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How can China achieve its Intended Nationally Determined Contributions by 2030? A multi-criteria allocation of China's carbon emission allowance



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HIGHLIGHTS

- We incorporate a variety of principles and indicators into an improved ZSG-DEA model.
- We conduct a multi-criteria allocation of China's CEA by 2030 to provincial shares.
- We measure the total and per capita space for carbon emissions by province.
- All provinces reach the DEA frontier with different CEA ranging from 4.21 to 16.77 Gt.
- Differentiated provincial reduction policies are the key to achieving China's INDCs.

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GRAPHICAL ABSTRACT



ABSTRACT

Accelerating global warming has suggested the importance of controlling greenhouse gas emissions associated with human activities. In striving to fulfill the Paris Agreement, China has announced its Intended Nationally Determined Contributions (INDCs) aimed at reducing its carbon dioxide (CO₂) emission intensity by 60-65% in 2030 against the level of 2005. However, China's INDCs cannot be fulfilled without formulating appropriate schemes for the allocation of carbon emission allowance (CEA) at sub-national scales. To help close the gap in our knowledge, this paper starts with measuring the overall CEA of China by 2030, and then proposes a sciencebased scheme for CEA allocation by developing an improved zero sum gains-data envelopment analysis (ZSG-DEA) model. It demonstrates that the final CEA of some northern provinces can be cut down as compared to their initial shares and, conversely, most southern provinces experience an increase in their CEA. Comparing the final share of CEA by province with current carbon emissions, we observe that provinces with abundant energy reserves, such as Shanxi, Inner Mongolia and Shaanxi, tend to be operating in a state of overshoot in terms of space for carbon emissions (SCE). In contrast, there remains SCE when it comes to Guangdong, Hunan, Fujian, etc. The remaining provinces, such as Heilongjiang, Hebei and Ningxia, are close to the break-even point. In view of the differing SCE of individual provinces, common but differentiated policies for CO₂ emission control would be the key to achieving China's INDCs. The research findings lay a scientific basis for the Chinese government to make its INDCs come true through inter-provincial collaboration on emission reduction, but also serve as a

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reference for fueling further scientific discussions and development of schemes for the allocation of responsibility for carbon emissions at multiple scales within and beyond China.

1. Introduction

Numerous studies have observed a near-linear relation between global warming and carbon dioxide (CO2) emissions associated with human activities since the pre-industrial era [1,2,3]. In striving to combat climate change through collaborative initiatives worldwide, more than 190 parties (nations and regions) to the United Nations Framework Convention on Climate Change (UNFCCC) formally reached an agreement in Paris in December 2015 that the global-average temperature rise should stay below 2 °C, preferably below 1.5 °C, above preindustrial levels [4]. The Paris Agreement on climate change represents a landmark in global environmental governance not only because it legitimates the agreed threshold level (< 2 °C) for increase in temperature, but also because it differs in nature from previously documented "top-down" international agreements, such as the Kyoto Protocol, in the sense that it leaves more room for individual parties to formulate their Intended Nationally Determined Contributions (INDCs). As the top-down approach has made little progress and is now at an impasse [5,2], there is a growing interest in assessing the effects of "bottom-up" INDCs on adaptation and mitigation of climate change [6,7].

As the largest CO_2 emitter in the world [8], China played a constructive role in the negotiation of the Paris Agreement by submitting its ambitious INDCs [9,10]. The overarching target of China's INDCs is to reduce the intensity of CO_2 emissions by 60–65% in 2030 as compared to the level of 2005. It represents a step ahead from the goal announced in 2009 to reduce the CO₂ emission intensity by 40-45% between 2005 and 2020 [11,12]. Meanwhile, Chinese economy has now entered "New Normal" - a new phase focusing more on quality than on speed [13]. A reasonable expectation for China's economic growth between 2020 and 2030 would be at an average rate of 4-6%, depending on the outcome of implementing structural reforms [14]. In that sense, future allowable carbon emissions for China will become a finite common-pool resource that must be shared among different parts of the country, especially at the provincial level [15]. This brings into focus the provincial allocation of China's carbon emission allowance (CEA) in keeping with INDCs.

While to our knowledge research into this question remains underexplored, lessons can be learned from existing literature seeking to determine the CEA by province in China in accordance to the goal for carbon emission control by 2020. For instance, a composite index was proposed by Yi et al. [16], who allocated China's CEA at the provincial level by 2020 by aggregating GDP per capita, accumulated carbon emissions and energy consumption per unit of industrial added value under four scenarios. In a similar study, Wang et al. [17] brought together per capita GDP, per capita emissions, energy consumption of industry per unit of value-added and the ratio of non-fossil fuel to primary energy consumption into a so-called China Regional Burden Differentiation Model to determine China's provincial CEA in 2020. Yu et al. [18] measured the contribution of 13 factors to the carbon emissions of 30 Chinese provinces and then allocated the national CEA to each province on the basis of the anticipated growth rate of each factor in 2020. By making use of the Shapley value method to China's CEA allocation for 2020, Zhang et al. [19] concluded that regions with indicators like higher GDP and carbon outflow should be allocated with more emission quotas.

To operationalize the CEA allocation, some researchers have chosen to focus on the cities as a unit of analysis. Han et al. [20] developed a similar system of indicators through an analytic hierarchy process method and accounted for the CEA of all the cities within Jing-Jin-Ji region in keeping with China's 2020 goal. Li et al. [21] applied a maximum deviation method to allocate the CEA increment from 2015 to 2020 to different Chinese cities in the Pearl River Delta region by taking into account population, GDP and historical carbon emissions. Despite the differing allocation schemes employed in these studies aforementioned, most of them consider the equity principle as the first principle of distributive justice. The significance of the equity principle to sharing climate burdens and emission rights has been demonstrated in an extensive literature, from diverse perspectives such as egalitarian (per capita emissions), ability-to-pay (per capita GDP), grandfathering (historical carbon emissions), etc. [22,23,24].

