Study on the extension of the dynamic benchmark system of per capita carbon emissions in China’s county

Fengmei Yang1,2 · Longyu Shi1 · Xiaotong Wang3 · Lijie Gao1

Received: 18 November 2021 / Accepted: 18 August 2022 / Published online: 7 September 2022
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
County is the center of China’s socio-economic development and the key node for urban–rural integration. Also, the county is an important carrier for promoting urban and rural green development. Improving green and low-carbon development capabilities and formulating county-level low-carbon standards will play a significant role in promoting China’s new people-oriented urbanization and rural revitalization. Although there have been extensive studies on low-carbon benchmarks, over half of the benchmarks tend to ignore the development stage of the evaluated region and its needs. When the region’s economy reaches a certain level, constraints from low-carbon targets may limit the local development process. This study firstly allocated county carbon intensity reduction targets (CIRT) by considering the differences in county carbon reduction capacity and responsibility. Secondly, a dynamic benchmark system of per capita carbon emissions (PCCE) in counties in China is constructed. Finally, we took Changxing County in Zhejiang Province as a research case to verify the dynamic benchmark of PCCE. According to the carbon intensity target reduction rate (CITRR), China’s counties can be divided into three categories: low carbon emissions reduction capability-responsible counties (L-CERCRC), medium carbon emissions reduction capability-responsible counties (M-CERCRC), and high carbon emissions reduction capability-responsible counties (H-CERCRC). The results show that (1) due to the national CO2 emission reduction target in 2030, the carbon intensity will be 60% lower than in 2005, the CITRR for China’s 1510 counties range from 8.36 to 137.83%; the average CITRR is 48.40%. (2) Changxing County’s CITRR is 57.71%, which belongs to the H-CERCRC. The PCCE of Changxing County will be much higher than the benchmark when the carbon peak is reached in the future. (3) For reaching the aiming benchmark, Changxing County is suggested to adjust its relevant influencing factors of PCCE for converting local’s PCCE reaching to the benchmark within a certain time period. The dynamic benchmark system for PCCE in China’s counties established in this study is economically sensitive, which not only takes the differences of counties into account, but also meets the needs of counties’ diverse development form stages. This system provides counties a few coordinated directions which can improve the local’s economic development and reduce greenhouse gas (GHGs) emissions through the development progress.

Keywords Carbon intensity reduction target allocation · Capacity-responsibility · County · Per capita carbon emissions · Dynamic benchmark

Responsible Editor: Roula Inglesi-Lotz

Lijie Gao
lgao@iue.ac.cn
Fengmei Yang
fmyang@iue.ac.cn
Longyu Shi
lyshi@iue.ac.cn
Xiaotong Wang
xzw5146@163.com

Key Laboratory of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China
2 University of Chinese Academy of Sciences, Beijing 100049, China
3 Xiamen Institute of Technology, Xiamen 361022, China

Springer
Introduction

The increasing global warming has become a common challenge for all mankind (World Meteorological Organization 2019). Numerous studies have shown that temperature rise exceeds 2 °C would have catastrophic consequences to the global environment and human society (the global climate in 2015–2019). Paris Agreement proposed to control average temperature rise globally within 2 °C by the end of this century, strive to control within 1.5 °C, and achieve the goal of global net-zero GHGs emissions by the middle of this century. In 2020, the global COVID-19 pandemic caused a short suspension in carbon dioxide (CO2) emissions. Despite that, today’s earth still faces the temperature rising crisis of exceeding 3 °C far exceeding the Paris Agreement goals of limiting global warming to well below 2 °C and pursuing 1.5 °C. Achieving the ultimate goal of keeping global warming below 2 °C requires countries to effectively control GHGs emissions (Leemans and Vellinga 2017). Currently, China plays a critical role in CO2 emissions. According to the data provided by The World Resources Institute, China’s carbon emissions in 2018 were 11.75 Gt CO2, which accounts for 23.93% of the world’s carbon emissions. In order to cope with climate change, China has been putting forward more demanding carbon emissions discharging targets. In 2016, China signed the Paris Agreement and formally committed that China will achieve the peak of GHGs emissions around 2030, and then reach the peak as soon as possible. In 2020, China announced that it was expanding its national commitments, with the goal of peaking GHGs emissions before 2030 and achieving “carbon neutral” before 2060. How to implement China’s commitment bottom-up is the key to the realization of the national GHGs emissions reduction target (Liu et al. 2013). The county, a complete basic unit in the Chinese administrative system, is the optimal scale for sustainable resource use, management, and planning (Zhu et al. 2014). In June 2021, fifteen central departments, including China’s Ministry of Housing and Urban–Rural Development, jointly issued the opinions on strengthening green and low-carbon construction in county towns, indicating that low-carbon counties play an important role in achieving carbon peak and carbon neutral goals. Through paving the road for low-carbon development, the primary issue to be considered is controlling carbon emissions. Constructing effective carbon emissions’ indicators, targets, and benchmarks plays a key role in achieving low-carbon goal. In the research on establishing effective carbon control and emissions reduction indicators and benchmarks, Gao et al. (2021) demonstrated that PCCE is a key carbon control index for low-carbon counties, and the benchmark should be dynamic, which indicates that the benchmark setting should reflect the evaluated region’s needs and development stage. When the local economy reaches a certain level, the benchmark should not be restricted by the static low-carbon target constraints. To this end, Gao et al. (2021) proposed a dynamic benchmark system for county PCCE based on the convergence theory and EKC theory (for CO2 emissions, the theory is called CO2 environmental Kuznets curve, CKC) (Gao et al. 2021). It has been verified that the best practices of Singapore’s CKC curve are suitable as a benchmark for the Changxing county PCCE because it successfully presents the relationship between PCCE and per capita GDP (PCGDP).

The dynamic benchmark system for county PCCE has provided an important method and reference for nation-wide counties to set scientific and reasonable targets for reducing carbon emissions. However, China has 2848 counties by the end of 2019. The natural, economic, and social conditions of counties vary greatly; there is a big variation in low-carbon emissions reduction responsibilities, capabilities, and needs for different counties. Ensuring fairness is the core for county low-carbon benchmarks’ formulation. Using Singapore’s CKC curve as a benchmark cannot fully meet the demand for differentiated PCCE benchmarks under the different status of China’s county-level carbon emissions reduction. Therefore, the better option is to extend the dynamic benchmark system for county PCCE, and this improvement would raise the result’s accuracy. This article based on Gao’s research: choose the best practice benchmark that can match the country’s development level, considering the discrepancy in carbon emissions at the county level for different types of counties in China.

How to classify county types is a basic issue that needs to be addressed. The allocation of carbon emissions rights is an effective way to reflect carbon emissions reduction capabilities and responsibilities (Chang and Chang 2016; Qin et al. 2017; Feng et al. 2018), which refers to the determination of carbon emissions allowances in different regions based on the amount of carbon emissions allowances or emissions reduction targets (Fang et al. 2020). The allocation of carbon emissions rights pursues fairness (Fang et al. 2019). In the regional decomposition of the country’s CO2 emissions, it is the most important manifestation of fairness to make each region’s CO2 quota conform to their respective responsibilities and capabilities. The United Nations Framework Convention on Climate Change (UNFCCC) segregates United Nations’ member states into developed (annex I) and developing (non-annex I) countries according to the principle of common but differentiated responsibilities. Annex I

---

1. https://www.unep.org/emissions-gap-report-2020
2. http://www.globalcarbonatlas.org/en/CO2-emissions
3. http://www.chinadaily.com.cn/a/202009/24/WS5f6c08aca31024ad0ba7b776.html
4. https://www.ndrc.gov.cn/xxgk/jd/jd/202006/c20200603_1229781.html
countries are required to undertake their emission reduction commitments in the first phase of the Kyoto Protocol (KP), while non-annex I countries are temporarily exempt from emission reduction obligations (Moffat 2010). The multi-stage method, developed by Gupta and Bhandari (1999) and refined by Den Elzen et al., is a quantitative plan consistent with UNFCCC goals. The multi-stage method is based on national/regional capabilities and responsibilities distinction rules. Such as the nation’s or region’s per capita income, PCCE or contributions to the share of global warming, the number of participating parties, and their commitment levels gradually increase (Berk and den Elzen 2001; Criqui et al. 2003; Maarten et al. 2015). The GHGs emissions development rights program considers the per capita income levels of different countries and their stage of economic and social development when allocating carbon emissions rights (Can tore 2011). These classification schemes provide ideas for the division of county types. That is to say, we must fully consider the factors that cause the differences in counties’ carbon emissions and classify the types of counties based on their carbon emissions reduction capabilities and responsibilities. Therefore, the study divides the types of counties through the allocation of carbon emissions rights.

