|---------------------------------------|
| Beijing   | 61819.0                | 2471.0                           | 9255.6                                     | 162306.1                       | 143.0                                 |
| Tianjin   | 24650.3                | 1674.3                           | 10880.0                                    | 366455.9                       | 215.0                                 |
| Hebei     | 61352.7                | 8572.6                           | 39864.7                                    | 429391.1                       | 1010.7                                |
| Shanxi    | 29757.8                | 4229.2                           | 26428.4                                    | 202481.9                       | 1920.7                                |
| Inner Mongolia | 30082.6 | 2892.5                           | 25276.3                                    | 387498.8                       | 1287.6                                |
| Liaoning  | 43534.7                | 4891.1                           | 28934.7                                    | 297432.3                       | 831.9                                 |
| Jilin     | 20495.2                | 3096.4                           | 11115.9                                    | 303494.8                       | 388.6                                 |
| Heilongjiang | 23791.1 | 4288.9                           | 16296.5                                    | 235264.9                       | 583.6                                 |
| Shanghai  | 66684.7                | 2756.9                           | 15395.1                                    | 140919.0                       | 266.4                                 |
| Jiangsu   | 174127.6               | 9015.1                           | 40709.4                                    | 615450.4                       | 991.1                                 |
| Zhejiang  | 108973.2               | 6452.3                           | 26372.0                                    | 334178.3                       | 613.2                                 |
| Anhui     | 64864.7                | 7106.6                           | 16564.8                                    | 299243.9                       | 585.0                                 |
| Fujian    | 74094.4                | 4528.1                           | 16278.7                                    | 428332.6                       | 343.6                                 |
| Jiangxi   | 43269.1                | 5340.4                           | 11204.9                                    | 172410.7                       | 249.4                                 |
| Shandong  | 124205.9               | 11297.1                          | 50202.0                                    | 704702.5                       | 1577.9                                |
| Henan     | 94829.7                | 10911.2                          | 30590.7                                    | 853971.2                       | 918.6                                 |
| Hubei     | 80094.9                | 6659.3                           | 22104.7                                    | 446281.0                       | 443.7                                 |
| Hunan     | 69475.4                | 7751.8                           | 20833.1                                    | 383052.8                       | 418.6                                 |
| Guangdong | 188178.5               | 13066.6                          | 40691.7                                    | 732021.3                       | 800.9                                 |
| Guangxi   | 37116.5                | 5552.0                           | 13113.5                                    | 382427.6                       | 289.3                                 |
| Hainan    | 9278.5                 | 1070.6                           | 2567.8                                     | 76946.0                        | 89.7                                  |
| Chongqing | 41256.2                | 3346.3                           | 11876.7                                    | 191967.4                       | 230.3                                 |
| Sichuan   | 81471.2                | 9171.3                           | 26876.9                                    | 325526.1                       | 480.9                                 |
| Guizhou   | 29308.1                | 4030.0                           | 13314.2                                    | 243419.2                       | 479.3                                 |
| Yunnan    | 40588.5                | 5483.2                           | 14113.8                                    | 448635.2                       | 300.0                                 |
| Shaanxi   | 45079.1                | 4351.5                           | 15595.8                                    | 312724.4                       | 794.1                                 |
| Gansu     | 15237.1                | 3030.1                           | 9983.6                                     | 109569.1                       | 279.4                                 |
| Qinghai   | 5183.6                 | 679.9                            | 5418.0                                     | 128985.0                       | 96.3                                  |
| Ningxia   | 6551.3                 | 797.8                            | 7281.3                                     | 116667.4                       | 303.0                                 |
| Xinjiang  | 23763.9                | 2758.0                           | 20859.0                                    | 241845.4                       | 636.3                                 |
Fig. 1 Provincial CEA based on “principles dimension” multi-criteria in 2030.

Fig. 2 Provincial final CEA in 2030 based on MFCAM
smaller under this paper. The key to sustainable development is to change the development mode, indicating that the CEA in this paper better reflects the intensive economic growth mode.

All in all, the CEA allocation approach proposed in this paper takes into account the constraint objectives of total GHG control, optimal carbon emission input-output efficiency, economic growth, energy structure upgrading, and industrial structure adjustment, and it is more conducive to promoting coordinated regional development.