At the same time, the need for multi-criteria allocation schemes has been noticed. A prominent advantage over single-criterion allocation is that multi-criteria allocation is likely to give rise to less difference between the smallest and largest targets for different entities, which enables more consensus-based entitlements [25]. Moreover, multi-criteria allocation schemes make it possible to bridge the gap between developed and developing countries who often give preferences to different allocation principles [24]. The inclusion of various allocation principles allows for the consideration of disparity among provinces, and ultimately facilitates the implementation of the CEA allocation scheme. Thus, in search of implementable allocation schemes for CEA, additional allocation principles such as efficiency, feasibility and sustainability have been increasingly adopted beyond the equity principle [26,17,16]. On the other hand, the challenge for mitigation and adaptation of climate change in different regions would depend primarily on their respective social, economic and environmental status [27,28]. In that sense, one-to-one correspondence can be identified between the different principles (i.e., equity, efficiency, feasibility and sustainability) and sustainability pillars (i.e., social, economic and environmental). For instance, the feasibility principle can be interpreted as the abatement cost of carbon emissions from the economic pillar [17], and the sustainability principle from the environmental pillar could refer to the absorptive capacity to sequestrate CO_2 [29].

In developing multi-criteria allocation schemes, various methods have been introduced. Examples include single indicator approach, composite index approach, and game theoretic approach [30]. Of these, the composite index approach aimed at bringing together diverse principles and indicators with determined weights has reached worldwide popularity [20,30]. However, the approach has been criticized for its subjectivity and arbitrariness, but also for the fact that it focuses on the absolute amount of indicators (e.g., provincial GDP, population) while looking down upon the relative performance of the inflows and outflows in the whole system [31,32,33]. As such, some provinces might obtain redundant CEA compared with its actual needs, and vice versa.

By contrast, an optimization approach aimed at improving the technical efficiency of the whole system, namely data envelopment analysis (DEA), has emerged as another common way of allocating CEA. The traditional DEA model was proposed by Charnes et al. [34] and Banker et al. [35], assuming that all decision making units (DMUs) in a free market can freely produce input and output variables, and that the DEA efficiency of DMUs can be measured through the ratio of multiple inputs to outputs. However, this hypothesis does not hold true when it comes to CEA allocation, as in this context the overall CEA of a given region should be limited to a certain range of values. To overcome this weakness, a revised DEA model, namely zero sum gains-DEA (ZSG-DEA), was proposed by Lins et al. [36]. The rationale of ZSG-DEA for allocating CEA is that when a DMU (e.g., a city, a province, a country, etc.) decreases its CEA to yield greater DEA efficiency, the CEA entitled

to any other DMUs must be increased by the same amount to maintain the overall CEA unchanged. By taking the relative performance of different DMUs into consideration without weighting (as opposed to the composite index approach), DEA or ZSG-DEA method allows for a reallocation of the redundant CEA among provinces given their individual technical efficiency.

By adopting population and energy consumption as input variables, and GDP and carbon emissions as output variables, Gomes and Lins [37] pioneered to allocate the CEA among the UNFCCC Annex I parties utilizing a ZSG-DEA model in order to achieve the goal of Kyoto Protocol. Afterwards, an increasing number of studies have implemented ZSG-DEA as a means to ensure a robust and reasonable allocation of resources and emission allowance. For instance, Wang et al. [38] introduced a ZSG-DEA model to allocate China's CEA by 2020 towards 30 provinces by selecting total energy consumption, CO₂ emissions and non-fossil energy consumption as inputs, and GDP and population as outputs. By creating a ZSG-DEA model that set population and energy consumption as inputs and GDP and carbon emissions as outputs, Pang et al. [39] redistributed the CEA among 124 countries that were subject to the Kyoto Protocol in 2010. Similarly, Chiu et al. [40] evaluated the DEA efficiency of 24 EU nations from 2005 to 2007 on the basis of a ZSG-DEA model where national CEA was an input variable and energy consumption, government spending and GDP were output variables. Wen and Zhang [41] developed a non-radial ZSG-DEA model in support of the allocation of CEA across the 30 Chinese provinces in 2020 by treating carbon emissions and GDP as outputs, and capital stock, population and energy consumption as inputs. Likewise, Miao et al. [32]

took advantage of a ZSG-DEA model to investigate the DEA efficiency of provincial carbon emissions in China from 2006 to 2010 by choosing capital stock, population and energy consumption as inputs, and GDP and carbon emissions as outputs.

Irrespective of the prevalence of ZSG-DEA models for determining the CEA particularly at the provincial level, it remains problematic not only due to the lack of transparency in defining allocation principles other than the equity and efficiency principles, but also in selecting indicators as a basis for quantifying the various principles and reflecting regional differences in a systematic way. Moreover, when it comes to running a ZSG-DEA model, the boundary between input and output variables often seems to be ambiguous. For instance, carbon emissions in some studies are modelled as inputs while in some others they are outputs. Besides, as noted above, existing literature focuses primarily on the way to achieve the China's 2020 goals; therefore, there is a great need for aligning timely provincial allocation schemes with China's INDCs towards 2030.

To promote the transparency, scientific robustness and policy relevance of CEA allocation, this paper is intended to introduce an improved ZSG-DEA model for the allocation of provincial CEA in accordance to China's INDCs responding to the Paris Agreement. Overall, the novel contributions of this article to the literature lie in: (1) integrating multi-criteria allocation principles and indicators into an improved ZSG-DEA model; (2) developing an optimal scheme for the allocation of CEA to achieve China's INDCs at the provincial level; (3) serving as a reference for determining the fair share of resources or emission permits across regions; and (4) providing policy



Fig. 1. Schematic of CEA allocation.

recommendations for closing the gap between INDCs and inter-provincial emission trading scheme (ETS).

To this end, the rest of this paper is structured as follows. In Section 2, the methodology and data for our analysis are introduced. Section 3 presents the empirical results derived from the ZSG-DEA model established in the paper. Section 4 compares the results with literature and offers insights into policy implications. Conclusions are drawn in Section 5.