The rest of the sections’ arrangements are set as follows. The “Literature review” section includes related literature and a brief methodology review of this article. The “Materials and Methods” section provided the method we used in this study and the related data sources. The “Results” section gives empirical results. The “Case Application” section verifies the applicability of the method. The “Discussion” section discusses the pros and cons of the methods. Finally, the “Conclusions” section concludes this study.

**Literature review**

**Allocation of carbon emissions quotas**

There are two main principles for carbon emissions allocation: equity and efficiency (Kong et al. 2019). Equity is paramount, and it is the core indicator for measuring the responsibility of different countries and regions to reduce emissions. Fairness is one of the core goals pursued by modern society. A fair and justifiable distribution plan is required to build a carbon emissions reduction responsibility system and achieve the nation’s carbon emissions discharge target. The principle of equity and its indicator representation system has become the main focus of research from the beginning. Den Elzen et al. (2003) came up with two keywords for the equity principles—capability and responsibility. The capability states that greater the capacity or ability, greater pressure or burden to take. The responsibility states that greater contribution to the situation, greater burden need to take (Den Elzen et al. 2003).

In subsequent studies, the capability and responsibility principle has been widely used. Pozo et al. (2020) used the capability, responsibility, and equality principles to distribute CO2 removal quotas globally (Pozo et al. 2020). Zhang et al. created an integrated index to combine the capacity, responsibility, and potential of the carbon emissions reduction and used the index to evaluate carbon emissions quotas among China’s 39 industry types in 2020, based on the 2015 level (Zhang and Hao 2017). Zhao et al. (2014) used the responsibility-capacity index as a footstone and calculated the expectation of carbon emissions reduction of international aviation in different countries by 2021 (Zhao et al. 2014). The research on carbon emissions allocation goes deeper, people more realize the fact that the “absolutely fairness” for carbon allocation cannot bring benefits to all countries. In place of equity, efficiency means maximizing benefits, becoming another vital principle of concern when allocating carbon right (Du et al. 2020). There are increasingly more researches on carbon emissions distribution based on the principle of efficiency, which pursues the optimal input–output ratio of allocation, that is, the most effective use of carbon emissions rights to meet the development needs of human society. Following the efficiency principle will maximize the total benefits but may increase the inequality in carbon emissions (Hubacek et al. 2017). Therefore, after considering the equity and efficiency principles integrally, some scholars have gradually changed their views from single principle and single perspective of carbon allocation to multi-principles and multi-perspectives (Chen et al. 2020b; Yang et al. 2020; Zhou et al. 2021).

Different ways of distributing carbon emissions quotas have been proposed, Zhou et al. summarized those approaches and put them into four categories: game theoretic approach, optimization method, hybrid approach, and indicator approach (Zhou and Wang 2016). For those categories, the game theoretic approach cannot be widely applied because of its lack of transparency and over-complexity (Du et al. 2020). DEA model is one of the main optimization methods. This model overly focuses on maximizing the distributive efficiency, which may cause the result’s unfairness and rationality, and easy to be questioned. Compared to other methods, the hybrid approach combines a few methods or models for carbon distribution, so, it can take advantages of multiple methods and be more comprehensive and systematic (Shi et al. 2020). The indicator approach is usually used as a part of the hybrid approach to reflect the value of indicators construction by applying other models. Qin et al. constructed an index system under the capacity criteria, responsibility and potential, and offered a multi-criteria decision analysis model, using the model to evaluate the fairness level of carbon emissions rights for China’s eastern coastal areas (Qin et al. 2017). Feng et al. proposed a
novel two-tier allocation scheme based on cluster analysis and a weighted voting model, in which multiple indicators were selected to comprehensively evaluate the voting power of each regional skew scheme (Feng et al. 2018). Kong et al. use three indicators, population, the accumulated historical carbon emissions, and the emission efficiency to form a comprehensive indicator. He also used the integrated weighting approach to simulate China’s 30 provinces’ carbon emissions allocation quotas (Kong et al. 2019). The hybrid approach, covering the indicator approach, can take into account multiple factors affecting the allocation of carbon emissions reduction targets, take regional differences into account, meet the principle of fairness, and easily accepted by all parties.

In this study, we fully consider the objective differences among counties and construct a capacity-responsibility index system (CR index system), then introduce the improved equal-proportion distribution method, using widely in the allocation of total pollutant reduction, to allocate county carbon emissions. The improved equal-proportion method distributes the total amount of pollutants based on the equity perspective. Considering the discrepancy among regions, while ensuring the achievement of the overall national carbon emissions reduction target, proper adjustments should be made based on the average reduction number to let the carbon reduction task for each area can match the area’s overall capacity. The improved equal-proportion distribution method was firstly used in the research on the allocation of chemical oxygen demand, water pollutants, and motor vehicle pollutants (Li et al. 2014; Liu et al. 2014; Liu et al. 2012). In recent years, the improved equal-proportion distribution method has been gradually applied in allocating carbon emissions. Wang et al. assigned China’s carbon emissions control targets in 2020 by considering the provinces’ differences in carbon emissions drivers, emission reduction capacity, emission reduction cost, and emission level (Wang et al. 2019). Shi et al. fully considered the differences in the economic, population, energy, and technological factors among cities to generate China’s 2030 carbon intensity discharge target (Shi et al. 2020). To meet the needs of county classification, we combine the index method with the improved equal-proportion distribution method to allocate carbon emissions targets. Such carbon emissions reduction allocation results will fully reflect the country’s emission reduction capacity and responsibility.

**The dynamic benchmark system for counties’ PCCE**

The benchmark of low-carbon indicators creates constraints for local carbon producers, which will push the local government to start to pave the low-carbon development road and gradually decrease GHGs emissions. Current low-carbon assessment tools and benchmarks come from a variety of sources, including average levels, local targets, international best practices, and typical performance (Zhou et al. 2015). In the current absence of county-level GHGs emissions reduction targets in China, the “best practices” can serve as a benchmark to make a low-carbon transition at the county level. Nevertheless, for counties that still focus on economic development, when the best practices performance value at a certain point in time is selected as the reference, too high benchmark will lead to evaluation deviation and low operability. Therefore, the dynamic and variable benchmark system will better meet the actual development situation of the county. PCCE is one of the most crucial criteria for the spatial equity of carbon emissions determination (Haider and Akram 2019). Research has shown that PCCE is more representative of China’s current situation than traditional GDP–based measures. Therefore, the use of PCCE allows policymakers to better prioritize resources to address climate issues and promote equity and efficiency (Chan et al. 2013).

In this study, we propose to take PCCE as the key carbon control index in low-carbon counties, and established benchmarks to effectively guide a reasonable local low-carbon transition at the microlevel, address the issues of efficiency and equity, thus promote overall regional emission reduction.

