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Evaluating China's carbon neutrality transition: a system framework using a two-stage dynamic non-radial directional distance function

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Given the increasingly severe impacts of global climate change on sustainable development worldwide, countries must accelerate carbon neutrality efforts. While China is the world's largest carbon emitter, it has made significant reductions in carbon emissions through advancements in renewable energy and enhanced afforestation carbon sinks. The study aims to establish the link between CO_2 emission sources and carbon reduction subsystems, and apply the two-stage dynamic non-radial directional distance function to construct a carbon neutrality transition evaluation framework. The main findings present the Carbon Neutrality Transition Efficiency (CNTE) of 30 provincial regions in China during 2013–2021. Regional differences in CNTE have shown a widening gap since 2020: the eastern region exhibits higher Carbon Emission Efficiency (CEE) compared to the western and central regions, yet its Carbon Reduction Efficiency (CRE) remains lower. In addition, the potential for improvement in renewable energy in China has narrowed, whereas that in afforestation carbon sinks has expanded. This study recognizes that financial expenditure and land resource endowment are key factors in improving CNTE. It offers systematic optimization pathways for the government side, including increased financial support and consideration of regional resource endowment differences.

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Introduction

Global warming has emerged as an existential threat to humanity, with its accelerating impacts undermining the foundation of sustainable development. Alarmingly, 2024 was documented as the warmest year in observational history, reaching ~1.55 °C above pre-industrial level (World Meteorological Organization, 2025) and surpassing the Paris Agreement's 1.5 °C long-term temperature goal—a threshold breach which IPCC AR6 models had originally projected would not occur before the 2030s. Carbon emissions are the primary cause of global warming; therefore, most countries have set targets to achieve carbon neutrality by the mid-21st century. However, resources for reducing carbon emissions are still very limited, with G20 countries only allocating 6% of their stimulus spending directed toward this area (Nahm et al., 2022). Therefore, to achieve carbon neutrality goals, it is urgent to establish an evaluation framework for carbon reduction efforts, which directly affects the sustainable development of humanity in the future.

Compared to the carbon reduction trends already observed in advanced economies, China's carbon emissions increased by 0.565 Gt, reaching a total of 12.6 Gt in 2023, accounting for 33.7% of the global total (International Energy Agency, 2024). Clearly, China's role in emission reduction is pivotal to global climate change mitigation, as evidenced by its 2020 commitment to achieve carbon neutrality by 2060. To achieve carbon neutrality, China must accelerate carbon intensity reductions. Although its carbon intensity had decreased by 48.4% from 2005 to 2020 (Liu et al., 2022), current projections indicate that the carbon intensity of end-use energy must decline by at least 60% by 2050 (Duan et al., 2021). Additionally, annual negative carbon emissions of 0.01–2.91 Gt will be required between 2050 and 2060 (Deng et al., 2024). Therefore, evaluating China's transition to carbon neutrality is crucial for advancing global climate governance.

Accounting for 27.7% of global fossil fuel consumption (IEA, 2024), China is a major contributor to worldwide carbon emissions, given that fossil fuel combustion is the primary source of CO_2. To reduce dependence on fossil fuels, the country considered developing renewable energy as a key measure to address climate change and achieve carbon reduction (Qin et al., 2024). A growing body of empirical evidence indicates that higher renewable energy consumption significantly reduces China's carbon emission intensity (Yao et al., 2019; Yu et al., 2020; Zheng et al., 2021). The Chinese government has actively promoted renewable energy development through strategic policy frameworks and targeted investments, driving a remarkable increase in the share of wind and solar power in total installed capacity from 7.4% in 2013 to 29.5% in 2022 (National Bureau of Statistics of China, 2023). China's installed capacity of renewable energy increased by 117 gigawatts (GW) in 2022 compared with that in 2021, accounting for 39.7% of the global increase of 295 GW (International Renewable Energy Agency, 2023). However, scholars have also examined challenges in China's renewable energy development. For instance, wind and solar power generation efficiency is constrained by the significant seasonality, volatility, and instability of local climate conditions, resulting in relatively low output levels (Matamala and Feijoo, 2021). Due to differences in resource endowments, a geographical mismatch exists between electricity demand centers and renewable energy generation centers (Jia et al., 2022). Therefore, one objective of this study is to evaluate regional disparities in renewable energy development across China, with the aim of optimizing the pathway toward carbon neutrality.

In addition to developing renewable energy, ecosystem carbon sinks, especially forest carbon sink, are considered another important way to achieve carbon neutrality (Mo et al., 2023). The potential forest land in the world will reach 1.7–1.8 billion hectares, and there is room for 0.9 billion hectares of canopy cover (Bastin et al., 2019). The global potential for climate change mitigation through afforestation is 1.5 billion tons CO_2 / year (Doelman et al., 2020). China is the fastest-growing country in afforestation worldwide. The annual carbon sink potential of afforestation in China is projected to reach 104 million metric tons of CO_2 during the period from 2015 to 2060 (Cai et al., 2022). In addition, scholars have noted that increasing carbon sinks through afforestation is more cost-effective than other approaches to achieving carbon neutrality (Xu et al., 2022; Cai et al., 2023). However, there are regional disparities in China's afforestation (Cao et al., 2023), and the impact of regional heterogeneity must be considered when evaluating afforestation effectiveness (Ge et al., 2023). Thus, this study integrates regional afforestation disparities to quantify the efficiency of China's carbon neutrality transition, with a focus on forest carbon sink contributions.

The Chinese government's long-term financial commitment to energy conservation and environmental protection, including policy support and funding, plays a crucial role in supporting the rapid development of renewable energy and afforestation. Figure 1 compares China's finance expenditure on energy conservation and environmental protection (EECEP), wind and solar power generation, and afforestation area from 2013 to 2022, with year-on-year change data for each category. In 2020, expenditure declines caused by COVID-19 reduced afforestation and renewable energy utilization, aligning with the trend observed by Matthews and Wynes (2022) in G20 countries.

Therefore, this study initially assumes that achieving carbon neutrality requires governments to allocate resources commensurate with their emission levels, thereby meeting specific reduction targets. Based on this initial assumption, this study develops a carbon neutrality transition evaluation framework to evaluate the Chinese government efforts toward carbon neutrality goals. First, using CO_2 emissions as the linkage, this study establishes an interaction mechanism between emission sources and carbon reduction subsystems, then applies a two-stage dynamic undesirable non-radial directional distance function (NDDF) to evaluate provincial carbon neutrality transition efficiency (CNTE) in China. Second, by accounting for regional disparities in resource endowments using land availability and expenditure as inputs, this study quantifies the potential for wind/solar power generation and afforested carbon sinks, thereby formulating policy recommendations for optimizing China's carbon neutrality transition pathways.

The rest of this study runs as follows. Section "Literature review" provides a literature review. Section "Research and data methodology" shows the research and data methodology. Section "Empirical analysis" presents the empirical study. Section "Discussions and policy recommendations" offers discussions and policy recommendations. Section "Conclusion and implications" summarizes conclusions and implications.