2. Methodology and data

The schematic of the CEA allocation employed in this paper is illustrated in Fig. 1. First, a suite of allocation principles and indicators are selected as output variables for CEA allocation that are expected to capture the three pillars of sustainability (i.e., social, economic and environmental) while reflecting the four principles (namely equity, efficiency, feasibility and sustainability). Second, historical carbon emissions by province lead to an estimate of initial CEA that would be reallocated across provinces given their DEA efficiency. Finally, we continue the process of reallocation until that all the provinces have reached the DEA efficiency of 100%. Comparing the final CEA with current carbon emissions (CCE) of provinces, the space for carbon emissions (SCE) by province can be measured.

2.1. Multi-criteria allocation scheme

As opposed to any single-criterion CEA allocation scheme, multicriteria ones accommodate indicators in a more systematic way reflecting common but differentiated responsibility for climate change mitigation. As suggested by Fang et al. [26], the equity, efficiency, feasibility and sustainability principles are adopted in this paper for CEA allocation. Furthermore, on the basis of a comprehensive review of literature, a suite of indicators intended for capturing these four principles are selected in accordance with the social, economic and environmental pillars (Fig. 2). However, some indicators, such as ecological resilience, are excluded due to the difficulty in measurement. The correlation analysis allows for further selection of the indicators, by which those correlated insignificantly with historical carbon emissions are deleted as well. Finally, the equity principle is expressed by population (social), GDP (economic) and historical carbon emissions (environmental), the efficiency principle by the ratio of expenditure on R& D to GDP (social) and energy intensity (economic), the feasibility principle by general public budget revenue (social), elasticity coefficient of energy consumption (economic) and the carrying capacity of carbon emissions (environmental), and the sustainability principle by the proportion of urban residence (social) and the share of tertiary industry (economic).

2.2. ZSG-DEA model

As noted, the hypothesis of the classical DEA that all DMUs are independent and have no impacts on others' actions is untenable for a competitive market, particularly given the fact that the overall CEA is bound to a value. What's more, through classical DEA model one could investigate the DEA efficiency of each DMU, yet it is unable to bring them together into the DEA frontier for CEA reallocation. To maximize the DEA efficiency while making constant the overall CEA by 2030 as inputs, this paper develops an input-oriented ZSG-DEA model.

One prominent merit of this model is that it allows for optimization of all the DMUs in order to reach the DEA frontier without altering the overall CEA. By improving the DEA efficiency of given DMUs and bringing them together to the DEA frontier, the inputs of inefficient DMUs (i.e., provincial CEA) must be declined. Meanwhile, the redundant CEA should be reallocated to other DMUs to keep the overall CEA unchanged. For instance, provided that DMU_k (k = 1, 2, ..., 30) with a CEA of X_k is an inefficient unit with its DEA efficiency θ , the CEA of DMU_k has to reduce by X_k (1- θ) to reach the DEA frontier and other DMUs would increase their CEA according to the weights expressed as $\frac{X_k(1-\theta)}{30} \cdot X_i$. In principle, the inefficient DMUs continue to be reallocated $\sum_{i=1}^{30} X_i$

until all reach the DEA frontier. After several rounds of reallocation, the DEA efficiency of all the DMUs will be equal to 1. The ZSG-DEA model is formulated as follows:

$$E_{ZSG} = \min \theta \tag{1}$$

$$\begin{cases} \sum_{i=1}^{30} \lambda_i \cdot y_i^{equily} \ge y_k^{equily} \\ \sum_{i=1}^{30} \lambda_i \cdot y_i^{efficiency} \ge y_k^{efficiency} \\ \sum_{i=1}^{30} \lambda_i \cdot y_i^{fassibility} \ge y_k^{fassibility} \\ \sum_{i=1}^{30} \lambda_i \cdot y_i^{sustainability} \ge y_k^{sustainability} \\ \sum_{i=1}^{30} \lambda_i \cdot X_i \left[1 + \frac{X_k \cdot (1-\theta)}{\sum_{i=1, i \neq k}^{30} X_i} \right] \le \theta \cdot X_k \\ \sum_{i=1}^{30} \lambda_i = 1 \\ \lambda_i \ge 0, i = 1, 2, ..., 30 \end{cases}$$
(2)

where θ refers to the DEA efficiency of DMUs; E_{ZSG} refers to the minimum DEA efficiency of DMU_k ; λ_i refers to the weight of DMU of i; X_i refers to the initial CEA as input; y_i^{equiv} , $y_i^{efficiency}$, $y_i^{feasibility}$ and $y_i^{sustainability}$ refer to the quantified principles of equity, efficiency, feasibility and sustainability, respectively.

To realize the allocation of CEA, the overall CEA must be measurable. Assuming that the annual GDP growth is at a rate of 6.0% on average during the phase of "New Normal", and that there will be a linear decline in emission intensity, the overall CEA for the next 15 years could be calculated as:

$$TCA_t = GDP_t \cdot (1+p)^{t-2015} \cdot I_{2015} \cdot (1-q)^{t-2015}$$
(3)

$$q = 1 - \sqrt[15]{\frac{I_{2030}}{I_{2015}}} = 1 - \sqrt[15]{\frac{I_{2005} \cdot (1 - \alpha)}{I_{2015}}}$$
(4)



Fig. 2. Multi-criteria indicators for CEA allocation. "Soc", "Eco" and "Env" represent social, economic and environmental, respectively.

where TCA_t refers to the overall CEA in year *t*; GDP_t refers to the GDP in year *t*; *p* refers to the projected rate of GDP growth in next 15 years; I_{2015} refers to the emission intensity in 2015; *q* refers to the rate of decline in emission intensity in the next 15 years; *a* refers to the targeted reduction in emission intensity in 2030 compared with the level of 2005.