Convergence theory and EKC theory provide new routes for studying the dynamic benchmark system for PCCE in China’s counties. Convergence theory shows that when the economic development gap between the developing and developed countries increasingly narrows down, the PCCE gap between the two groups will gradually shrink. It means that by adjusting parameters such as income level, energy potential, and industrial structure, the PCCE of local counties and best practices can be expected to converge empirically, which provides a reasonable basis for best practices and benchmarking of local counties in China. Developed and developing countries with different convergence behavior are relevant to the EKC theory (Payne and Apergis 2020). EKC theory supports the assumption that when a country or region is in the early stages of economic development, its income will increase while the environmental quality will decrease. However, when countries or regions reach a certain income level (middle or high income), their demand for environmental quality is higher, followed by low emissions (Brock and Taylor 2010; Payne and Apergis 2020). In the long run, the relationship between economic growth and PCCE can be described as an inverted U-shape (Liu et al. 2019). Countries having similar development levels will have the same level of PCCE. For this reason, the developing country would be eager to improve living environment quality once it stands at a higher income level, so it will also start to discharge the emissions and fight to catch up developed countries. This process is exactly what the EKC shown (Strazicich and List 2003). If PCCE tends to converge, equity issues and distribution strategies related to PCCE will no longer be the focus,
which reflects the equal rights of human beings to survive and use atmospheric resources (Aldy 2006; Sørensen 2008; Payne and Apergis 2020). Therefore, selecting the CKC curve of the best practices as the dynamic benchmark of PCCE for counties in China can meet the requirements of equity and efficiency, low-carbon transition, and efficient development to the maximum extent. The process that the county benchmarks with the best practices are the process of the local county benchmarks with the best practices’ CKC curve. Here, the relationship between the income level and PCCE is depicted by the CKC curve.

**Materials and methods**

**Technical route of the research**

The flowchart below can visually and intuitively reveal this research’s technical route (Fig. 1).

Step 1, we calculated the county’s CITRR. Firstly, building the CIRT index system from the direction of carbon emissions reduction capacity and responsibility. Secondly, applying the entropy method to get the index weight. Then, combining the county’s baseline year carbon intensity data and the target year’s economic aggregate data, the improved equal-proportion distribution method was used to calculate each county’s CITRR.

Step 2, we screened the potential best practices. Based on the principles of best practices, comparability, data integrity, and CKC hypothesis acceptance (Gao et al. 2021), best practices were selected; unit root stationarity test and co-integration test were performed on the PCCE and PCGDP data for best practices to demonstrate the accuracy of best practices. Finally, Singapore, Korea, and Japan were screened as best practices.

Step 3, based on the CITRR, we divided China’s counties into three categories: L-CERCRC, M-CERCRC, H-CERCRC, and plan to use Singapore, Korea, and Japan’s CKC curve as the dynamic benchmark of PCCE for L-CERC-
CRC, M-CERCRC, and H-CERCRC respectively, according to the size of the turning point of the CKC curve of three countries.

**Allocation of CIRT**

**CIRT allocation index system**

**Differences in carbon emissions reduction capacity**  The stronger the county’s ability to reduce carbon emissions, the more cuts should be made based on the overall average reduction level. Economic factors, including economic development level and industrial structure, are essential factors that affect regional emission reduction capacity. As each region’s scope is different, resulting in different economic aggregates, regional economies with large economic aggregates are not necessarily very developed, so PCGDP is a comparable index reflecting the level of regional economic development. Nag and Ang think the growth of PCGDP is the key reason for carbon intensity increases; the relationship between those two is an inverted U-shape (Ang and Liu 2006). Since the relationship between China’s economic development and carbon emissions is still on the left side of the inverted U-shaped curve (China Sustainable Development Strategy Report 2009), PCGDP is a positive indicator. The industrial structure can make changes for energy efficiency, resulting in CO₂ emissions’ positive and negative changes (Chang 2015). In the relevant literature, the GDP of the secondary or tertiary industry is likely to be used to represent the industrial structure (Huang 2018; Ren et al. 2014). However, the level of energy consumption varies by industry. In recent years, China’s tertiary industry has accounted for more than 50% of the total, which is more energy efficient than other industrial structures. Therefore, it is one-sided to use the proportion of a single industry to examine the level of industrial structure (Song et al. 2018). In this study, we used the industrial upgrading coefficient method to calculate the industrial structure, adopted by Gu et al. (2020) and Song et al. (2018). The calculation formula is shown in Eq. (1):

\[
\text{Industrial structure} = (\text{proportion of primary industry} \times 1 + \text{proportion of secondary industry} \times 2 + \text{proportion of tertiary industry} \times 3)
\]

**Differences in carbon emissions reduction responsibilities**  The higher the responsibilities of the county to reduce carbon emissions, the more reductions should be made at the overall average emission reduction level. In this paper, two indicators, PCCE and the proportion of CO₂ emissions in the total carbon emissions of the study area, were selected to reflect a region’s actual carbon emissions from different perspectives. Both of them were positive indicators. At the same time, regions’ population and carbon intensity are picked to show their diverse carbon emissions reduction responsibilities. As explained by economic principles, demand is the power source of supply, so the population size may influence the demand scale, which in turn affects the size of industrial production and ultimately CO₂ emissions. Therefore, the population size is a positive indicator in this study. The greater the carbon intensity, the greater the room for improving the county’s energy use efficiency. Therefore, counties that have higher carbon intensity should cut more carbon emissions on the basis of the overall average emission reduction level (Table 1).

**Improved equal-proportion distribution method**

The improved equal-proportion distribution method is based on the differences between regions. The method makes a few proper adjustments based on the whole average reduction range, matching the emission reduction tasks of each region with the region’s current conditions. The improved equal-proportion distribution method can ensure the basic equality of emission reduction targets of different regions and facilitate practical implementation. Meanwhile, the method fully considers the objective differences

---

**Table 1** CIRT allocation index system

| Principle of allocation | Index | Index attribute |
|-------------------------|-------|----------------|
| Capacity                | PCGDP | +              |
|                         | Industrial structure | + |
| Responsibility          | PCCE  | +              |
|                         | The proportion of CO₂ emissions in the total carbon emissions of the study area | + |
|                         | Population | + |
|                         | Carbon intensity | + |

“+” means that carbon intensity increases with the increase of the index value, and “−” means that carbon intensity decreases with the increase of the index value.
between regions. While achieving the overall carbon emissions reduction target, it makes the allocation scheme more acceptable to all parties (Liu and Wang 2012).

This study used \( n \) counties involved in the CIRT allocation, and \( C \) is the overall CITRR compared to the base period emissions.

Average reduction and relative reduction are two concepts that are considered emphatically when processing carbon reduction and carbon allocation. This method introduces average reduction rate and relative reduction factor as two variables. The average reduction rate is the reflection of the equal proportion distribution criterion, and relative reduction is a factor that makes a fair adjustment based on the system of fairness criteria. The CITRR in each county is the product of the average carbon emissions intensity reduction rate and the relative reduction factor. The relationship among the three can be written as shown in Eq. (2):

\[
x_i = \bar{x} \times \alpha_i
\]  

(2)

where \( x_i \) is the CITRR assigned to the \( i \) county; \( \bar{x} \) is the average CITRR for \( n \) participating counties; \( \alpha_i \) is the relative reduction factor of the CIRT for \( i \) county.