Provinces classification based on final CEA

According to the final CEA of China’s province in 2030 under the MFCAM model (see Fig. 2), we calculated the CEI for China’s province in 2030 and compared them with the data in 2015. Finally, we calculated the CEI reduction tasks that China’s province needs to complete in 2030 compared to 2015. Figure 5 a shows the distribution results of China’s province CEI in 2015. Among them, regions of Shanxi, Ningxia, Xinjiang, and Inner Mongolia have larger CEI. As a large province of energy and carbon emission, Shanxi has the highest CEI, about 11.550 t/10 thousand yuan. The pillar industries of Shanxi province are coal and steel, which are the industries of high energy consumption, high pollution, and high emission. Among them, coal and non-fossil fuels account for 90% and 3% of total energy consumption, respectively. Although Ningxia has actively carried out coal equivalent and reduction substitution in recent years and vigorously developed renewable energy, the continuous growth of investment in the Ningdong base, the high carbon emission characteristics of energy and industrial structure still appear.

Xinjiang shows high energy consumption and underutilized in the process of industrialization and urbanization. Inner Mongolia is also a large energy region, rich in mineral resources, with a significant coal consumption proportion, high energy consumption, and high emission. Its economic development is highly dependent on energy consumption. What is more, China’s southeastern coastal provinces CEI was uniformly low, which are the country’s most economically developed regions. In 2015, the CEI of Beijing, Tianjin, Shanghai, and Guangdong were 0.362 t/10 thousand yuan, 0.498 t/10 thousand yuan, 0.644 t/10 thousand yuan, and 0.696 t/10 thousand yuan, respectively. The emphasis of economic development in the southeast coastal areas is to transform industrial technology and develop new and technology-intensive industries. Therefore, the production process consumes fewer resources.

Figure 5 b shows the distribution results of China’s province CEI in 2015. CEI of northern China is generally higher. For example, Qinghai and Ningxia have the highest CEI, with 3.82 t/10 thousand yuan and 2.92 t/10 thousand yuan, respectively. CEI of southern China is generally lower. Among them, Shanghai’s CEI is relatively low, about 0.44 t/10 thousand yuan. The province of Beijing, Zhejiang, Jiangsu, and Guangdong also have low CEI (0.47 t/10 thousand yuan, 0.59 t/10 thousand yuan, 0.64 t/10 thousand yuan, and 0.69 t/10 thousand yuan, respectively).

To know the carbon emission reduction tasks of China’s province, we calculated the CEI reduction in 2030 compared with 2015. The results are shown in Fig. 6. From 2015 to 2030, Guangdong, Fujian, and Henan show little changes in CEI, whereas, Shanxi, Shaanxi, Xinjiang, Ningxia, Inner Mongolia, Guizhou, and Anhui have seen their CEI decline by more than 50%, and these provinces will take on a greater responsibility to reduce carbon emission in the future. In contrast, CEI is increasing in Tianjin, Qinghai, Guangxi, Jilin, Yunnan, Beijing, Hunan, and Hubei, which will be able to sell CEA to other provinces in the future.

We use the natural breakpoint method to classify China’s provinces into category A, category B, and category C.

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Fig. 3 Comparison of CEA by historical emissions and this paper in 2030

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6 The natural breakpoint method can minimize the difference with class and maximize the difference between classes by grouping similar values appropriately.
Fig. 4 CEA efficiency values by the province in China in 2030

according to the CEI reduction. Among them, the CEI reduction in category A is less than −34.2%, including one province, namely Tianjin, with a small emission reduction task. The reduction in category B is between −34.2 and 1%, including 10 regions, namely Qinghai, Guangxi, Jilin, Yunnan, Beijing, Hunan, Hubei, Fujian, Guangdong, and Henan, with moderate emission reduction tasks. The CEI of category C decreased between 1 and 87.7%. This category includes 19 regions, namely Chongqing, Sichuan, Heilongjiang, Jiangxi, Hainan, Liaoning, Jiangsu, Shanghai, Zhejiang, Hebei, Shandong, Gansu, Anhui, Guizhou, Inner Mongolia, Ningxia, Xinjiang, Shaanxi, and Shanxi, with a large emission reduction task.

Whereas large emission reduction tasks do not mean high emission reduction pressure, regions with large emission reduction tasks should seize the opportunity of green development. Evidence from developed countries shows that it is possible to significantly reduce emissions without reducing long-term growth. Environmental improvement and economic growth can complement each other to some extent. That is, high economic growth and low-carbon emissions can be achieved simultaneously and mutually reinforcing.