Literature review

Progress in carbon neutrality transition evaluation. Accurate carbon neutrality evaluation is a prerequisite for meeting carbon neutrality targets (Chen et al., 2024). Current studies show that carbon neutrality evaluation focuses on regional emission accounting and efficiency analysis. As a key indicator for evaluating environmental quality and carbon neutrality, carbon emission efficiency (CEE) lays an important fundamental for evaluation frameworks (Dong et al., 2022). Given that the precision of carbon emission data directly determines the effectiveness of global climate governance, it constitutes a core basis for

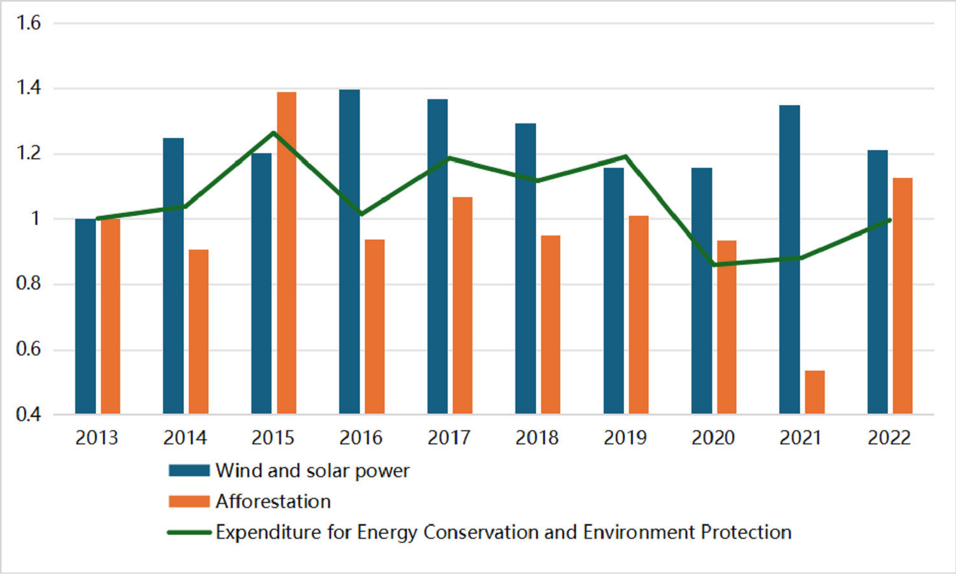

Fig. 1 Comparison of China's expenditure on energy conservation and environmental protection, wind and solar power generation, and afforestation with Year-on-Year Changes.

formulating emission reduction policies and setting quantifiable targets (Li et al., 2024). However, due to variations in data availability, measurement tools, and methodological approaches, the scope of emission accounting exhibits significant heterogeneity across different studies (Huovila et al., 2022). Additionally, regional carbon neutrality levels are typically characterized by the ratio or difference between carbon emissions and carbon sinks (Cai et al., 2023; Zhan et al., 2024; Li et al., 2025). This metric effectively reflects the potential of regional carbon sequestration capacity to offset anthropogenic emissions (Li et al., 2024).

In recent years, scholars have also developed multidimensional frameworks to more systematically advance the assessment of carbon neutrality progress (Niu et al., 2021; Yang et al., 2022; Chun et al., 2023). For instance, Xi et al. (2024) highlighted the importance of embodied carbon flows and transregional carbon sink services and consequently proposed an integrated assessment framework that incorporates both. Furthermore, as the role of non-fossil alternatives in the energy supply side becomes increasingly prominent, Chen et al. (2025) advocated for using clean energy outputs, such as hydropower, wind power, nuclear power, and solar energy as core indicators, thereby extending carbon neutrality progress assessment from emission control to energy system transformation.

As a natural solution, afforestation is considered a cost-effective and readily available option for mitigating climate change (Alkama et al., 2016; Rogelj et al., 2018; Duffy et al., 2020; Doelman et al., 2020). Afforestation and reforestation contribute to climate change mitigation via enhanced carbon storage in biomass and soils (Wang et al., 2025). As the duration of afforestation and reforestation increases, the net ecosystem exchange of forests shows a declining trend, indicating that forests restored through ecological recovery can rapidly become carbon sinks (He et al., 2024). Simultaneously, coastal wetlands and marine carbon sinks show growing potential for absorbing CO_2 (Howard et al., 2017; Iversen et al., 2023). Nevertheless, the annual mean ocean carbon sink varies primarily caused by changes in the sources and sinks of natural CO_2, with a lesser role for variations in atmospheric CO_2 growth rates impacting the uptake of anthropogenic CO_2 (Gruber et al., 2023). Compared to enhancing ocean carbon sinks, afforestation offers greater implementation feasibility. For instance, Xu et al. (2023) formulated an afforestation roadmap aligned with China's 2060 carbon neutrality goal. Zhai et al. (2023) emphasized that China's Three-North Shelterbelt Program, the world's largest afforestation initiative, primarily combats desertification while enhancing forest carbon sequestration capacity.

In the field of energy transition, the shift to renewable energy has become a critical strategy in response to the depletion of fossil fuels and growing global energy demand (Gunathilake et al., 2024). Renewable power generation can significantly reduce carbon emissions and improve environmental quality (Bilgili et al., 2025). The power sector is the primary source of CO_2 emissions in China and represents a pivotal domain for achieving carbon emission reduction targets (Sun et al., 2022; Wei et al., 2024). Increasing the share of renewable energy in the power generation mix can effectively reduce dependence on fossil fuels, thereby significantly decreasing greenhouse gas emissions (Paraschiv et al., 2023). Li et al.(2022) reported that China's annual wind power generation potential ranges between 12,900 and 15,000 TWh, while its solar energy potential ranges from 3100 to 5200 TWh. The theoretical maximum capacity could triple the total national electricity consumption recorded in 2019, and this capacity is sufficient to support the goal of carbon neutrality by 2060. Although both wind and solar power have continuously increased their installed capacity and proportion of electricity generation in the power system (Liu et al. 2022, 2024), their actual contribution to emission reduction still lacks systematic quantitative assessment. To address this gap, Teng et al. (2022) introduced the Carbon Emission Reduction Capacity (CERC) indicator using the IPCC 2006 carbon emission factors. However, this indicator assumes lossless year-round operation of wind and solar power generators year-round, overlooking the impact of extreme weather on power generation facilities—a simplification that requires optimization using real-world power generation data.

In addition, nuclear energy continues to play an important role in the global energy transition due to its near-zero emissions, mature technology, and reliable power supply (Carrara, 2020). However, due to national security concerns, it is difficult to obtain consistent panel data on nuclear power generation. Furthermore, carbon capture, utilization, and storage (CCUS) technology is regarded as a key support for achieving carbon peak and carbon neutrality goals (Davoodi et al., 2024). Direct Air Capture (DAC) technology directly separates carbon dioxide from the atmosphere through chemical or physical methods, providing an innovative solution for deep decarbonization (Jiang et al., 2023). However, technologies such as CCUS and DAC remain constrained by high costs and storage safety concerns (Kar et al., 2025). Moreover, Chu et al. (2024) conducted a comprehensive assessment of three mitigation measure categories—energy system upgrades, biotechnology applications, and CCUS—within national policy frameworks, highlighting that their selection requires balancing economic conditions and natural resource endowments across different countries.

Building on existing literature, this study integrates carbon reduction systems into carbon emission evaluation frameworks to develop a comprehensive evaluation model for the transition to carbon neutrality, thus enabling the quantification of government-led decarbonization efforts. Given the disparities in factor endowments across Chinese regions, the afforestation area and the modified CERC will be proposed as the key indicators for tracking China's carbon neutrality transition.

Evolution of DEA method. Data envelopment analysis (DEA) is an efficiency evaluation method traceable to Farrell (1957) and applicable to systems with multiple inputs and outputs. One early application of the Charnes-Cooper-Rhodes (CCR) (Charnes et al., 1978) and Banker-Charnes-Cooper (BCC) (Banker et al., 1984) models in evaluating China's energy performance can be traced back to Hu and Wang (2006), which took labor, capital, energy consumption and total sown area as multiple input variables, GDP as a single output variable, and China's provinces as decision-making units (DMUs). Subsequently, Wei et al. (2009) and Chang and Hu (2010) established a basic framework for evaluating China's energy efficiency, which takes labor, capital, and energy consumption as input variables and GDP as the output variable. With increasing academic attention to CO_2 emissions, Yeh et al. (2010) employed the CCR and BCC models to assess regional energy efficiency in China, explicitly treating CO_2 as an undesirable output.