The initial CEA by province can be determined in accordance with the weights of historical carbon emissions for different provinces, with the aim of not causing a lot of derivation from a grandfathering perspective. As Formula (5) shows, $ICEA_p$ refers to the initial CEA of Province p and CE_p refers to the historical carbon emissions of Province p. The resulting *ICEA* is adopted as input variables that would be reallocated through the ZSG-DEA model afterwards.

$$ICEA_p = TCA \cdot \frac{CE_p}{\sum CE_p}$$
(5)

As illustrated in Fig. 3, a multi-criteria allocation scheme has been constructed as a benchmark for CEA reallocation. To quantify all the selected indicators, GM (1,1) is employed to project the trends between 2016 and 2030, which is a grey model proposed by Deng [42] and has been widely applied to the projections of resources and emissions [43,44]. Given the complexity that multiple indicators may show similar trends along the time-series, we run a principal component analysis to aggregate these indicators for each principle and the resulting components within single principles are weighted equally. Hence, each principle can be quantified through the projections of all the indicators involved. The formulas are as follows:

$$PR = \sum w \cdot F_i = w \cdot \sum \sum \alpha_{ij} \cdot Ind_{ij}$$
(6)

$$PR^* = \frac{PR - PR_{\min}}{PR_{\max} - PR_{\min}}$$
(7)

$$PR^* = \frac{PR_{\max} - PR}{PR_{\max} - PR_{\min}}$$
(8)

where *PR* and *PR*^{*} refer to the quantified principles before and after standardization, respectively; *w* refers to the weights of each prominent component *n*, w = 1/n; a_{ij} refers to the score of each indicator *j* within the resulting components of the principle *i*; Ind_{ij} refers to indicator *j* for principle *i*. Unlike the equity and efficiency principles, higher ranking of the feasibility principle would lead to less share of CEA according to the principal component analysis, because it is dominated by general public budget revenue that corresponds to enhanced ability to control carbon emissions and, therefore, to less CEA. The same applies to the sustainability principles. For this reason, the standardization of these two principles could be conducted with Formula (8).

2.3. Data

Table 1 summarizes the indicators adopted for the measurement of the overall CEA, the initialization of provincial CEA and the construction of the multi-criteria allocation scheme. It is worth mentioning that the carrying capacity of CO_2 sequestration within the principle of feasibility is calculated according to the respective capacity of different land use types within a region to store CO_2 through photosynthesis. For details of the data and calculation, please see Fang et al. [29,45–46].

Besides, we utilize the Data Processing System (DPS) software to predict aforementioned indicators for the period 2016–2030 with the GM (1,1) model. SPSS 16.0 is applied to investigate the correlation among indicators as well as the principal component analysis to quantify the principles. DEAP software and Excel are used for DEA efficiency calculation and provincial CEA reallocation.

3. Results

3.1. Changes in carbon emission allowance through reallocation

Fig. 4 tracks the DEA efficiency of the initial allocation and its reallocation. Ten out of the 30 provinces have DEA efficiency that is higher than the average of initial efficiency (0.44). Beijing, Hainan and Qinghai already reach the DEA frontier where the DEA efficiency is equal to 1, whereas Shanxi reports the lowest DEA efficiency of 0.08. The average DEA efficiency increases to 0.61 after the first reallocation, even though no additional provinces reach the DEA frontier. The DEA efficiency of Shanxi almost triples while still ranking the last. The average DEA efficiency amounts to 0.81 and 0.96, respectively, as a result of the second and third reallocation, whereas the number of provinces with the DEA efficiency of 1 remains constant. Tremendous changes are found in the fourth reallocation, in which Liaoning, Jilin, Jiangsu, Fujian, Jiangxi, Shandong, Henan, Guangdong and Ningxia reach the DEA frontier in addition to Beijing, Hainan and Qinghai. Nevertheless, the average DEA efficiency slightly increases from 0.96 to 0.99. Ultimately, all the provinces achieve the maximum DEA efficiency of 1 after the final reallocation.

Fig. 5 depicts the changes in the provincial shares of the overall CEA. The average CEA of the 30 provinces granted in the initial allocation is estimated at 8.44 Gt with a standard variance of 6.20 Gt. Shanxi and Hainan are found to make up the largest and smallest share of the CEA, respectively, with an estimation of 26.62 Gt and 3.91 Gt. This is because of the fact that the initial allocation is solely dependent on the historical carbon emissions by province, which could be interpreted as a grandfathering perspective. Through all the five rounds of reallocation, the CEA of Shanxi, Inner Mongolia, Shandong, Liaoning, Hebei, Shaanxi and Xinjiang decreases by 165.6%, 34.7%, 43.6%, 28.4%, 35.3% and 232.1%, respectively. Conversely, an increase in the share of CEA is witnessed in the remaining 21 provinces. For instance, Guangdong, Jiangxi, Beijing, Fujian and Guangxi enlarge their CEA by 44.1%, 140.0%, 227.6%, 96.0% and 109.8%, respectively.

By looking deeper into the geographical distribution of the changes to CEA by province, one may notice the agglomeration effect as evident from the fact that numerous provinces located in north China experience a significant decline in the CEA as compared to their initial shares and, conversely, many of the southern provinces have an increment of CEA. Slight changes occur mostly in middle China, where provinces either increase their CEA up to 4.00 Gt or decrease their CEA up to 3.00 Gt.



Fig. 3. Schematic of the ZSG-DEA model developed in this paper.

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Table 1

Indicators of the DEA-ZSG model and the data sources.

Composition	Indicators	Data sources
The overall CEA	GDP of China	China Statistic Yearbooks 2006–2016
	Emission intensity of China	China Emission Accounts & Datasets (CEADs)
Input variables	Historical carbon emissions by province	CEADs
Output variables	GDP by province	Statistical Yearbooks of each province 2006-2016
	Population by province	
	Energy intensity by province	
	Ratio of expenditure on R&D to GDP by province	
	General public budget revenue by province	
	Elasticity coefficient of energy consumption by province	
	Proportion of urban residence by province	
	Share of tertiary industry by province	
	Carrying capacity of CO ₂ sequestration by province	[29,45]



Fig. 4. The DEA efficiency of initial allocation and reallocation.