The fairness criterion system determines the relative reduction factor, reflecting the differential responsibility of each county to reduce emissions on an equal proportion basis. According to the CR index system we discussed above, each county’s relative reduction factors of carbon emissions intensity were determined according to the numerical size and weight of each index. The formula is given as Eq. (3):

\[
\alpha_i = \frac{\sum_{j=1}^{m} z_{ij} \times w_j}{\frac{1}{x} \sum_{i=1}^{n} \sum_{j=1}^{m} z_{ij} \times w_j}
\]  

(3)

where \( j \) is the \( j \)th index (assuming that there is a total of \( m \) indexes in the CR index system); \( z_{ij} \) is the normalized value of the \( j \)th index in the \( i \) county; \( w_j \) represents the weight of the \( j \)th index. We use the entropy method to determine index weight (Wang et al. 2019).

The average reduction rate of carbon emissions intensity of each county shows the concept of equal distribution, which is calculated in Eq. (4). Calculating the target reduction rate \( C \) required by the whole county and the relative reduction factor of each county:

\[
\bar{x} = \frac{C \sum_{i=1}^{n} G_i I_i}{\sum_{i=1}^{n} G_i I_i \alpha_i}
\]  

(4)

where \( I_i \) is the carbon intensity of \( i \) county in the baseline year, and \( G_i \) is the gross product of \( i \) county in the target year.

Then the CITRR of \( i \) county is calculated as Eq. (5):

\[
x_i = \frac{C \sum_{i=1}^{n} G_i I_i}{\sum_{i=1}^{n}(\frac{1}{C} \sum_{j=1}^{m} z_{ij} \times G_i I_i) \times \frac{1}{x} \sum_{i=1}^{n} \sum_{j=1}^{m} z_{ij} \times w_j}
\]  

(5)

Data source and data processing

According to the CR index system built in the “Allocation of CIRT” section, together with China’s CIRT made in the Paris Agreement, i.e., China’s carbon intensity in 2030 will be 60–65% lower than that in 2005 (this study used 60% as the decline percentage). Taking 2005 as the baseline year, we separated the 2030 CIRT into 1510 Chinese counties.

The carbon emissions data of the counties in 2005 used in this study came from the data published in scientific data (Chen et al. 2020a). Socio-economic data is from the Statistical Yearbook of Provinces and Regions (2006) and Statistical Yearbook of Cities (2006). Referring to Li’s study’s results (Li et al. 2005), we projected each county’s GDP in 2030.

China’s county PCCE dynamic benchmark system

Best practices filtering

Based on the principles of the dynamic benchmark system for counties’ PCCE, best practices, comparability, data integrity, and CKC hypothesis acceptance, we selected the potential best practices from the best practices candidate database (Fig. 2). In terms of size and population density, Asian cities are more comparable. Therefore, this study selected the best practices from the Asian Green City Index (AGCI) as the benchmark for PCCE. Tokyo, Yokohama, Osaka, Delhi, Hong Kong, Jakarta, Seoul, Singapore, and Taipei scored above average in the AGCI. Most of these excellent cities lack complete PCCE data. Countries with AGCI were selected as best practices to compensate for the lack of city data. Thus, candidates for best practices include Singapore, Japan, Korea, India, and Indonesia.

CKC model building

EKC is a widely admisive economic model, which describes the relationship between economic development and environmental quality as an inverted U-shaped curve. Based on the well-studied classical equations, we established an econometric model to test best practices’ CKC. In the CKC model, PCCE, as a representative variable, represents environmental quality; PCGDP, as an independent variable, represents economic growth. This model depicts the deceleration of PCCE in an economy from a low level to a high level of income, reflecting the convergence relationship between income level and growth.

5 In 2019, there were 2848 counties in China. Due to the lack of data related to index, we selected 1510 counties as case areas in this study.
rate (Selden et al. 1994). To reduce data fluctuations and eliminate heteroscedasticity, most studies adopt logarithmic transformation of relevant data to simplify the study (Zhao et al. 2017). The equation is expressed as follows:

$$\ln PCCE_{it} = \alpha + \beta_1 \ln PCGDP_{it} + \beta_2 \ln PCGDP^2_{it} + \beta_3 \ln PCGDP^3_{it} + \epsilon_{it}$$  \hspace{1cm} (6)

where \(PCCE_{it}\) is PCCE in tCO2e/person, \(PCGDP_{it}\) is PCGDP in USD (constant USD 2010)/person, and \(\epsilon_{it}\) represents the random error term. Subscript \(i\) is the country or region, and \(t\) refers to time. \(\alpha\) is a constant, and \(\beta_k\) is the coefficient of the explanatory variable, both of which are estimated constants.

When \(\beta_1 > 0, \beta_2 < 0, \text{ and } \beta_3 = 0\), indicating that the relationship between PCGDP and PCCE shown as an inverted U-shaped relationship, presenting a classic Kuznets curve, the turning point is \(-\beta_1/2\beta_2\).

**Data source**

Extract the PCCE and PCGDP data of Singapore, Japan, Korea, India, and Indonesia from the World Bank during 1960–2016.

**Data processing**

The unit root stationarity test and co-integration test were performed on the logarithm \(\ln PCCE\) of the dependent variable PCCE and the logarithm \(\ln PCGDP\) and \(\ln^2 PCGDP\) of the independent variable PCGDP to determine whether the best practices candidate follows CKC regularity. The results showed that Singapore, Korea, Japan, and India follow CKC regularity, but the relationship between PCCE and PCGDP in Indonesia do not have CKC regularity. The calculation process proceeds in EVEIWS 10.0, and the verification process shows in Appendix A. The following is the CKC co-integration equation for each country.

**Singapore CKC model** The Singapore CKC cointegration equation comes from Gao et al. (2021).

\[
\ln PCCE = 17.65462 + 0.887645 \cdot \ln PCGDP - 85.073568 \hspace{1cm} (7)
\]

**Korea CKC model**

\[
\ln PCCE = 3.621354 + 0.160318 \cdot \ln PCGDP - 17.78758 \hspace{1cm} (8)
\]

**Japan CKC model**

\[
\ln PCCE = 7.152428 + 0.320972 \cdot \ln PCGDP - 37.52280 \hspace{1cm} (9)
\]

**India CKC model**

where PCCE represents per capita carbon emissions, PCGDP is PCGDP in USD (constant USD 2010)/person.

**Results**

**CITRR in each county**

We obtained each index’s weight based on the entropy method (Table 2). Due to the CO2 emission target that in 2030, the carbon intensity will reduce 60% compared to 2005: the national average CITRR is 48.40%. After the adjustment for carbon emissions’ relative reduction factor of the influence factors, the CITRR of the counties showed a significant diversity, with CITRR ranging from 8.36 to 137.83%.
The Moran index was used to analyze the spatial correlation of CITRR. The analysis showed a $p$ value of 0.00, which passed the significance test at the 0.01% level. The Moran index was 0.165120, indicating that CITRR shows a positive spatial correlation. The higher the CITRR, the higher the capacity and responsibility of carbon emissions reduction. In ArcGIS10.6, we applied the quantile method to divide CITRR values for each county into three levels. Among them, 0.01–37.57% (excluding 0, the same below) is the target reduction rate of L-CERCRC; 37.57–53.93% are the target reduction rates of M-CERCRC and 53.93–137.83% are the target reduction rates of H-CERCRC. The 1510 counties were divided into 503 L-CERCRC, 503 M-CERCRC, and 504 H-CERCRC (Fig. 3). According to the calculation results of the CKC curve, we selected the dynamic benchmark of PCCE that matches its emissions reduction capacity and responsibility, establishing a dynamic benchmark system for PCCE in China’s counties.