However, both the CCR and BCC models are linear programming approaches grounded in the underlying assumption of proportional relationships between inputs and outputs. This inherent limitation may lead to measurement errors when analyzing non-proportional scale changes or systems generating undesirable outputs (e.g., CO_2 emissions). Tone (2001) proposed the Slacks-Based Measure (SBM) model, which solves the problem when an input or output is not being adjusted proportionally to achieve optimal efficiency. Subsequently, Färe and Grosskopf (2010) proposed a NDDF by integrating the SBM model with the directional distance function (Chung et al., 1997), providing more reasonable and accurate results for evaluating undesirable outputs.

NDDF has been widely applied in evaluating CO_2 emission performance of energy systems. For instance, Wang et al. (2013) used NDDF to analyze improvements in energy efficiency and productivity, finding that the main driver of energy productivity growth in China was technological change rather than efficiency enhancement. Li and Lin (2015) employed a metafrontier NDDF framework to evaluate China's regional energy performance, finding that eastern China exhibited the highest efficiency, followed by western and central China.

The aforementioned CCR, BCC, SBM, and NDDF models are static DEA frameworks, which limits their applicability for cross-period efficiency comparisons and trend change analysis. As emphasized by Kao (2013), dynamic efficiency analysis is essential when data allow, since system efficiency is defined as a linear combination of period efficiencies in dynamic systems. Thus, ignoring this dynamic nature leads to efficiency overestimation. Early dynamic DEA models applied to energy efficiency evaluation primarily include the DEA window analysis model (Charnes and Cooper, 1984) and the Malmquist index (Caves et al., 1982). However, since both focus on individual time periods and neglect carry-over activities between consecutive time periods, they can only achieve local optimization for each time period independently (Tone and Tsutsui, 2010). To address this limitation, Tone and Tsutsui (2010) proposed a dynamic SBM model that incorporates carry-over activities and enables the measurement of period-specific efficiencies via long-term optimization across the entire timeframe. The dynamic SBM model has been widely employed to evaluate regional energy efficiency and carbon emissions performance, as evidenced by studies of OECD countries (Guo et al., 2017), APEC economies (Ke, 2017), and Belt and Road economies (Mills et al., 2021). Teng et al. (2021) developed a dynamic SBM framework that incorporating afforestation as an exogenous variable to evaluate China's energy efficiency performance, thereby emphasizing its role as a critical climate change mitigation strategy.

By allowing flexible quantification of slack variables for multiple input-output dimensions, the NDDF model improves evaluation accuracy. This capability has driven recent integrations of the DDF framework with dynamic analysis, which assess multi-variable impacts on energy efficiency. For instance, Teng et al. (2022) examined the role of renewable energy deployment in enhancing energy efficiency by constructing a dynamic NDDF framework. This framework incorporated the CERC of wind and solar power as an output variable to evaluate China's energy efficiency performance. Teng et al. (2023) incorporated the annual increment of live wood stock as a desirable output and proposed that regional disparities in forest carbon sequestration across China should be accounted for in the evaluation of energy efficiency. Xie et al. (2023) incorporated financial expenditure as an input variable to evaluate China's energy efficiency, emphasizing that increased investment in energy conservation and environmental protection could improve energy efficiency. The limitation lies in the fact that the above study only quantified the improvement potential of individual variables for carbon reduction, failing to reflect the overall performance of these measures.

This limitation, stemming from sub-technologies regarded as a "black box", can be evaluated using a network DEA framework to assess their efficiency at different stages. Färe et al. (2007) proposed network DEA, which applied sub-technologies to examine the impact of intermediate products on the production process, avoiding the treatment of such products as "black box" excluded from evaluation. Following Färe et al. (2007), Tone and Tsutsui (2009) set up a weighted SBM-DEA model, which considered intermediate products between departments as linkages and used it to find optimal solutions. Subsequently, Tone and Tsutsui (2014) proposed the weighted SBM dynamic network DEA model, which introduced carry-over variables to link time periods and enable dynamic analysis of network structures over time.

Many scholars have applied the two-stage network DEA method to inter-sectoral efficiency evaluation. For instance, Wang et al. (2022) constructed a two-stage SBM DEA model and analyzed the linkage between ports and regional economic systems, demonstrating the contribution of ports on the regional economy. For applications of the SBM dynamic network DEA model, Lin et al. (2021) employed the undesirable outputs of first-stage energy consumption as inputs for second-

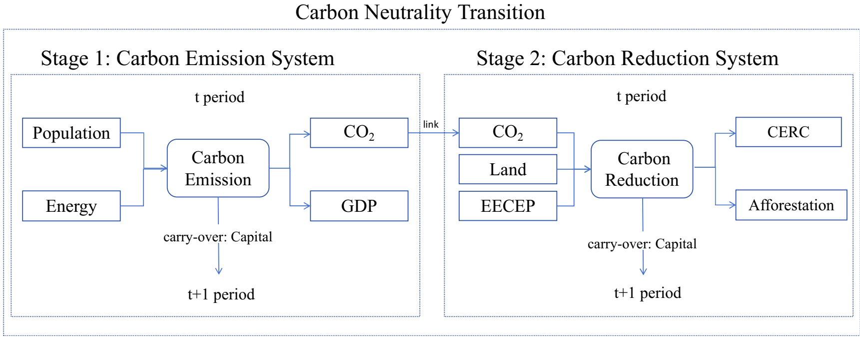

Fig. 2 Framework for evaluating carbon neutrality transition efficiency.

stage healthcare efficiency evaluation, concluding that China's energy consumption efficiency is superior to its healthcare efficiency. Wang et al. (2021) used pollutants to link the evaluation of production and treatment performance of China's industrial sector, finding that production efficiency outperformed treatment efficiency. The two-stage dynamic NDDF has also been applied in recent research. Teng et al. (2024) evaluated China's energy performance in the first stage and established CO_2 emissions as a linking variable to evaluate performance in coping with extreme weather in the second stage, finding that the efficiency in coping with extreme weather was far lower than energy efficiency. Jiang et al. (2025) used energy as a link to evaluate energy extraction efficiency in the first stage and energy utilization efficiency in the second stage, and obtained results for 35 key fossil energy-producing Belt and Road Initiative (BRI) countries.

The key difference lies in this study's application of a two-stage dynamic NDDF to evaluate the efficiency of China's carbon neutrality transition. Following traditional energy efficiency evaluation frameworks, CO_2 emissions are designated as an undesirable output in the first stage of the carbon emission subsystem and are linked to the second stage. Based on the review in Section "Progress in carbon neutrality transition evaluation", the second stage is defined as the carbon reduction subsystem, with afforestation area and CERC as its output variables. Input variables encompass land use (Teng et al., 2023) and financial expenditure (Xie et al., 2023), in addition to first-stage CO_2 emissions, to reflect governmental resource allocation and carbon reduction initiatives. Based on the efficiency values and the improvement potential of variables across the two stages, this study proposes policy recommendations to optimize system transition pathways for carbon neutrality in China.

Research and data methodology

In the first stage, CEE is evaluated as a key metric for the carbon emission system's performance. According to the China Statistical Yearbook, year-end population (i.e., Population) and total regional energy consumption (i.e., Energy) are set as input variables, while gross regional product (i.e., GDP) is designated as the desirable output variable. Furthermore, according to the China Energy Statistical Yearbook, CO_2 emissions in the region are set as the undesirable output variable, calculated using the IPCC 2006 emission factors based on fossil fuel consumption (including coal, coke, crude oil, gasoline, kerosene, diesel oil, and natural gas).