Fig. 5. Geographical distribution of provincial CEA through reallocation. All the provinces are marked on the basis of the changes to the provincial CEA between the initial allocation and final reallocation. Tibet, Taiwan, Hong Kong and Macau are not displayed due to the lack of data.



Fig. 6. Frequency distribution of provincial CEA through reallocation.

Fig. 6 represents the distribution of frequency that refers to the number of provinces whose CEA falls into a range of value prior to and during the reallocation. As shown, the distribution of the initial CEA covers the largest spectrum ranging from 1.29 Gt to 26.62 Gt with a standard variance of 6.20 Gt, suggesting that a CEA between 2.24 Gt and 14.64 Gt is entitled to more than two thirds of the provinces. After the first reallocation, the spectrum is shortened to between 2.23 Gt and 19.80 Gt, and two thirds of the provinces own a CEA ranging from 3.87 Gt to 13.02 Gt. Through the second reallocation, the CEA of 70% of the provinces stays within a range of 5.01-11.87 Gt. The third reallocation corresponds to the shortest spectrum of CEA shares ranging from 4.05 Gt to 16.47 Gt. The fourth and fifth reallocation finally witnesses that the CEA of each province remains stable (between 4.21 Gt and 16.76 Gt), while the standard variance decreases to 3.26 Gt eventually. As a result, one may conclude that this reallocation driven by the ZSG-DEA model could not only maximize the DEA efficiency of individual provinces but also contribute to the convergence of all the provinces by shrinking the CEA gap to some extent.

3.2. Final carbon emission allowance of provinces

Fig. 7 delineates the ranking of provinces as per the principles of equity, efficiency, feasibility and sustainability, respectively. As shown, the first two principles are gained prominence in eastern provinces such as Shandong, Guangdong and Jiangsu. In the case of Guangdong, for instance, our principal component analysis indicates that GDP (89.2%) and population (9.9%) contribute the most to the equity principle, while the ratio of expenditure on R&D to GDP dominates the efficiency principle (over 90.0%). More than 20 provinces (e.g., Guizhou, Yunnan, Gansu) have the advantage of reflecting the principles of feasibility and



Fig. 7. The ranking of all the provinces based on the four principles. After the quantification of each principle by province, we standardize these 30 scores within each of the four principles, respectively, resulting in a range of value between 0 and 1. Hence the spectrum primarily shows the provincial ranking within each principle instead of quantifying the contributions of various principles to single provinces.

sustainability through the CEA reallocation, many of which are located in southwest and northwest China. In the case of Guizhou, the general public budget revenue contributes the most (over 90.0%) to the feasibility principle, while the proportion of urban residence (49.1%) and the proportion of the tertiary industry (50.9%) contribute equally to the sustainability principle.

Fig. 8 displays the discrepancy of geographical distribution between the annual average and per capita CEA of 30 provinces. The spatial pattern of the annual average CEA is prominent in the sense that provinces in south and east China tend to account for a large share of the overall CEA. This is particularly true for Guangdong, Shandong, Jiangsu and Henan, whose CEA is at least over 0.70 Gt. On the contrary, those in northeast and northwest China occupy a smaller CEA (less than 0.60 Gt). A definitely different pattern occurs when it comes to the per capita CEA. The northwestern provinces of China (e.g., Ningxia, Qinghai) own a larger per capita CEA than others. These two patterns underline the need for a complementary use of the total and per capita metrics in interpreting the allocation scheme proposed in this paper.

Fig. 9 compares the CEA of each province with their CCE and examines the SCE defined as CEA minus CCE. Amongst, negative SCE can be found in Shanxi, Inner Mongolia, Shaanxi, Xinjiang, Shandong and Liaoning, whose CCE has already exceeded their annual average CEA by 0.99 Gt, 0.44 Gt, 0.19 Gt, 0.13 Gt, 0.05 Gt and 0.04 Gt, respectively. Heilongjiang, Hebei, Ningxia, Gansu, Anhui, Hainan, Tianjin, Sichuan, Qinghai, Chongqing, Shanghai and Guizhou are approaching to the break-even point with a slight surplus of SCE (less than 0.30 Gt). On the contrary, Guangdong, Hunan, Fujian, Jiangxi, Guangxi, Beijing, Hubei, Yunnan, Henan, Zhejiang and Jilin are under relatively low levels of



Fig. 8. Geographical distribution of (a) the annual average CEA and (b) the per capita CEA by province. Tibet, Taiwan, Hong Kong and Macau are not displayed due to the lack of data.



Fig. 9. Annual carbon emission balance by province. Negative SCE denotes that annual average CEA could not offset CCE. SCE break-even point denotes that annual average CEA exceeds CCE by less than 0.30 Gt. Positive SCE denotes that annual average CEA exceeds CCE by at least 0.30 Gt.

stress to control carbon emissions. However, this does not necessarily represent an absolute SCE, because the carbon emissions of most provinces have not peaked yet and thus will continue to rise [47,48].

4. Discussion

4.1. Comparison with literature

In general, this paper proposes a moderate CEA allocation scheme, as witnessed by Fig. 10 that provides a comparison between existing studies on CEA allocation across 30 Chinese provinces with ours. In some research, however, the highest provincial CEA exceeds the lowest one by over 26 times! That can hardly be implemented because of the absence of the equity principle in any recognizable sense. Except for Fang et al. [26], all these papers set the overall CEA in compliance with China's 2020 goal and conducted allocation by establishing ZSG-DEA models that took into account only few indicators (e.g., GDP per capita, energy consumption, and/or population) as either input or output variables without unambiguous criteria. Although a number of indicators were chosen by Fang et al. [26] and the overall CEA was determined by China's INDCs towards 2030, their allocation procedure corresponds to a composite indicator approach that incorporates multiple indicators into a single-score metric for ease of understanding [30]. While this approach has received much attention from academia, it differs in nature from DEA method which is capable of integrating a variety of principles and indicators in a more sophisticated manner. For this reason, our improved ZSG-DEA model allows for a more equitable, efficient, feasible and sustainable allocation scheme that gives preference to those of the provinces that would have considerable potential to increase the outputs without causing increase in the overall CEA of China.