### County carbon emissions reduction capability-responsibility classification

According to the chart of PCGDP of countries in AGCI over the years (Fig. 4), the PCGDP of Indonesia and India, as developing countries, has developed more slowly than China since 2000. Indonesia’s PCCE and PCGDP have not passed the CKC test, so they are not suitable for best practices areas. We finally selected the CKC curves of Singapore, Japan, and Korea as the dynamic benchmark system for PCCE in China’s counties. According to the development trend of their PCGDP, Japan had the fastest economic growth in the early stage and entered a relatively stable period of economic development in the 1990s, maintaining a relatively high economic level. The economic development of Singapore and Korea is in a continuous upward process. They are all developed countries and have mature experience in low-carbon construction (Chen 2018; Kim 2016; Luan et al. 2013). For this reason, using them as the best practices of PCCE in China counties can be beneficial in encouraging counties to implement carbon emissions reduction measures.

According to the CKC curve formula of Singapore, Japan, and Korea, the maximum PCCE of the CKC curve of the three countries are 15.04t, 10.20t, and 14.34t, respectively. L-CERCRC indicates that this type of county allows having more carbon emissions. Therefore, the CKC curve of Singapore, which has the largest turning point of PCCE, is selected as the dynamic benchmark of PCCE in L-CERCRC. Similarly, the CKC curve of Korea is selected as the dynamic benchmark of PCCE in M-CERCRC, while the CKC curve of Japan is selected as the dynamic benchmark of PCCE in H-CERCRC.

### Case application

The verification of PCCE’s dynamic benchmark system needs to be combined with the county carbon emissions situation. The rich and detailed prediction of PCCE and peak of carbon emissions in the county compared with the PCCE’s dynamic benchmark system can provide a strong basis for the county’s future policy path of carbon emissions reduction. However, the lack of carbon emissions accounting data at the county scale results in relatively few studies on carbon emissions accounting and prediction. In the existing studies, scholars have conducted in-depth studies on carbon emissions in Changxing County. Long et al. (2021) calculated carbon emissions from energy, industrial process and product use, agriculture and other land use, and waste in Changxing County; based on point source, line source, and area source, carbon emissions is spatialized from bottom to top and from top to bottom (Long et al. 2021). Qian et al. (2020) simulated the total emission of energy-related CO$_2$ under different scenarios in 2018–2035 and found that the total emission of CO$_2$ in Changxing County would reach the peak in 2030, and the energy structure was the decisive factor restricting the total emission of CO$_2$ in Changxing County (Qian et al. 2020). Their research results can provide better comparative analysis for verifying PCCE’s dynamic benchmark system. Therefore, this paper selects Changxing County as the case application area. Changxing County locates in the center area of the Yangtze River Delta, one of the high-speed growing urbanizing areas in China. It is a relatively developed area with a dense population. In 2020, the proportion of the structure of tertiary industries in Changxing County was 52.49:545.3, with industry as the leading industry. The county’s energy consumption per GDP unit is higher than per GDP unit of Zhejiang Province and per GDP unit of China in the same year, facing the challenge of economic development and low-carbon transformation. Taking Changxing County as a case application area can provide some reference for other counties that has similar problems to formulate reasonable and effective low-carbon emissions reduction targets.

Through the county carbon emissions reduction capability-responsibility classification, the CITRR in Changxing County
is 57.71%, belonging to the H-CERCRC, and benchmarks against the Japan’s CKC curve (in Gao’s study, Changxing’s PCCE benchmarks against Singapore’s CKC curve).

The forecast data for PCCE and PCGDP in Changxing County in 2025, 2030, and 2035 are obtained from Qian et al. (2020). County dynamic benchmark means via benchmarking the best practices’ CKC curve, developing a dynamic benchmark according to different income levels. Using the PCGDP forecast data of Changxing County in formula 9, we can then calculate the PCCE benchmark of Changxing County under different levels of economic development. Table 3 displays the calculation result.

According to Japan’s CKC curve, when the PCGDP of Changxing County reaches 19,172.92 US dollars in 2025, 24,483.01 US dollars in 2030, and 29,366.11 US dollars in 2035, the corresponding benchmark should be 6.03 tons of CO₂/person, 7.23 tons of CO₂/person, and 8.07 tons of CO₂/person. The PCCE of each year in the research period is far lower than the carbon emissions predicted by Qian. According to Qian et al. (2020), the PCCE of Changxing County is expected to reach its peak in 2030 (23.07tCO₂/person) (Qian et al. 2020), so it can be seen that the PCCE of Changxing County will be much higher than the benchmark when the carbon reaches the peak. Because of the benchmark constraint, it is necessary to adjust...
the relevant influencing factors of local PCCE, such as energy structure, energy efficiency, and income level, to promote the convergence of PCCE to the benchmark within a predetermined time.

**Discussion**

**Non-proportional allocation**

The counties’ CITRR is between 8.36% and 137.83%, and thirty-seven counties’ CITRR exceed 100%. The CITRR value that exceeds 100% does not require these counties to decrease the local carbon intensity to zero or even a negative value but reveals the truth that these counties, compared to other groups, have a strong capacity and responsibility on carbon emissions reduction. The reason for CITRR that exceeds 100% is that counties have different social and economic conditions, energy conditions, and technological conditions. Those differences create a large span on counties’ relative reduction factors. Also, the existence of exceed 100% CITRR can confirm the necessity of setting the non-equal distribution of CIRT. When decomposing the national carbon reduction target into regions, we should fully consider the factor of CO₂ emissions from region difference, making each region’s carbon emissions quota following their responsibilities and abilities. On the one hand, the central government can evaluate a region’s degree of efforts to reduce emissions by evaluating whether the region’s CO₂ emissions are within the emission quota. On the other hand, the emission reduction targets and economic and social development targets can be combined to conduct a comprehensive result evaluation for the region. Today, we expect to change the way we used to assess regions based on GDP alone, and expect to assess the development of a region in a more scientific and comprehensive way (He 2013).

**Dynamic benchmark of PCCE**

For China’s economic development, low-carbon has become the must choice (Liu et al. 2011). For counties that are still dominated by local economic development, the local economic development approach should be shifted to green and gradually reduce carbon emissions. Otherwise, those counties would undertake high pressure on develop low-carbon emissions economy, and counties’ sustainable development would suffer negative impact in the near future. Policy guidance is indispensable for constructing a low-carbon economy. When formulating government policies, policymakers are encouraged to use the PCCE economic-sensitive dynamic benchmark as a scientific basis. The PCCE economic-sensitive dynamic benchmark

---

**Table 3** Changxing County PCCE benchmark calculation results

| Forecast period (year)         | PCGDP<sub>Changxing</sub><sup>1</sup> (dollar) (Qian et al. 2020) | PCCE<sub>Changxing</sub> (t) (Qian et al. 2020) | ln PCGDP | lnPCCE<sub>Benchmark</sub> | PCCE-Benchmark (t) |
|-------------------------------|---------------------------------------------------------------|-----------------------------------|---------|----------------------------|-------------------|
| Recent period (2025)          | 19172.92                                                     | 22.94                             | 9.86125437 | 1.796402111 | 6.03              |
| Mid-term period (2030)        | 24483.01                                                     | 23.07                             | 10.1057347 | 1.978193846 | 7.23              |
| Long-term period (2035)       | 29366.11                                                     | 22.09                             | 10.2875964 | 2.088536665 | 8.07              |

<sup>1</sup>PCGDP here is in 2010 dollars
assists counties in exploring emission reduction paths adapted to different development stages, linking economic development patterns with carbon reduction issues, and strongly supporting counties in building low-carbon economic systems.