In the second stage, Carbon Reduction Efficiency (CRE) is evaluated as a key metric for the carbon reduction system's performance. The input variables comprise CO_2 emissions (a linkage variable transferred from the first stage), along with EECEP and land use (i.e., Land). The afforestation area is defined as a desirable output variable based on EECEP and land input. This metric can be directly obtained from the China Statistical Yearbook, which also provides input data for both EECEP and land-related variables. According to Teng et al. (2022), CERC is defined as an additional desirable-output variable in the second stage. Following this definition, this study calculates CERC based on actual wind and solar power generation using the following formula:

$$CERC = \frac{(E_{wind} + E_{solar}) * CF_{coal}}{EF_{coal}} \tag{1}$$

E_{wind} and E_{solar} represent wind and solar power generation, respectively, with data sourced from the China Electric Power Statistical Yearbook. CF_{coal} denotes the emission coefficient of coal-fired power generation, which is 1.08 kg CO_2/kWh, calculated based on the IPCC 2006 CO_2 emission factors, the assumed 33% power generation efficiency, and the lower heating value of lignite. EF_{coal} represents the standard coal CO_2 emission factors from IPCC guidelines, which is 2640 kg CO_2/tce.

According to the China Statistical Yearbook, the total fixed-asset investment in the whole region (i.e., Capital) serves as a carry-over variable to link period t with period $t+1$ across the two stages. Figure 2 presents the framework for evaluating CNTE.

NDDF provides more accurate evaluation results when dealing with multiple types of input and output variables. Thus, we modify the traditional NDDF (Färe and Grosskopf, 2010) to develop an enhanced version, which is then integrated with the dynamic network DEA framework (Tone and Tsutsui, 2014) to construct a two-stage dynamic NDDF for evaluation.

Suppose there are t time periods ($t = 1, \ldots, T$). In each time period, there are two stages, including carbon emission stage and carbon reduction stage. The former has m inputs $x_{ij}^t (i = 1, \ldots, m)$ to generate D intermediate products $z_{dj}^t (d = 1, \ldots, D)$, K desirable outputs $q_{kj}^t (k = 1, \ldots, K)$ and L undesirable outputs $m_{lj}^t (l = 1, \ldots, L)$. The latter stage produces S desirable outputs $y_{rj}^t (r = 1, \ldots, s)$ and O undesirable outputs $p_{oj}^t (o = 1, \ldots, O)$ from D intermediate products $z_{dj}^t (d = 1, \ldots, D)$ and G inputs $w_{gj}^t (g = 1, \ldots, G)$, where $c_{hj}^{d^{t-1}} (h = 1, \ldots, H)$ is a carry-over variable.

Equations (1)–(4) are used to calculate the overall efficiency of CNTE and the efficiency of each stage, as shown below. The objective function for the overall efficiency of CNTE is defined as follows:

$$\text{Max} \sum_{t=1}^{T} \gamma_t (w_1^t \theta_1^t + w_2^t \theta_2^t) \tag{2}$$

Subject to:

$$
\begin{array}{ll}
\text{Carbon emission stage} & \text{Carbon reduction stage} \\
\sum_{j}^{n} \lambda_j^t x_{ij}^t \le \theta_1^t x_{ip}^t \forall i, \forall t & \sum_{j}^{n} \mu_j^t z_{dj}^t \le \theta_2^t z_{dp}^t \forall d, \forall t \\
\sum_{j}^{n} \lambda_j^t z_{dj}^t \le \theta_1^t z_{dp}^t \forall d, \forall t & \sum_{j}^{n} \mu_j^t p_{oj}^t \ge \theta_2^t p_{op}^t \forall s, \forall t \\
\sum_{j}^{n} \lambda_j^t q_{kj}^t \ge \theta_1^t q_{kp}^t \forall k, \forall t & \sum_{j}^{n} \mu_j^t y_{sj}^t \ge \theta_2^t y_{sp}^t \forall s, \forall t \\
\sum_{j}^{n} \lambda_j^t m_{lj}^t \le \theta_1^t m_{lp}^t \forall k, \forall t & \sum_{j}^{n} \mu_j^t w_{gj}^t \le \theta_2^t w_{gp}^t \forall g, \forall t \\
\sum_{j}^{n} \lambda_j^t \le 1 & \sum_{j}^{n} \mu_j^t = 1 \\
\lambda_j^t \ge 0 \, \forall j, \forall t & \mu_j^t \ge 0 \, \forall j, \forall t
\end{array}
\tag{3}
$$

Link of the two stages

$$\sum_{j=1}^{n} \lambda_j^t Z_{dj}^t = \sum_{j=1}^{n} \mu_j^t Z_{dj}^t \ \forall d, \forall t \tag{4}$$

Link of the two periods

$$\sum_{j=1}^{n} \lambda_j^{t-1} c_{hj}^t = \sum_{j=1}^{n} \lambda_j^t c_{hj}^t \ \forall h, \forall t \tag{5}$$

Among them γ_t is the weight assigned to period t, and w_1^t and w_2^t are the weights assigned to the carbon emission stage and the carbon reduction stage in time period t, respectively. Therefore, for each time period t $w_1^t, w_2^t, \gamma_t \ge 1$ *and* $\sum_{t=1}^{T} \gamma_t = 1$. For the sake of analytical clarity and grounded in the research motivation and theoretical justification, both the period weights and stage weights are assumed to be equal to 1.

Based on the above methods, this study evaluates the overall efficiency defined as CNTE and defines the division efficiencies as CEE and CRE of 30 provinces in China from 2013 to 2022. Table 1 reports the statistical description of variables.

Empirical analysis

Efficiency results. This study analyzes 30 provinces in China as DMUs to evaluate their CNTE during 2013–2022. The overall efficiency, calculated using a two-stage dynamic NDDF, is defined as CNTE. It can be decomposed into two component efficiencies: CEE in the first stage and CRE in the second stage. Using CO_2 emissions as the linkage, this approach establishes a causal relationship between emission systems and reduction systems, and calculates CNTE as the product of CEE and CRE. Table 2 reports the average CNTE and the changes in CEE and CRE during the evaluation period. All efficiency values range from 0 to 1, and DMUs achieving an efficiency of 1 constitute the benchmarks for calculating the efficiency of other DMUs. Figures 3 and 4 present regional comparisons of the 10-year averages for CEE and CRE, respectively. The main findings are summarized as follows.

i. The CNTE shows an initial increase from 2013 to 2017, followed by a decrease from 2018 to 2022. This trend is basically consistent with the finance expenditure increase rate trend reported in Fig. 1. After decomposing the CNTE, the CEE averaged ~0.7 from 2013 to 2019. However, its average for 2020–2022 dropped to 0.68, which is lower than the 2013–2019 average level. The CRE rose from 0.73 in 2013 to 0.77 in 2019, before declining to 0.73 in 2022, thereby returning to its 2013 level. In contrast, the impact of CRE on CNTE is greater than that of CEE.

ii. The CEE of DMUs in eastern region (e.g., Beijing, Fujian, Guangdong, Hainan, Jiangsu, Shanghai, and Zhejiang) is generally better than those in CRE. These DMUs share a common characteristic: lower energy and CO_2 emission intensities per unit of GDP, yet their land resource endowments are less favorable than those of central and western DMUs. In contrast, DMUs in the central and western regions (e.g., Chongqing, Gansu, Guangxi, Guizhou, Hunan, Jiangxi, Qinghai, Shaanxi, Xinjiang and Yunnan) demonstrate significant advantages in CRE.

iii. Some provinces exhibit marked contrasts between their CEE and CRE values. For certain DMUs (e.g., Chongqing, Gansu, Guangxi, Hebei, Hunan, and Qinghai), the low CNTE is primarily due to a decline in CEE. In contrast, for others (e.g., Guangdong, Jiangsu, and Zhejiang), low CNTE results from a deterioration in CRE. Meanwhile, some provinces (e.g., Hainan, Heilongjiang, Henan, Shandong and Sichuan) show low performance in both CEE and CRE, and thus have low CNTE. Resource endowment and government input are the key factors contributing to these regional differences, which will be further analyzed in Section "Discussions and policy recommendations" of this study.