4.2. Policy implications

Our study offers novel insights into the implementation of China's



Fig. 10. Comparison of different schemes for the allocation of China's carbon emission allowance derived from literature [26,55–57]. All the results have been converted into (a) annual average CEA and (b) per capita CEA, respectively.

INDCs at the provincial level. The allocation scheme proposed in this paper allows policymakers to determine not only the CEA of Chinese provinces, but also the corresponding SCE, which is a key to understanding differentiated emission reduction commitments and pressures confronted by individual provinces. The findings are particularly suited for pinpointing provinces with negative SCE (e.g., Shanxi, Inner Mongolia, Shaanxi) - those that face the challenge of achieving an absolute decoupling of their CO₂ emissions from economic growth. Furthermore, it should be noted that our analysis provides an optimistic estimate of provinces running a slight surplus of SCE (e.g., Anhui, Hainan, Hebei), since the SCE is defined as CEA minus CCE and overlooks the fact that the emissions of many provinces show negative or weak decoupling from economic growth and thus will continue to rise [49]. Though the remaining provinces (e.g., Yunnan, Jiangxi, Guangxi) are not necessarily involve absolute emission reduction targets, there is still a need for controlling their emissions and reinforcing decoupling from economic growth.

In addition to laying a basis for formulating regional strategies for climate change mitigation and emission reduction, the findings would also be informative for the market construction of Chinese ETS — an inter-provincial cap-and-trade system that was formally launched in the end of 2017 and remains limited to electric power generation industry that accounts merely for a fraction of carbon emissions within Chinese territory. In other words, the proposed allocation scheme would help close the gap between INDCs and ETS, both of which the Chinese government is committed to. Nevertheless, the determination of carbs for trading should be made cautiously. Only a tiny fraction of CEA of provinces with positive SCE should be allowed for sale. Those provinces with negative SCE must be prevented from selling CEA but they can be a buyer. In principle, provinces might sell their redundant CEA proportional to the positive SCE.

To our knowledge, this study, for the first time, takes into consideration the difference of provincial performance on the social, economic and environmental pillars of sustainability simultaneously, by bringing together a systematic set of diverse principles and indicators into the ZSG-DEA model. Because of this, the resulting allocation scheme is able not only to reconcile the INDCs with regional development goals but to contribute to the trade-offs between various provinces — the key to consensus building on implementable schemes for regional CEA allocation. Moreover, the underlying methodology is also appropriate for use in allocating the permits of additional emissions or resources at multiple scales in the pursuit of optimal system efficiency.

4.3. Uncertainties and limitations

We acknowledge that our analysis remain the following limitations that should be addressed in future research: (1) the accounting of historical carbon emissions as a basis for initial CEA merely considers emissions from fossil fuels, and therefore neglects those from cement production and land use, especially for those embodied in interregional trade of goods and services [50,51]. This leads to calls for input-output analysis (IOA), by which the consumption-based accounting of provincial carbon emissions could enhance the scientific robustness of initial allocation of CEA [52], (2) when estimating China's overall CEA by 2030, we presume a linear reduction of emission intensity and a fixed rate of GDP growth, which is not consistent with the reality and needs to be improved through the development of scenario analysis aiming to track the dynamics of emission intensity and GDP growth but also other input and output variables adopted in the modelling where economic sense is insufficiently considered in its current form; (3) in addition to the goal of reducing emission intensity by 60-65% in 2030, China's INDCs are also committed to peaking the carbon emissions around 2030. To fulfill these dual goals, it makes sense to conduct additional assignments of CEA for each province on a yearly basis in accordance to the anticipated trajectories of provincial carbon emissions; (4) DEA or ZSG-DEA method has the merit of assessing the technical efficiency

among DMUs, whereas this may bring the risk of overemphasizing technical efficiency and overlooking other principles; (5) CO_2 emissions are often found to be accompanied by other pollutants (e.g., NO_x , SO_2), even though in this paper we take the former as the only undesirable emissions to control. With the consideration of multi-pollutants, there seems to be much room for investigation into the trade-offs and cobenefits of regulations for different emissions when doing allocation [53,54]; and (6) the principles of equity, efficiency, feasibility and sustainability are treated without weighting, but no two entities actually hold the same importance. Therefore, it may make sense to employ unequal weighting that reflects stated or revealed preferences and judgments of provincial performance on social, economic and environmental sustainability.

5. Conclusions

This paper begins with the measurement of the overall CEA by 2030 and further establishes an improved ZSG-DEA model to allocate the CEA to the 30 Chinese provinces, where the initial provincial CEA determined by the historical carbon emissions is treated as inputs and a suite of indicators pertaining to the equity, efficiency, feasibility and sustainability principles are selected as outputs. Ultimately, all the provinces reach the DEA frontier with a CEA ranging from 4.21 Gt to 16.77 Gt. Specifically, some northern provinces are found to cut down their CEA while most southern provinces experience an increase in their CEA, as opposed to the initial shares. Comparing the final share of CEA by province with CCE, we observe that positive SCE is witnessed in 12 provinces including Guangdong, Hunan, Fujian, etc. The SCE of remaining provinces such as Heilongjiang, Hebei, Ningxia is approaching to the break-even point. The findings are particularly suited for pinpointing provinces with negative SCE, highlighting the need for regionspecific policies and inter-provincial collaboration that would help China achieve a sustainable transition. As such, the multi-criteria allocation scheme proposed in this paper not only lays a scientific basis for the Chinese government to make the INDCs implementable at the provincial level, but also serves as a reference for fueling further scientific discussions and development of schemes for the allocation of responsibility at multiple scales within and beyond China. Moreover, the analysis is of benefit to closing the gap between INDCs and ETS, with the recognition that a tiny fraction of CEA of provinces with positive SCE can be allowed for sale, and that those with negative SCE can be a buyer merely.