Conclusions and policy suggestions

Based on the realization of China’s carbon emission reduction target in 2030, we use MFCAM to study China’s provincials CEA from “principle-dimension” multi-criteria. First, we turned the target from CEI reduction into China’s overall carbon emissions in 2030. Secondly, on the premise of achieving China’s 2030 carbon emission reduction target, we construct the indicators system and use the entropy method to obtain the comprehensive value, from four principles and three dimensions. Thirdly, we modified the FCAM model, embed the comprehensive value of the “principle-dimension” multi-criteria into the objective function of the FCAM model, and calculated China’s province final CEA in 2030 by using MFCAM. Then, we compared and analyzed the final CEA obtained in this paper with the results in reality. Finally, we measured China’s province CEI in 2030 and the reduction of CEI in 2030 compared to 2015. The main conclusions are as follows.

First, when China’s CEI in 2030 is 65% lower than that in 2005, we conclude that China’s overall carbon emissions in 2030 will be 17567.9 Mt.

Second, we used the entropy method to calculate the CEA of China’s province in 2030 based on the “principle-dimension” multi-criteria. The results show that on the whole, the southeast half of Hu line has a higher CEA than that in the northwest half under the “principles-dimensions” multi-criteria.

Third, we obtained China’s province final CEA by embedding the CEA results of the “principle-dimension” multi-criterion into the objective function of the FCAM. Henan has the largest final CEA. Gansu, Qinghai, Ningxia, and Hainan are the four provinces with the least final CEA.

Forth, in reality, CEA based on historical emissions has limitations. We calculated the final CEA taking into account multiple targets, which is superior to historical emission-based CEA in terms of fairness, efficiency, feasibility, and sustainability.

Fifth, the regions of Shanxi, Shaanxi, Xinjiang, Ningxia, Inner Mongolia, Guizhou, and Anhui will take on greater responsibility for carbon reduction in the future. On the contrary, the zones of Tianjin, Qinghai, Guangxi, Jilin, Yunnan, and Beijing will be able to sell CEA in the future.

Sixth, from the perspective of CEI reduction, Chinese provinces are divided into three categories: category A (small emission reduction task), category B (moderate emission reduction task), and category C (high emission reduction tasks). Among them, most resource-based provinces have large emission reduction tasks.

Based on the above research conclusions, we propose the following policy recommendations.

First, improve the allocation of carbon allowances in China. The allocation method proposed in this paper provides an idea for government departments to design carbon emission allowances. Carbon emission allowances are both a scientific issue and a social issue of human well-being. Carbon emission allowances are not only related to greenhouse gas emission reduction efficiency but also affect low-carbon technology research and development, high-quality economic development, energy structure upgrading, and industrial structure adjustment. Therefore, regional differences should be fully considered in carbon quotas, and the way of carbon quota allocation should be further improved.
Second, accelerate the elimination of backward production capacity and improve energy-saving and emission reduction technology. Governments can use carbon emission allowances to promote coordinated regional development and transform economies into intensive development. On the one hand, undeveloped regions should learn from developed areas, introduce new technologies conducive to energy conservation and emission reduction, establish low-carbon industrial systems, and improve energy use efficiency. On the other hand, developed regions should also speed up R&D and provide support for underdeveloped areas.

Third, develop policies related to energy conservation and emission reduction, establish a market-oriented emission reduction mechanism, and use the law to restrict emissions. The

![Fig. 5](image_url) The distribution of CEI of China’s province in a 2015 and b 2030

![Fig. 6](image_url) The CEI reduction of China’s province during 2015–2030.
government should strengthen the publicity of emission reduction, improve residents’ environmental awareness, and encourage green consumption. What is more, the governments should improve infrastructure for green development and increase R&D in renewable energy and energy efficiency projects.

Then, encourage regions to explore different development models. Each region can formulate corresponding emission reduction measures and vigorously develop clean energy based on local characteristics. For example, in areas rich in mineral resources such as Xinjiang, Inner Mongolia, and Shaanxi, clean energy such as solar energy and wind energy should be developed to increase the proportion of non-fossil energy in the energy structure. In addition, areas with large emission reduction tasks should innovate business models to promote the development of emerging green technologies and services such as high value-added agriculture, cultural tourism, ecotourism, training center, and conference center.

Finally, the government should narrow the gap between underdeveloped and developed regions through an appropriate policy mix. For less developed regions that are more affected by emission reduction policies, the regions with large CEI reductions can be compensated through fiscal transfers (taxes or trading permits). Governments can also tilt towards less developed regions in terms of integrated policies, regulations, and investment. In particular, environmental protection and energy efficiency, new energy, high-end manufacturing, next-generation information technology, clean energy vehicles, and high-tech materials are the leading industries for future growth. In addition, governments should increase investment in key infrastructure for green development.

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