Robustness analysis. This subsection discusses the robustness analysis by further examining the consistency of efficiency results across different models through correlation tests.

First, based on the input and output framework presented in Fig. 2, the robustness of the DDF and SBM models is analyzed. Next, building on the economic production theory which emphasizes labor as a fundamental and essential input in production, this study conducts a robustness analysis by replacing the original population input with labor input.

H0: The Carbon Neutrality Transition Efficiency (CNTE), Carbon Emission Efficiency (CEE), and Carbon Reduction Efficiency (CRE) derived from the DDF model are positively correlated.

H1: The CNTE, CEE, and CRE derived from the SBM model are positively correlated.

H2: The CNTE, CEE, and CRE before and after substituting the input variable are positively correlated.

Under the DDF model framework, Table 3 presents the correlation test results of CNTE, CEE, and CRE from 2013 to 2022. Overall, the correlation coefficients among CNTE, CEE, and CRE all exceed 0.5, and the p-values are less than 0.05, indicating a high degree of correlation. Therefore, the null hypothesis (H0) is accepted.

Under the SBM model framework, Table 4 shows the correlation test results of CNTE, CEE, and CRE from 2013 to 2022. Overall, the correlation coefficients among CNTE, CEE, and CRE all exceed 0.5, and the p-values are less than 0.05, indicating a strong correlation. Therefore, the alternative hypothesis (H1) is accepted.

A comprehensive review of Tables 3 and 4 clearly indicates that, regardless of whether the DDF model or the SBM model is used, there exists a strong correlation among CNTE, CEE, and CRE across both efficiency evaluation frameworks.

As shown in Table 5, there is no significant difference between the results before and after the substitution of the input variable. Therefore, the hypothesis H2 is accepted.

Discussions and policy recommendations

The path to improving carbon neutrality transition efficiency. Based on empirical findings, CNTE is synergistically driven by CEE improvement in Stage 1 and CRE improvement in Stage 2. To identify strategic optimization pathways for CNTE, the following analysis focuses on core metrics of these dual drivers.

Table 1 Descriptive statistics of variables.

Year	Variable	Unit	Average	SD	Min	Max
2013	Population	10,000 persons	4507	2728	578	10,644
	Energy	10,000 tce	14,250	8389	1720	35,358
	GDP	100 million RMB	21,118	15,542	2122	62,475
	CO_2	10,000 mt	42,590	28,401	6236	121,092
	Land	1000 hectares	19,315	18,292	587	84,220
	EECEP	100 million RMB	111	60	23	308
	CERC	10,000 tce	200	304	3	1532
	Afforestation	hectares	200,348	165,763	862	805,156
	Capital	100 million RMB	14,659	8953	2361	36,789
2014	Population	10,000 persons	4531	2740	583	10,724
	Energy	10,000 tce	14,665	8536	1820	36,511
	GDP	100 million RMB	22,781	16,810	2303	67,810
	CO_2	10,000 mt	43,135	29,159	6128	129,496
	Land	1000 hectares	19,369	18,024	560	82,581
	EECEP	100 million RMB	115	57	23	259
	CERC	10,000 tce	250	344	7	1681
	Afforestation	hectares	181,787	136,676	899	559,247
	Capital	100 million RMB	16,823	10,331	2861	42,496
2015	Population	10,000 persons	4559	2759	588	10,849
	Energy	10,000 tce	14,911	8681	1938	37,945
	GDP	100 million RMB	24,058	18,046	2417	72,813
	CO_2	10,000 mt	43,185	30,122	5644	137,691
	Land	1000 hectares	19,983	18,643	605	84,750
	EECEP	100 million RMB	145	76	32	322
	CERC	10,000 tce	300	373	12	1812
	Afforestation	hectares	252,707	178,158	3241	704,054
	Capital	100 million RMB	18,505	11,588	3211	48,312
2016	Population	10,000 persons	4588	2785	593	10,999
	Energy	10,000 tce	15,192	8861	2006	38,723
	GDP	100 million RMB	25,964	19,938	2572	80,855
	CO_2	10,000 mt	43723	31,421	6583	147,296
	Land	1000 hectares	20,597	19,286	651	86,920
	EECEP	100 million RMB	147	77	37	363
	CERC	10,000 tce	418	467	17	2238
	Afforestation	hectares	237,057	182,105	3941	618,484
	Capital	100 million RMB	19,983	13,056	3528	53,323
2017	Population	10,000 persons	4616	2810	598	11,169
	Energy	10,000 tce	15,562	8945	2103	38,684
	GDP	100 million RMB	28,194	22,025	2625	89,705
	CO_2	10,000 mt	44,899	32,006	6293	146,785
	Land	1000 hectares	21,211	19,952	696	89,090
	EECEP	100 million RMB	174	102	36	458
	CERC	10,000 tce	572	586	20	2716
	Afforestation	hectares	252,485	199,791	2680	680,453
	Capital	100 million RMB	21,501	14,161	3728	55,203
2018	Population	10,000 persons	4644	2834	603	11,346
	Energy	10,000 tce	15,790	9388	2170	40,581
	GDP	100 million RMB	30,441	23,731	2865	97,278
	CO_2	10,000 mt	46,338	34,464	6156	151,944
	Land	1000 hectares	22,144	21,106	778	93,165
	EECEP	100 million RMB	194	120	61	567
	CERC	10,000 tce	739	678	25	3117
	Afforestation	hectares	240,030	173,045	3183	600,956
	Capital	100 million RMB	22,669	14,836	3344	55,994
2019	Population	10,000 persons	4668	2855	608	11,521
	Energy	10,000 tce	16,311	9632	2264	41,390
	GDP	100 million RMB	32,788	25,775	2966	107,671
	CO_2	10,000 mt	48,034	35,920	6077	155,782
	Land	1000 hectares	23,077	22,283	860	97,240
	EECEP	100 million RMB	231	141	54	747
	CERC	10,000 tce	856	744	33	3391
	Afforestation	hectares	242,626	177,036	5003	720,285
	Capital	100 million RMB	23,986	15,785	3000	58,850
2020	Population	10,000 persons	4688	3004	593	12,624
	Energy	10,000 tce	16,534	9817	2271	41,845
	GDP	100 million RMB	33,684	26,489	3006	110,761

Table 1 (continued)

Year	Variable	Unit	Average	SD	Min	Max
	CO_2	10,000 mt	48,457	36,762	5617	154,381
	Land	1000 hectares	23,080	22,290	860	97,239
	EECEP	100 million RMB	198	114	49	518
	CERC	10,000 tce	991	823	41	3739
	Afforestation	hectares	226,975	154,978	2535	649,981
	Capital	100 million RMB	25,462	16,990	2691	61,851
2021	Population	10,000 persons	4690	3011	594	12,684
	Energy	10,000 tce	17,462	10,333	2446	44,611
	GDP	100 million RMB	37,855	29,776	3347	124,370
	CO_2	10,000 mt	50,520	37,028	6715	154,397
	Land	1000 hectares	23,083	22,297	860	97,238
	EECEP	100 million RMB	174	99	47	494
	CERC	10,000 tce	1338	1120	41	4823
	Afforestation	hectares	121,937	94,778	2740	338,830
	Capital	100 million RMB	27,277	18,322	2750	65,439
2022	Population	10,000 persons	4687	3010	595	12,657
	Energy	10,000 tce	17,844	10,823	2424	48,167
	GDP	100 million RMB	40,044	31,126	3610	129,119
	CO_2	10,000 mt	50,863	37,406	6421	147,678
	Land	1000 hectares	23,086	22,304	860	97,237
	EECEP	100 million RMB	173	90	29	465
	CERC	10,000 tce	1620	1279	58	5407
	Afforestation	hectares	137,420	106,862	35	381,952
	Capital	100 million RMB	28,824	19,672	3030	67,925

tce is tons of standard coal equivalent, RMB is renminbi, and mt is metric tons.