**Carbon emissions peak and dynamic benchmark**

In the absence of low-carbon targets, Chinese provinces and cities will reach peak carbon emissions after 2030 (Liu et al. 2017; Lu et al. 2018). Thus, the low-carbon target constraint is key in guiding carbon emissions peak. The right of carbon emissions is the right to develop. In order to leave enough space for economic development, PCCE should be set to a fair number. Too low’s PCCE will limit the scale of economic development; too high’s PCCE will put high pressure on achieving the emission reduction target (Hou et al. 2019). China’s county PCCE dynamic benchmarking system links economic development to PCCE benchmarking by benchmarking the relationship between PCGDP and PCCE in developed countries, making the low-carbon target dynamic and solving the problem of too high or too low PCCE target. Whether China can achieve carbon emissions peak by 2030 will not show a direct quantitative effect. Setting a dynamic PCCE target can promote the reduction of carbon emissions and provide enough carbon emissions space for later’s economic development. As demonstrated by the case application, even if Changxing County, which relies on industry to drive economic development, can achieve carbon emissions peak at a predetermined time, its PCCE at the peak is still higher than the benchmark. Therefore, to achieve national carbon reduction targets in time, strong regulatory solutions are needed to reduce PCCE at peak times.

**Uncertainties and limitations**

We acknowledge that our analysis still has the following limitations: (1) This paper constructs the CKC curve of PCGDP and PCCE, and use the turning point size of the CKC curve as the basis for the target of different emission reduction capabilities and responsibility areas. In fact, the choice of PCCE’s benchmark is much more complicated. It is necessary to consider whether each county’s economic development history, level of industrial development, energy mix, and other factors are similar to best practices areas. We have not been able to analyze the development of each county in detail, only roughly divided into three types. Future research can analyze the PCCE’s benchmarks of various typical counties from the macro to the micro. (2) This paper divides three types of emission reduction capability-responsible counties. Due to the problem of obtaining carbon emissions accounting and forecast data in the county region, we only verify the H-CERCRC. Future research can further verify the PCCE’s dynamic benchmark of the other two types of counties.

**Conclusions**

In this study, we constructed a CR index system, making 2005 work as the base year and 2030 work as the target year to distribute China’s CIRT on the county level. The counties are classified into three types according to CTIRR. The CKC curve of Japan, Korea, and Singapore can be used as the PCCE benchmark for each type according to the construction idea of China’s county PCCE dynamic benchmark system. The main conclusions are as follows:

1. According to the calculation results of carbon intensity target reduction rate of each county, the range of carbon intensity target reduction rate is relatively large, reflecting the socio-economic situation, the energy situation, and the technology situation difference between counties is big. Counties should choose their low-carbon economic development roads based on the local heterogeneity in resource endowment, industrial structure, and economic base.
2. Original PCCE’s dynamic benchmark system only selected Singapore’s CKC curve as a benchmark. Our research on different types of the best practices of county to explore the multiple benchmarks, build a national system, and further selected Changxing county for verification (Changxing County has fairly good data on carbon emissions), strengthened the scientific nature of the research on the dynamic benchmark system for PCCE. The improved PCCE’s dynamic benchmark system not only considers different counties and their different carbon emissions reduction capability-responsibility but also is economically sensitive to different development stages of counties, making the results of the dynamic benchmark system for counties’ PCCE more general.

**Appendix**

We used ADF test to test the stationarity of time series for PCCE and PCGDP, respectively, to analyze whether the two series are in a stable state in the empirical analysis, and determine whether the estimation results of model construction are meaningful for this paper.

**CKC hypothesis test of Japan**

**Stationarity test**

Table 4 shows that, Japan’s PCGDP and PCCE series belong to the first-order single integration, which satisfies the integration condition of the same order and can be tested for co-integration.
Cointegration test and CKC estimation

Carried out the ordinary least squares (OLS) estimation and added the ar (1) term to eliminate autocorrelation, and gives the following results:

\[ \text{lnPCCE} = 7.152428 \times \text{lnPCGDP} - 0.320972 \times \text{ln}^2 \text{PCGDP} - 37.52280 + [\text{ar}(1) = 0.908807] \]

\[ t = (3.235164) \ (−2.871468) \ (−3.446079) \ (14.09330) \]

\[ R^2 = 0.986750 \]

\[ R^2_a = 0.986000 \]

\[ SE = 0.040357 \]

\[ F = 1315.684 \]

\[ DW = 1.836761 \]

CKC hypothesis test of Korea

Stationarity test

Table 6 shows that, Korea’s PCGDP and PCCE series belong to the first-order single integration, which satisfies the integration condition of the same order, and can be tested for co-integration.

Cointegration test and CKC estimation

Carried out the OLS estimation and added the ar (1) term to eliminate autocorrelation, and gives the following results:

\[ \text{lnPCCE} = 3.621354 \times \text{lnPCGDP} - 0.160318 \times \text{ln}^2 \text{PCGDP} - 17.78758 + [\text{ar}(1) = 0.812748] \]

\[ t = (7.018854) \ (−5.285079) \ (−8.248042) \ (8.426005) \]

\[ R^2 = 0.997246 \]

\[ R^2_a = 0.997090 \]

\[ SE = 0.050586 \]

\[ F = 6396.303 \]

\[ DW = 1.797576 \]
CKC hypothesis test of India

Stationarity test

Table 8 shows that, India’s PCGDP and PCCE series belong to the first-order single integration, which satisfies the integration condition of the same order, and can be tested for co-integration.

Cointegration test and CKC estimation

Carried out the OLS estimation and added the ar (1) term to eliminate autocorrelation, and gives the following results:

\[ \lnPCCE = 5.622127 + \lnPCGDP - 0.298130 + \ln^2PCGDP - 25.38366 + \]

\[ (ar(1)) = 0.519915 \]

\[ r = (7.018854) (-5.285079) (-8.248042) (8.426005) \]

\[ R^2 = 0.987531 \quad SE = 0.082565 \quad F = 1029.602 \quad DW = 1.755797 \]

The stationarity test is performed on the residual sequence of the cointegration equation (Eq. A-3), and the test results are shown in Table 9. The results demonstrate that the residual sequence is stable at the significance level of 1%. Therefore, \( \lnPCCE \) has a cointegration relationship with \( \lnPCGDP \) and \( \ln^2PCGDP \), which means there is an inverted U-shaped curve relationship between India’s PCCE and PCGDP, i.e., India’s CKC curve can serve as a dynamic benchmark for PCCE.

CKC hypothesis test of Indonesia

Stationarity test

Table 10 shows that, Indonesia’s PCGDP and PCCE series belong to the first-order single integration, which satisfies the integration condition of the same order, and can be tested for co-integration.

Cointegration test and CKC estimation

Carried out the OLS estimation and added the ar (1) term to eliminate autocorrelation, and gives the following results (Table 11):

The correlation coefficient \( P \) value is greater than 0.05, indicating that there is no CKC curve rule, so there is no co-integration relationship between \( \lnPCCE \) and \( \lnPCGDP \) and \( \ln^2PCGDP \), which means there is an inverted U-shaped curve relationship between India’s PCCE and PCGDP, i.e., India’s CKC curve can serve as a dynamic benchmark for PCCE.

| Variable     | Coefficient | Std. error | t statistic | Prob  |
|--------------|-------------|------------|-------------|-------|
| lnPCGDP      | -1.496215   | 1.549418   | -0.965663   | 0.3387|
| ln^2PCGDP    | 0.159115    | 0.121737   | 1.307037    | 0.1970|
| C            | 2.444029    | 4.833309   | 0.505664    | 0.6152|
| AR(1)        | 0.995340    | 0.023574   | 42.22196    | 0.0000|
| SIGMASQ      | 0.001425    | 0.000303   | 4.699098    | 0.0000|