However, the complexity and heterogeneity embodied in the regional allocation of CEA convince us that no single scheme should be interpreted as the "golden standard". Our allocation scheme, which takes into consideration the difference of provincial performance on the social, economic and environmental pillars of sustainability, is not an exception. Thus, it does not pretend to be useful for all purposes, and it is not surprising that more elaborated or alternative schemes for the allocation of China's CEA at multiple scales will continue to emerge as the next step towards a more comprehensive implementation of China's INDCs. To that end, we suggest that further improvements need to focus on the following prioritized directions: (1) methodological integration of DEA and IOA to fully capture the provincial responsibility for carbon emissions from a consumption perspective; (2) development of scenario analysis to track the dynamics of input and output variables (e.g., emission intensity, GDP) so as to ensure accurate estimates in future trends; (3) inclusion of simulation of provincial peak emissions with the aim of achieving the dual control of emission intensity and total amount of CO₂ by 2030, as regulated in China's INDCs; and (4) linking the resultant CEA to the national ETS for policy simulation in marketing.

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References

- Intergovernmental Panel on Climate Change, 2015. Climate Change 2014: Mitigation of Climate Change (Vol. 3). Cambridge University Press.
- [2] Raupach MR, Davis SJ, Peters GP, Andrew RM, Canadell JG, Ciais P, et al. Sharing a quota on cumulative carbon emissions. Nat Clim Change 2014;4(10):873–9.
- [3] Tokarska KB, Gillett NP, Weaver AJ, Arora VK, Eby M. The climate response to five trillion tonnes of carbon. Nat Clim Change 2016;6(9):851–5.
- [4] United Nations Framework Convention on Climate Change, 2010. UNFCCC. Outcome of the work of the Ad Hoc Working Group on long-term Cooperative Action under the Convention, Home, Cancun Agreements, Draft decision/CP.16.
- [5] Grasso M, Roberts JT. A compromise to break the climate impasse. Nat Clim Change 2014;4(7):543–9.
- [6] Hof AF, den Elzen MG, Admiraal A, Roelfsema M, Gernaat DE, van Vuuren DP. Global and regional abatement costs of Nationally Determined Contributions (NDCs) and of enhanced action to levels well below 2 °C and 1.5 °C. Environ Sci Policy 2017;71:30–40.
- [7] Rogelj J, Den Elzen M, Höhne N, Fransen T, Fekete H, Winkler H, et al. Paris Agreement climate proposals need a boost to keep warming well below 2 C. Nature 2016;534(7609):631–9.
- [8] Energy Information Administration (EIA). International Energy Outlook 2009; Energy Information Administration, Washington, DC, USA; 2009.
- [9] Chu KW. Screening environmental challenges in China: three modes of ecocinema. J Chinese Govern 2017;2(4):437–59.
- [10] Ye B, Jiang J, Li C, Miao L, Tang J. Quantification and driving force analysis of provincial-level carbon emissions in China. Appl Energy 2017;198:223–38.
- [11] Guan T, Delman J. Energy policy design and China's local climate governance: energy efficiency and renewable energy policies in Hangzhou. J Chinese Govern 2017;2(1):68–90.
- [12] Shao S, Liu J, Geng Y, Miao Z, Yang Y. Uncovering driving factors of carbon emissions from China's mining sector. Appl Energy 2016;166:220–38.
- [13] Lin JY. China and the global economy. China Econ J 2011;4(1):1-14.
- [14] Green F, Stern N. China's "New Normal": structural change, better growth, and peak emissions. Policy Brief; 2015.
- [15] Ju Y, Fujikawa K. Modeling the cost transmission mechanism of the emission trading scheme in China. Appl Energy 2019;236:172–82.
- [16] Yi WJ, Zou LL, Guo J, Wang K, Wei YM. How can China reach its CO₂ intensity reduction targets by 2020? A regional allocation based on equity and development. Energy Policy 2011;39(5):2407–15.
- [17] Wang JN, Cai BF, Cao D, Zhou Y, Liu LC. Scenario study on regional allocation of CO₂ emissions allowance in China. Acta Scientiae Circumstantiae 2011;31(4):680–5.
- [18] Yu SW, Wei YM, Wang K. Provincial allocation of carbon emission reduction targets in China: an approach based on improved fuzzy cluster and Shapley value decomposition. Energy Policy 2014;66:630–44.
- [19] Zhang YJ, Wang AD, Da YP. Regional allocation of carbon emission quotas in China: evidence from the Shapley value method. Energy Policy 2014;74:454–64.
- [20] Han R, Tang BJ, Fan JL, Liu LC, Wei YM. Integrated weighting approach to carbon emission quotas: an application case of Beijing-Tianjin-Hebei region. J Cleaner Prod 2016;131:448–59.
- [21] Li L, Li Y, Ye F, Zhang L. Carbon dioxide emissions quotas allocation in the Pearl River Delta region: evidence from the maximum deviation method. J Cleaner Prod 2018;177:207–17.
- [22] Pan J. Emissions rights and their transferability: equity concerns over climate change mitigation. Int Environ Agreements 2003;3(1):1–16.
- [23] Pan X, Teng F, Wang G. Sharing emission space at an equitable basis: allocation scheme based on the equal cumulative emission per capita principle. Appl Energy 2014;113:1810–8.
- [24] Wang L, Chen W, Zhang H, Ma D. Dynamic equity carbon permit allocation scheme to limit global warming to two degrees. Mitig Adapt Strat Glob Change 2017;22(4):609–28.
- [25] Ringius L, Torvanger A, Holtsmark B. Can multi-criteria rules fairly distribute climate burdens?: OECD results from three burden sharing rules. Energy Policy 1998;26(10):777–93.
- [26] Fang K, Zhang Q, Ye R, Zhou Y. Allocating China's carbon emission allowance to the provincial quotas in the context of the Paris Agreement. Acta Scientiae Circumstantiae 2018;38:1224–34.