As shown in the results of Wang et al. (2013) and Li and Lin (2015), DMUs in the central and western regions exhibit higher energy intensity (i.e., energy consumption per unit of GDP), which generates more CO_2 emissions and indicates lower energy efficiency. However, existing studies fail to quantify the government's emission reduction efforts and their actual carbon mitigation effects. To address this gap, this study introduces EECEP as a verifiable indicator for evaluating reduction efforts in the analysis.

Figure 5 shows that DMUs with lower energy intensity do not necessarily have better CNTE, which may be attributed to insufficient government investment in carbon reduction initiatives. Specifically, in the first quadrant —where DMUs exhibit both high energy intensity and a high proportion of EECEP to GDP—most regions have CNTE values exceeding the average by 0.71, such as Ningxia, Inner Mongolia, Gansu, Hebei, and Guizhou. Conversely, in the third quadrant—where DMUs exhibit lower energy intensity and a smaller proportion of EECEP to GDP—most of them perform poorly in terms of CNTE, such as Guangdong, Jiangsu, Zhejiang, Shandong, and Fujian. The above observations indicate that increasing expenditure on carbon reduction is more effective in improving CNTE than reducing energy intensity. Moreover, sustained increases in EECEP represent an effective pathway to enhance carbon reduction efforts and improve CNTE.

China's primary carbon reduction approaches currently include replacing traditional fossil fuels with renewables like wind and solar power, and expanding ecosystem carbon sinks through afforestation efforts. Figure 6 quantifies the effectiveness of carbon reduction pathways using the ratio of CERC to total CO_2 emissions and the proportion of afforested area to total land use, and further correlates these indicators with CNTE. Figure 6 shows that only Ningxia and Hebei perform above average in both afforestation and CERC. This dual strength correlates with their relatively better CNTE performance. Across DMUs in the second and fourth quadrants, the effectiveness of these two carbon reduction pathways varied, and natural resource endowment influenced the pathway selection. For instance, in Xinjiang, a region with extensive desertified land, developing wind and solar power is more effective in reducing carbon emissions than expanding afforestation. However, more DMUs are located in the third quadrant, where the development of the two carbon reduction pathways significantly lags behind, resulting in lower CNTE performance. It is necessary to further explore optimizing carbon emission reduction pathways by analyzing improvement potential in order to provide more targeted policy recommendations.

Policy recommendations for improving carbon neutrality transition efficiency. As mentioned above, China's primary strategies for achieving carbon neutrality involve expanding renewable energy (e.g., wind and solar) to replace fossil fuels and enhancing afforestation. In evaluating CNTE, this study derives potential improvement indicators for input-output variables by comparing the performance of actual DMUs against benchmark targets. Tables 6 and 7 report changes in these improvement indicators for CERC and afforestation variables from 2013 to 2022, serving as the basis for the policy recommendations that follow.

According to Table 6, the improvement potential of CERC shows a declining trend, with its average value dropping from 25.4% in 2013 to 14.8% in 2022. This indicates progress toward balanced renewable energy deployment nationwide. However, there remain significant opportunities for improvement in some DMUs, such as Fujian, Guangdong, Hainan, Heilongjiang; Shandong, Sichuan, and Zhejiang. In contrast, Anhui, Hubei, and Liaoning show a rising trend in their potential for improvement. The aforementioned DMUs are mostly situated in densely populated and industrially concentrated eastern region, where land scarcity has become a critical constraint on developing land-intensive renewable energy. Notably, several DMUs (e.g., Jiangsu and Hebei) with comparable natural resource

Table 2 Regional CNTE and change of CEE & CER from 2013 to 2022.