Table 8 Stationarity test results of PCCE and PCGDP of India

| Inspection type (c,t,k) | lnCEPC (c,t,0) | lnCEPC (c,t,1) | lnGDPPC (c,t,1) | lnGDPPC (c,t,0) | ln^2GDPPC (c,t,0) | ln^2GDPPC (c,t,1) |
|------------------------|---------------|---------------|----------------|----------------|------------------|------------------|
| ADF                    | -2.559961     | -6.980780    | -3.243011      | -5.242874      | -3.475721        | -5.314776        |
| T value                | -3.174802     | -4.137279*** | -3.175693      | -4.133838***   | -3.175693*       | -4.133838***     |
| (P value)              | 0.2996        | 0.0000        | 0.0869         | 0.0004         | 0.0521           | 0.0003           |

Table 9 Results of stationarity test for residual series of India’s CKC co-integration equation

| Variable | Examination form (c,t,k) | ADF | T Value (P Value) |
|----------|--------------------------|-----|-------------------|
| e        | (c,t,1)                  | -5.594629 | -4.133838*** (0.0001) |

Table 10 Stationarity test results of PCCE and PCGDP of Indonesia

| Inspection type (c,t,k) | lnCEPC (c,t,0) | lnCEPC (c,t,1) | lnGDPPC (c,t,1) | lnGDPPC (c,t,0) | ln^2GDPPC (c,t,0) | ln^2GDPPC (c,t,1) |
|------------------------|---------------|---------------|----------------|----------------|------------------|------------------|
| ADF                    | -1.570757     | -7.782234     | -0.062307      | -7.189038      | 0.520976         | -6.795010        |
| T value                | -3.174802     | -4.133838***  | -3.174802      | -4.144584***   | -3.174802        | -4.144584***     |
| (P value)              | 0.7920        | 0.0000        | 0.9944         | 0.0000         | 0.9991           | 0.0000           |

Table 11 Test results of OLS estimation of Indonesia
ln\textsuperscript{2}PCGDP, i.e., Indonesia does not meet the principle of CKC hypothesis acceptance.

**Acknowledgements** The authors would like to thank the anonymous reviewers for their valuable comments on this paper.

**Author contribution** Fengmei Yang and Lijie Gao conceived and designed the methodologies; Fengmei Yang analyzed the data and wrote the paper; Lijie Gao and Longyu Shi revised the paper; Longyu Shi and Lijie Gao acquired Funding. Xiaotong Wang made language polishing.

**Funding** This work was supported by the National Key Research and Development Program of China (2018YFC0704703) and National Natural Science Foundation of China (Grant No. 42107506).

**Data availability** Not applicable.

**Declarations**

**Ethics approval** Not applicable. This article does not contain any studies with human participants or animals performed by any of the authors.

**Consent to participate** Not applicable. This article does not contain any studies with human participants or animals performed by any of the authors.

**Consent for publication** Not applicable. This article does not contain any individual person’s data in any form.

**Conflict of interest** The authors declare no competing interests.

**References**

Aldy J (2006) Per capita carbon dioxide emissions: convergence or divergence? Environ Resource Econ 33:533–555. https://doi.org/10.2139/ssrn.881086

Ang BW, Liu N (2006) A cross-country analysis of aggregate energy and carbon intensities. Energy Policy 34(15):2398–2404. https://doi.org/10.1016/j.enpol.2005.04.007

Berk MM, den Elzen MGI (2001) Options for differentiation of future commitments in climate policy: how to realise timely participation to meet stringent climate goals? Clim Pol 1(4):465–480. https://doi.org/10.1016/S1469-3062(01)00037-7

Brock W, Taylor M (2010) The Green Solow model. J Econ Growth 15. https://doi.org/10.1007/s10887-010-9051-0

Cantore N (2011) Distributional aspects of emissions in climate change integrated assessment models. Energy Policy 39(5):2919–2924. https://doi.org/10.1016/j.enpol.2011.02.070

Chan EHW, Choy LHT, Yung EHK (2013) Current research on low-carbon cities and institutional responses. Habitat Int 37(none). https://doi.org/10.1016/j.habitatint.2011.12.007

Chang N (2015) Changing industrial structure to reduce carbon dioxide emissions: a Chinese application. J Clean Prod 103:40–48. https://doi.org/10.1016/j.jclepro.2014.03.003

Chang K, Chang H (2016) Cutting CO\textsubscript{2} intensity targets of interprovincial emissions trading in China. Appl Energy 163:211–221. https://doi.org/10.1016/j.apenergy.2015.10.146

Chen J, Gao M, Cheng S, Hou W, Song M, Liu X et al (2020a) County-level CO\textsubscript{2} emissions and sequestration in China during 1997–2017. Sci Data 7(1):391. https://doi.org/10.1038/s41597-020-00736-3

Chen L, He Y, Li G, Li C, Ren J (2020b) Initial allocation model of CO\textsubscript{2} emission allowances based on the equity-efficiency tradeoff. Asia Pac J Oper Res (1). https://doi.org/10.1142/S0217595920500487

Chen G (2018) Clean technology and sustainable urban solutions in Singapore. World Scientific Book Chapters. Green Development of Asia-Pacific Cities, pp 107–117. https://doi.org/10.1142/9789813236820_0005

Cirigoi P, Kitous A, Berk M, Den Elzen M, Eickhout B, Lucas P, Van Vuuren D, De Vries B, Eerens H, Oostenrijk R, Kouvaritakis N, Paroussos L, Vanregemorter D (2003) Greenhouse Gas Reduction Pathways in the UNFCCC Process up to 2025. Technical Report. Belgium: N. p., Web.

Den Elzen MGI, Berk MM, Lucas P, Eickhout B, van Vuuren DP (2003) Exploring climate regimes for differentiation of commitments to achieve the EU climate target. RIVM-Report 728001023, RIVM, Bilthoven

Du J, Pan M, Chen Y, Duan Y (2020) An efficiency-based allocation of carbon emissions allowance: a case study in China. J Clean Prod 251:119346. https://doi.org/10.1016/j.jclepro.2019.119346

Fang K, Zhang Q, Long Y, Yoshida Y, Sun L, Zhang H et al (2019) How can China achieve its intended nationally determined contributions by 2030? A multi-criteria allocation of China’s carbon emission allowance. Appl Energy 241:380–389. https://doi.org/10.1016/j.apenergy.2019.03.055

Fang K, Li S, Ye R, Zhang Q, Long Y (2020) New progress in global climate governance: a review on the allocation of regional carbon emission allowance. Acta Ecol Sin 40(01):1–14 (In Chinese)

Feng Z, Tang W, Niu Z, Wu Q (2018) Bi-level allocation of carbon emission permits based on clustering analysis and weighted voting: a case study in China. Appl Energy 228:1122–1135. https://doi.org/10.1016/j.apenergy.2018.07.005

Gao L, Shang X, Yang F, Shi L, Scuibba E (2021) A dynamic benchmark system for per capita carbon emissions in low-carbon counties of China. Energies. https://doi.org/10.3390/en14030599

Gu W, Chu Z, Wang C (2020) How do different types of energy technological progress affect regional carbon intensity? A spatial panel approach. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-020-10327-9

Gupta S, Bhandari MP (1999) An effective allocation criterion for CO\textsubscript{2} emissions. Energy Policy 27(12):727–736. https://doi.org/10.1016/S0301-4215(99)00058-0

Haider S, Akram V (2019) Club convergence of per capita carbon emission: global insight from disaggregated level data. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-019-04573-9

He Y (2013) Chinese energy carbon dioxide emissions control objectives and geographical distribution statistics [D]. Southwestern University of Finance and Economics (In Chinese)

Hou L, Tang L, Qian Y, Chen H, Wang L (2019) Study of county-level low-carbon standards in China based on carbon emissions per capita. Int J Sust Dev World 26(8):698–707. https://doi.org/10.1080/11356406.2019.1672589

Huang J (2018) Investigating the driving forces of China’s carbon intensity based on a dynamic spatial model. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-018-2307-5