- [27] Kriegler E, O'Neill B, Hallegatte S, Kram T, Moss RH, Lempert R, Wilbanks TJ. Socioeconomic scenario development for climate change analysis. CIRED Working Papers; 2010. p. 23.
- [28] Marangoni G, Tavoni M, Bosetti V, Borgonovo E, Capros P, Fricko O, et al. Sensitivity of projected long-term CO₂ emissions across the Shared Socioeconomic Pathways. Nat Clim Change 2017;7(2):113.
- [29] Fang K, Zhang Q, Yu H, Wang Y, Dong L, Shi L. Sustainability of the use of natural capital in a city: measuring the size and depth of urban ecological and water footprints. Sci Total Environ 2018;631:476–84.
- [30] Zhou P, Wang M. Carbon dioxide emissions allocation: a review. Ecol Econ 2016;125:47–59.
- [31] Chiu YH, Lin JC, Hsu CC, Lee JW. carbon emission allowances of efficiency analysis: application of super SBM ZSG-DEA model. Polish J Environ Stud 2013;22(3):653–66.
- [32] Miao Z, Geng Y, Sheng J. Efficient allocation of CO₂ emissions in China: a zero sum gains data envelopment model. J Cleaner Prod 2016;112:4144–50.
- [33] Zhang YJ, Hao JF. Carbon emission quota allocation among China's industrial sectors based on the equity and efficiency principles. Ann Oper Res 2017;255(1–2):117–40.
- [34] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res 1978;2(6):429–44.
- [35] Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci 1984;30(9):1078–92.
- [36] Lins MPE, Gomes EG, de Mello JCCS, de Mello AJRS. Olympic ranking based on a zero sum gains DEA model. Eur J Oper Res 2003;148(2):312-22.
 [37] Gomes EG, Lins ME, Modelling undesirable outputs with zero sum gains data en-
- [37] Gomes EG, Lins ME. Modelling undesirable outputs with zero sum gains data envelopment analysis models. J Operat Res Soc 2008;59(5):616–23.
 [38] Wang K, Zhang X, Wei YM, Yu ShW. Regional allocation of CO₂ emissions allowance
- [30] Wang K, Zhang X, Wei TW, HUGWIN Regional and cation of CO₂ emissions andwarded over provinces in China by 2020. Energy Policy 2013;54:214–29.
 [39] Pang RZ, Deng ZQ, Chiu YH. Pareto improvement through a reallocation of carbon
- [49] Pang RZ, Deng ZQ, Chiu TH. Partor improvement introgra a removation of carbon emission quotas. Renew Sustain Energy Rev 2015;50:419–30.
 [40] Chiu YH, Lin JC, Su WN, Liu JK. An efficiency evaluation of the EU's allocation of
- [40] Child FH, Ehl JC, Su WN, Eld JK. All efficiency evaluation of the Eo sanocation of carbon emission allowances. Energy Sources Part B 2015;10(2):192–200.
 [41] Wen L, Zhang EN, Regional allocation of carbon emissions in China based on zero
- sum gains data envelopment analysis model. Environ Eng Res 2016;21(1):91–8.
- [42] Deng JL. Control problems of grey systems. Syst Control Lett 1982;1(5):288–94.
 [43] Hamzacebi C, Es HA. Forecasting the annual electricity consumption of Turkey using an optimized grey model. Energy 2014;70:165–71.
- [44] Pao HT, Fu HC, Tserg CL. Forecasting of CO₂ emissions, energy consumption and economic growth in China using an improved grey model. Energy 2012;40(1):400–9.
- [45] Fang K, Dong D, Lin Z, Shen W. Calculation method of energy ecological footprint based on global net primary productivity. Acta Ecologica Sinica 2012;32:2900–9.
- [46] Fang K, Heijungs R, de Snoo GR. Theoretical exploration for the combination of the ecological, energy, carbon, and water footprints: overview of a footprint family. Ecol Ind 2014;36:508–18.
- [47] Li F, Xu Z, Ma H. Can China achieve its CO₂ emissions peak by 2030? Ecol Ind 2018;84:337–44.
- [48] Zhang Q, Liao H, Hao Y. Does one path fit all? An empirical study on the relationship between energy consumption and economic development for individual Chinese provinces. Energy 2018;150:527–43.
- [49] Zhao MM, Li R. Decoupling and decomposition analysis of carbon emissions from economic output in Chinese Guangdong Province: a sector perspective. Energy Environ 2018;29(4):543–55.
- [50] Liang S, Qu S, Zhu Z, Guan D, Xu M. Income-based greenhouse gas emissions of nations. Environ Sci Technol 2017;51(1):346.
- [51] Shao L, Li Y, Feng K, Meng J, Shan Y, Guan D. Carbon emission imbalances and the structural paths of Chinese regions. Appl Energy 2018;215:396–404.
- [52] Mi Z, Zhang Y, Guan D, Shan Y, Liu Z, Cong R, et al. Consumption-based emission accounting for Chinese cities. Appl Energy 2016;184:1073–81.
- [53] Cai B, Bo X, Zhang L, Boyce JK, Zhang Y, Lei Y. Gearing carbon trading towards environmental co-benefits in China: measurement model and policy implications. Global Environ Change 2016;39:275–84.
- [54] Yang H, Liu J, Jiang K, Meng J, Guan D, Xu Y, et al. Multi-objective analysis of the co-mitigation of CO₂ and PM_{2.5} pollution by China's iron and steel industry. J Cleaner Prod 2018;185:331–41.
- [55] Fu JY, Huang F. Study on the distribution efficiency of CO₂ emissions in China's carbon trading market. China Popul Resour Environ 2016;26(2):1–9.
- [56] Zeng S, Xu Y, Wang L, Chen J, Li Q. Forecasting the allocative efficiency of carbon emission allowance financial assets in China at the provincial level in 2020. Energies 2016;9(5):329.
- [57] Zheng L. Sharing the carbon emission reduction responsibility across Chinese Provinces: a Zero Sum Gains DEA model. Resources Sci 2012;34(11):2087–96.