DMU	CNTE	2013		2014		2015		2016		2017		2018		2019		2020		2021		2022	
		CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE	CEE	CRE
Beijing	**0.78**	1.00	0.83	1.00	0.55	1.00	0.43	1.00	0.47	1.00	0.78	1.00	0.67	1.00	0.73	1.00	0.79	1.00	0.89	1.00	0.22
Fujian	**0.65**	0.72	0.52	0.67	0.40	0.72	0.75	0.70	0.68	0.71	0.60	0.67	0.67	0.67	0.82	0.68	0.70	0.68	0.50	0.71	0.53
Guangdong	**0.56**	0.83	0.23	1.00	0.32	0.73	0.76	0.71	0.56	0.73	0.45	0.70	0.46	0.67	0.45	0.62	0.47	0.68	0.20	0.68	0.53
Hainan	**0.35**	0.69	0.20	0.65	0.16	0.67	0.27	0.59	0.17	0.57	0.15	0.58	0.11	0.57	0.21	0.59	0.18	0.52	0.15	0.56	0.16
Hebei	**0.71**	0.60	0.79	0.53	0.91	0.52	0.82	0.75	1.00	0.57	1.00	0.59	1.00	0.55	1.00	0.47	0.93	0.50	0.68	0.48	0.90
Jiangsu	**0.63**	0.80	0.37	0.82	0.38	0.83	0.39	0.82	0.40	0.83	0.44	0.84	0.50	0.78	0.53	0.76	0.56	0.77	0.62	0.80	0.73
Liaoning	**0.69**	0.69	0.77	0.67	0.85	0.63	0.63	0.83	0.63	0.68	0.51	0.93	0.75	0.68	0.68	0.75	0.74	0.72	0.47	0.76	0.56
Shandong	**0.53**	0.61	0.61	0.61	0.71	0.60	0.65	0.58	0.39	0.57	0.43	0.56	0.43	0.47	0.50	0.48	0.48	0.50	0.50	0.50	0.57
Shanghai	**0.98**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.82	0.98	0.87
Tianjin	**1.00**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	**0.45**	0.74	0.23	0.74	0.19	0.73	0.27	0.72	0.22	0.71	0.23	0.70	0.28	0.66	0.32	0.62	0.42	0.62	0.22	0.64	0.31
Eastern region	**0.67**	**0.79**	**0.60**	**0.79**	**0.59**	**0.77**	**0.63**	**0.79**	**0.59**	**0.76**	**0.60**	**0.78**	**0.62**	**0.73**	**0.66**	**0.72**	**0.66**	**0.72**	**0.55**	**0.74**	**0.58**
Anhui	**0.80**	0.85	1.00	0.85	1.00	0.87	1.00	0.87	1.00	0.88	1.00	0.96	0.68	0.92	0.57	0.77	0.73	0.81	0.44	0.80	0.42
Guangxi	**0.76**	0.67	0.81	0.66	0.69	0.66	0.67	0.70	1.00	0.67	1.00	0.67	1.00	0.61	1.00	0.57	1.00	0.54	1.00	0.53	1.00
Heilongjiang	**0.35**	0.58	0.26	0.44	0.30	0.42	0.25	0.49	0.27	0.40	0.21	0.40	0.36	0.42	0.21	0.40	0.22	0.38	0.33	0.38	0.33
Henan	**0.52**	0.50	0.69	0.49	0.79	0.48	0.44	0.48	0.34	0.55	0.35	0.56	0.37	0.59	0.45	0.60	0.46	0.64	0.52	0.61	0.59
Hubei	**0.68**	0.59	0.77	0.57	0.84	0.59	0.59	0.60	0.68	0.65	0.88	0.71	0.67	0.72	1.00	0.65	0.62	0.64	0.65	0.63	0.62
Hunan	**0.82**	0.67	1.00	0.66	1.00	0.69	1.00	0.69	1.00	0.70	1.00	0.72	1.00	0.67	1.00	0.63	1.00	0.62	1.00	0.61	1.00
Inner Mongolia	**1.00**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00
Jiangxi	**0.84**	0.84	0.82	0.80	0.90	0.80	0.88	0.81	0.88	0.82	0.83	0.82	0.93	0.77	0.94	0.72	0.94	0.71	1.00	0.69	1.00
Jilin	**0.57**	0.88	0.29	0.60	0.47	0.62	0.56	0.76	0.46	0.70	0.40	0.76	0.43	0.76	0.33	0.70	0.42	0.49	0.86	0.52	0.80
Shanxi	**0.86**	0.99	1.00	1.00	1.00	0.41	0.95	0.39	0.79	0.43	0.79	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Central region	**0.72**	**0.76**	**0.76**	**0.71**	**0.80**	**0.65**	**0.73**	**0.68**	**0.74**	**0.68**	**0.75**	**0.76**	**0.74**	**0.75**	**0.75**	**0.70**	**0.74**	**0.68**	**0.78**	**0.68**	**0.78**
Chongqing	**0.81**	0.63	1.00	0.62	1.00	0.63	1.00	0.65	1.00	0.63	1.00	0.68	1.00	0.66	1.00	0.64	1.00	0.65	1.00	0.75	1.00
Gansu	**0.74**	0.55	1.00	0.54	1.00	0.57	1.00	0.56	1.00	0.54	1.00	0.56	1.00	0.53	1.00	0.51	1.00	0.53	1.00	0.52	1.00
Guizhou	**0.78**	0.64	1.00	0.61	1.00	0.64	1.00	0.69	1.00	0.66	1.00	0.65	1.00	0.62	1.00	0.57	1.00	0.57	1.00	0.52	0.86
Ningxia	**1.00**	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Qinghai	**0.65**	0.44	1.00	0.44	1.00	0.42	1.00	0.43	1.00	0.41	1.00	0.41	1.00	0.37	1.00	0.37	1.00	0.37	1.00	0.38	1.00
Shaanxi	**0.72**	0.64	0.93	0.74	0.87	0.65	0.66	0.56	0.76	0.66	0.60	0.64	0.72	0.61	0.71	0.59	0.75	0.84	1.00	0.74	1.00
Sichuan	**0.49**	0.48	0.21	0.47	0.21	0.47	0.54	0.53	1.00	0.56	0.66	0.55	0.63	0.53	0.58	0.49	0.50	0.51	0.48	0.45	0.34
Xinjiang	**0.75**	0.42	0.52	0.50	0.94	0.67	1.00	0.63	1.00	0.64	1.00	0.65	1.00	0.66	1.00	0.65	1.00	0.68	1.00	0.61	0.81
Yunnan	**0.71**	0.60	1.00	0.53	1.00	0.52	1.00	0.52	1.00	0.53	1.00	0.56	1.00	0.57	1.00	0.53	0.96	0.54	0.74	0.47	0.66
Western region	**0.74**	**0.60**	**0.85**	**0.61**	**0.89**	**0.62**	**0.91**	**0.62**	**0.97**	**0.63**	**0.92**	**0.63**	**0.93**	**0.62**	**0.92**	**0.59**	**0.91**	**0.63**	**0.91**	**0.60**	**0.85**
Average	**0.71**	**0.72**	**0.73**	**0.71**	**0.75**	**0.68**	**0.75**	**0.70**	**0.76**	**0.69**	**0.74**	**0.73**	**0.76**	**0.70**	**0.77**	**0.68**	**0.76**	**0.68**	**0.74**	**0.68**	**0.73**

The data for the eastern region is displayed as the average of the 11 provinces mentioned above, the central region as the average of the 10, and the western region as the average of the 9.

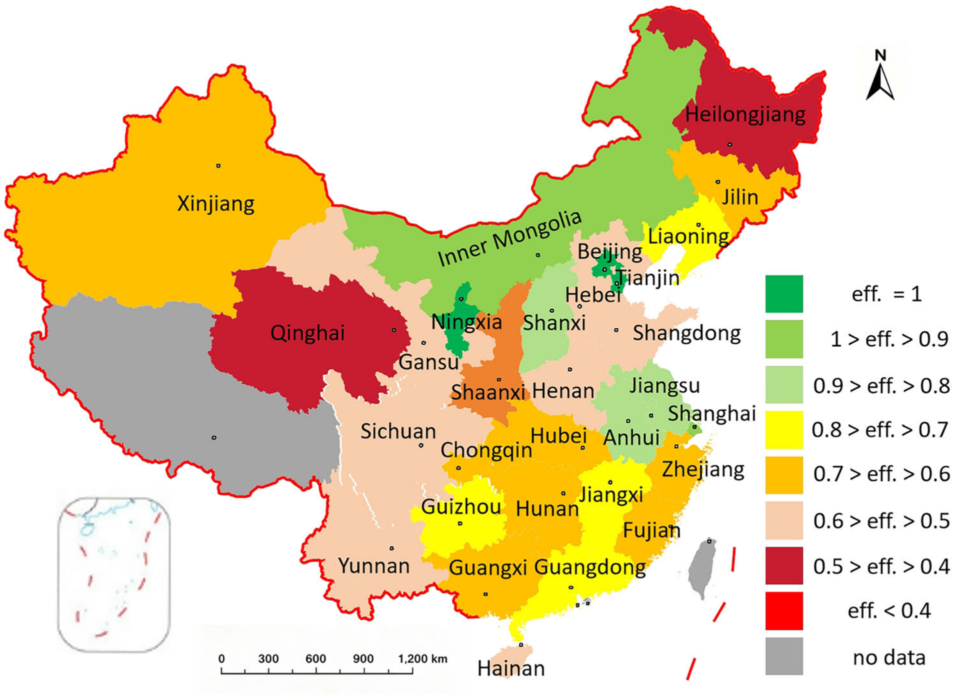

Fig. 3 Regional comparison of carbon emission efficiency.

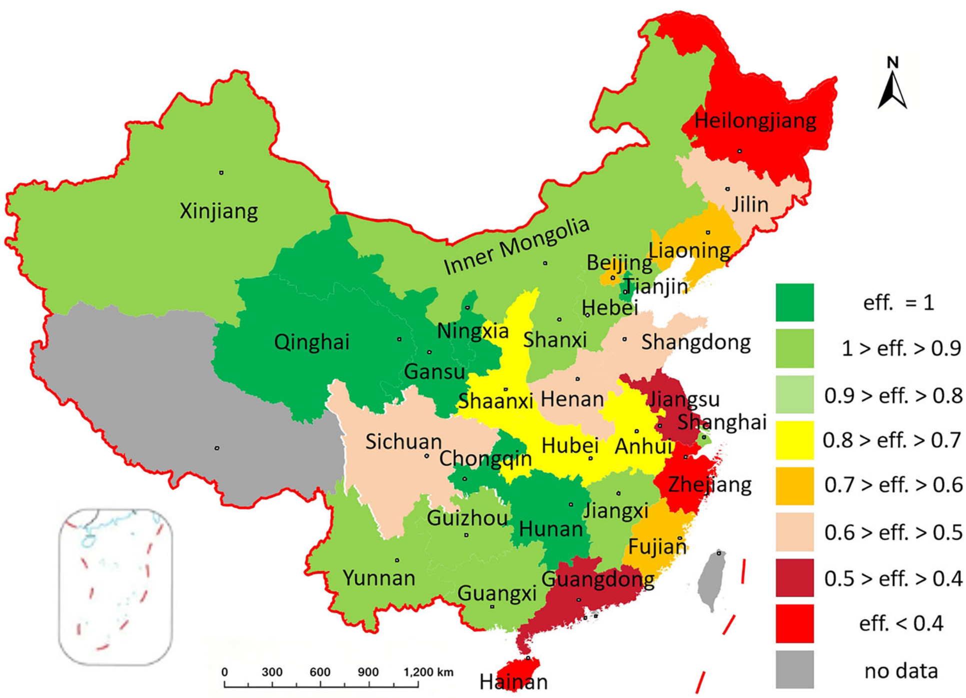

Fig. 4 Regional comparison of carbon reduction efficiency.

endowments have achieved significant advancements in renewable energy development, providing valuable operational benchmarks for peer regions.