Hubacek K, Baiocchi G, Feng K, Castillo RMO, Sun L, Xue J (2017) Global carbon inequality. Energy Ecol Environ 2(6):361–369. https://doi.org/10.1007/s40794-017-0072-9

Kim ES (2016) The politics of climate change policy design in Korea. Environ Polit 25(3):454–474. https://doi.org/10.1080/10072912.2015.1104804

Kong Y, Zhao T, Yuan R, Chen C (2019) Allocation of carbon emission quotas in Chinese provinces based on equality and efficiency principles. J Clean Prod. https://doi.org/10.1016/j.jclepro.2018.11.178

Leemans R, Vellinga P (2017) The scientific motivation of the internationally agreed “well below 2 °C” climate protection target: a historical perspective. Curr Opin Environ Sustain 26–27(JUN):134–142
Li J, Li Y, Wang Q (2014) Characteristics of total emission of regional motor vehicle pollutants and allocation of reduction amount. China Popul Resour Environ 24(08):141–148 (In Chinese)

Liu Q, Wang Q (2012) Pollutant reduction allocation based on regional differences - COD reduction allocation between provinces as a case. Resour Environ Yangtze Basin 21(04):512–517 (In Chinese)

Liu L-Q, Liu C-X, Sun Z-Y (2011) A survey of China’s low-carbon application practice—opportunity goes with challenge. Renew Sustain Energy Rev 15(6):2895–2903. https://doi.org/10.1016/j.rser.2011.02.034

Liu N, Jiang H, Lu Y, Zhang J (2014) Study on allocation of water pollutant total control target - consider the environmental constraints of the main functional areas. China Popul Resour Environ 24(05):80–87 (In Chinese)

Liu Q, Li Q, Zheng X (2017) The prediction of carbon dioxide emissions in Chongqing based on fossil fuel combustion. Acta Sci Circum 37(4):1582–1593 (In Chinese)

Liu J, Song X, Chen H et al (2019) Study on the long-term equilibrium and causality of the influencing factors of China’s per capita carbon-based on structural break ARDL model and VECM model. Oper Res Manag Sci 9:57–65 (In Chinese)

Liu C, Cai B, Chen C et al (2013) Review of carbon mitigation targets allocation in China[J]. Scientia Geographica Sinica 33(9):1089–1096 (In Chinese)

Long Z, Zhang Z, Liang S, Chen X, Ding B, Wang B et al (2021) Spatially explicit carbon emissions at the county scale. Resour Conserv Recycl 173:105706. https://doi.org/10.1016/j.resconrec.2021.105706

Lu Y, Li X, Yang Z (2018) Current situation and peak forecast of energy carbon emissions in Guizhou Province. Environ Sci Technol 41(11):173–180 (In Chinese)

Luan Z, Pu Z (2013) Assessment of Sino-Singapore Tianjin eco-city planning base on experience of low-carbon eco-city development in Japan and South Korea. Urban Plan Forum 02:46–56 (In Chinese)

Maarten VDB, Hof AF, van Vliet J, van Vuuren DP (2015) Impact of the choice of emission metric on greenhouse gas abatement and costs. Environ Res Lett 10(2):024001. https://doi.org/10.1088/1748-9326/10/2/024001

Moffat J (2010) Arranging deckchairs on the titanic: climate change, greenhouse gas emissions and international shipping. Australian and New Zealand Maritime Law Journal 24(02)

Payne JE, Apergis N (2020) Convergence of per capita carbon dioxide emissions among developing countries: evidence from stochastic and club convergence tests. Environ Sci Pollut Res (4). https://doi.org/10.1007/s11356-020-09506-5

Pozo C, Galán-Martín N, Reiner DM, Dowell NM, Guillén-Gosálbez G (2020) Equity in allocating carbon dioxide removal quotas. Nature Clim Change 10(3). https://doi.org/10.1038/s41558-020-0802-4

Qian Y, Sun L, Qiu Q, Tang L, Shang X, Lu C (2020) Analysis of CO2 drivers and emissions forecast in a typical industry-oriented county: Changxing County, China. Energies 13:1212. https://doi.org/10.1007/j.jclepro.2017.08.220

Qin Q, Liu Y, Li X, Li H (2017) A multi-criteria decision analysis model for carbon emission quota allocation in China’s east coastal areas: efficiency and equity. J Clean Prod 168:410–419. https://doi.org/10.1016/j.jclepro.2017.08.220

Ren X, Zhao T (2014) Study on dynamic causal relationship between carbon emission intensity and its influencing factors in China - from the perspective of the extended Kaya formula. J Arid Land Resour Environ 28(03):6–10 (In Chinese)

Selden, Song (1994) Environmental quality and development: is there a Kuznets curve for air pollution emissions? Acad Press 27(2). https://doi.org/10.1006/jecm.1994.1031

Shi L, Yang F, Gao L (2020) The allocation of carbon intensity reduction target by 2030 among cities in China. Energies. https://doi.org/10.3390/en13226006

Song M, Chen Y, An Q (2018) Spatial econometric analysis of factors influencing regional energy efficiency in China. Environ Sci Pollut Res 25(14):13745–13759. https://doi.org/10.1007/s11356-018-1574-5

Størensen B (2008) Pathways to climate stabilisation. Energy Policy 36(9):3505–3509. https://doi.org/10.1016/j.enpol.2010.02.073

Strazdins M, List J (2003) Are CO2 emission levels converging among industrial countries? Environ Res Econ 24(3):263–271. https://doi.org/10.1023/A:102290701857

Sustainable Development Strategy Research Group, Chinese Academy of Sciences (2009) China sustainable development strategy report 2009: exploring a low carbon path with Chinese characteristics. Science Press (In Chinese). https://bdp.cast.cn/zlyjwqgl/202110/20211013_4809291.html

Wang Q, Zhao X (2019) Allocation of carbon dioxide emission reduction targets in China based on the improved equal proportion distribution. J Arid Land Resour Environ 33(01):1–8 (In Chinese)

Wang Y, Li X, Kang Y, Chen W, Zhao M, Li W (2019) Analyzing the impact of urbanization quality on CO2 emissions: what can geographically weighted regression tell us? Renew Sustain Energy Rev 104:127–136. https://doi.org/10.1016/j.rser.2019.01.028

World Meteorological Organization (2019) The global climate in 2015–2019. https://public.wmo.int/en/media/press-release/global-climate-status-report-2019

Yang B, Li X, Su Y, Liu C, Xue F (2020) Carbon quota allocation at the provincial level in China under principles of equity and efficiency. Carbon Manag 11(1):11–23

Zhang YJ, Hao JF (2017) Carbon emission quota allocation among China’s industrial sectors based on the equity and efficiency principles. Ann Oper Res 255(1-2):117–140

Zhao Q (2018) Whether industrial structure optimization and upgrading can promote the efficiency of technological innovation. Stud Sci Sci 36(002):239–248 (In Chinese)

Zhao Q, Shao J (2017) An empirical study on the relationship between carbon emissions and economic growth in China - based on the EKC model. Econ Vision 26(5):15–26 (In Chinese)

Zhao F-C, Yin L-G, Gao L (2014) Establishing the fair allocation of carbon-based on structural break ARDL model and VECM model. Adv Econ Sci Res 5(3):142–148. https://doi.org/10.1016/j.acser.2014.08.001

Zhou P, Wang M (2016) Carbon dioxide emissions allocation: a review. Ecol Econ 125(May):47–59. https://doi.org/10.1016/j.ecolecon.2016.03.001

Zhou N, Zhang Y, We H (2014) Spatial differentiation of carbon emissions in Chongqing based on fossil fuel combustion. Acta Sci Circum 36(9):3505–3509. https://doi.org/10.13738/j.issn.1008-1023/A:20140912016

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under Springer’s terms of use; author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.