According to Table 7, whereas the improvement potential in CERC decreases, that of afforestation shows an opposite trend, increasing from 14% in 2013 to 26.7% in 2022. From 2021 to 2022, the growth in improvement potential indicates a significant decline in afforestation's contribution to carbon neutrality, likely caused by reduced EECEP during the COVID-19 pandemic. In addition, regional disparities in afforestation are widening, particularly in eastern regions such as Jiangsu, Shandong, Shanghai, and Zhejiang, where significant potential for afforestation improvement remains. This reflects how land use restrictions constrain the continuous expansion of afforestation.

Based on the above analysis of potential improvements, we propose the following policy recommendations to enhance the efficiency of China's transition to carbon neutrality.

i. EECEP is the key to supporting carbon emission reduction measures, and sustained growth of EECEP should be ensured. A special fund for carbon neutrality is recommended to be established based on the existing EECEP, with primary objectives including supporting renewable energy generation and enhancing ecosystem carbon sinks.

ii. Eastern regions must overcome the structural limitations of their land resource endowments to advance carbon neutrality transition. It is suggested that provinces in the eastern region increase support for Building Integrated Photovoltaics and incorporate afforestation measures into urban development frameworks to promote forest city construction, given their high urbanization rates. Coastal provinces should formulate differentiated support policies and increase subsidies for offshore wind power projects and associated equipment manufacturing—including power distribution, energy storage, and transmission equipment—to mitigate land resource constraints on renewable energy development.

iii. Western and central regions should leverage resource endowments to systematically advance carbon neutrality transition and improve decarbonization outcomes. While leveraging land resource advantages to scale up renewable energy and promote afforestation, the central and western regions should focus on converting carbon reduction potential into economic benefits. It is recommended that the central and western regions develop industrial policies aligned with their renewable energy capacity, accelerate workforce training, and facilitate the orderly transfer of energy-intensive industries from the eastern region. This approach will establish a sustainable development path in which economic growth provides long-term financial support for the transition to carbon neutrality.

Table 3 Correlation tests of CNTE, CEE, and CRE from 2013 to 2022 under the DDF model framework.

CEE	CNTE	CRE	CNTE
2013	0.55172 (0.0013)	2013	0.81583 (<0.0001)
2014	0.59355 (0.0004)	2014	0.78575 (<0.0001)
2015	0.59186 (0.0005)	2015	0.78771 (<0.0001)
2016	0.58443 (0.0006)	2016	0.74385 (<0.0001)
2017	0.62546 (0.0002)	2017	0.81923 (<0.0001)
2018	0.70702 (<0.0001)	2018	0.83227 (<0.0001)
2019	0.71366 (<0.0001)	2019	0.81180 (<0.0001)
2020	0.69652 (<0.0001)	2020	0.87086 (<0.0001)
2021	0.71742 (<0.0001)	2021	0.76035 (<0.0001)
2022	0.69278 (<0.0001)	2022	0.70371 (<0.0001)

Table 4 Correlation Tests of CNTE, CEE, and CRE from 2013 to 2022 under the SBM model framework.

CEE	CNTE	CRE	CNTE
2013	0.61901 (0.0003)	2013	0.65220 (<0.0001)
2014	0.64959 (0.0001)	2014	0.64401 (0.0001)
2015	0.66291 (<0.0001)	2015	0.69130 (<0.0001)
2016	0.69987 (<0.0001)	2016	0.71367 (<0.0001)
2017	0.69127 (<0.0001)	2017	0.70538 (<0.0001)
2018	0.80918 (<0.0001)	2018	0.80438 (<0.0001)
2019	0.74112 (<0.0001)	2019	0.62728 (0.0002)
2020	0.61065 (0.0003)	2020	0.61703 (0.0003)
2021	0.59486 (0.0005)	2021	0.62516 (0.0002)
2022	0.56962 (0.0010)	2022	0.69544 (<0.0001)

Conclusion and implications

Main conclusions and contributions. Global warming is accelerating beyond projected rates and poses a critical threat to global sustainability efforts. However, since 2020, the COVID-19 pandemic has compelled countries worldwide to scale back resources allocated to combating global warming. Evaluating governmental carbon reduction initiatives and optimizing pathways toward carbon neutrality represent a critical research problem demanding urgent scholarly attention. While current research predominantly focuses on measuring CEE, systematic methods to evaluate carbon reduction potential remain underdeveloped. To fill the gap in this field, this study attempts to establish a link between carbon emission sources and carbon reduction subsystems and to apply a two-stage dynamic NDDF for the preliminary construction of a carbon neutrality transition evaluation framework.

This study empirically demonstrates that regional disparities in China's CNTE have exhibited a widening trend since 2020. Government EECEP is a key driver of the aforementioned changes. Regional disparities are further manifested through the eastern region's efficiency advantage in carbon emission subsystem, whereas central and western regions excel in carbon reduction subsystem. This demonstrates that China's current wind and solar based renewable energy development and its afforestation path toward carbon neutrality are both heavily influenced by land resource endowment. Based on the above findings, the following are identified as core policy recommendations: (1) establishing a carbon neutrality special fund to ensure financial investment; (2) addressing resource endowment constraints in the eastern region; and (3) transforming western carbon reduction advantages into economic development advantages.

Table 5 Correlation Tests of CNTE, CEE, and CRE from 2013 to 2022 before and after input variable substitution.

CEE	CNTE		CRE	CNTE	
	Before	After		Before	After
2013	0.55172 (0.0013)	0.43616 (0.0160)	2013	0.81583 (<0.0001)	0.57175 (0.0010)
2014	0.59355 (0.0004)	0.53764 (0.0022)	2014	0.78575 (<0.0001)	0.50812 (0.0041)
2015	0.59186 (0.0005)	0.56740 (0.0011)	2015	0.78771 (<0.0001)	0.61506 (0.0003)
2016	0.58443 (0.0006)	0.65910 (<0.0001)	2016	0.74385 (<0.0001)	0.64297 (0.0001)
2017	0.62546 (0.0002)	0.61096 (0.0003)	2017	0.81923 (<0.0001)	0.59144 (0.0006)
2018	0.70702 (<0.0001)	0.71951 (<0.0001)	2018	0.83227 (<0.0001)	0.76021 (<0.0001)
2019	0.71366 (<0.0001)	0.79492 (<0.0001)	2019	0.81180 (<0.0001)	0.73929 (<0.0001)
2020	0.69652 (<0.0001)	0.80379 (<0.0001)	2020	0.87086 (<0.0001)	0.81696 (<0.0001)
2021	0.71742 (<0.0001)	0.78610 (<0.0001)	2021	0.76035 (<0.0001)	0.83543 (<0.0001)
2022	0.69278 (<0.0001)	0.73220 (<0.0001)	2022	0.70371 (<0.0001)	0.69298 (<0.0001)

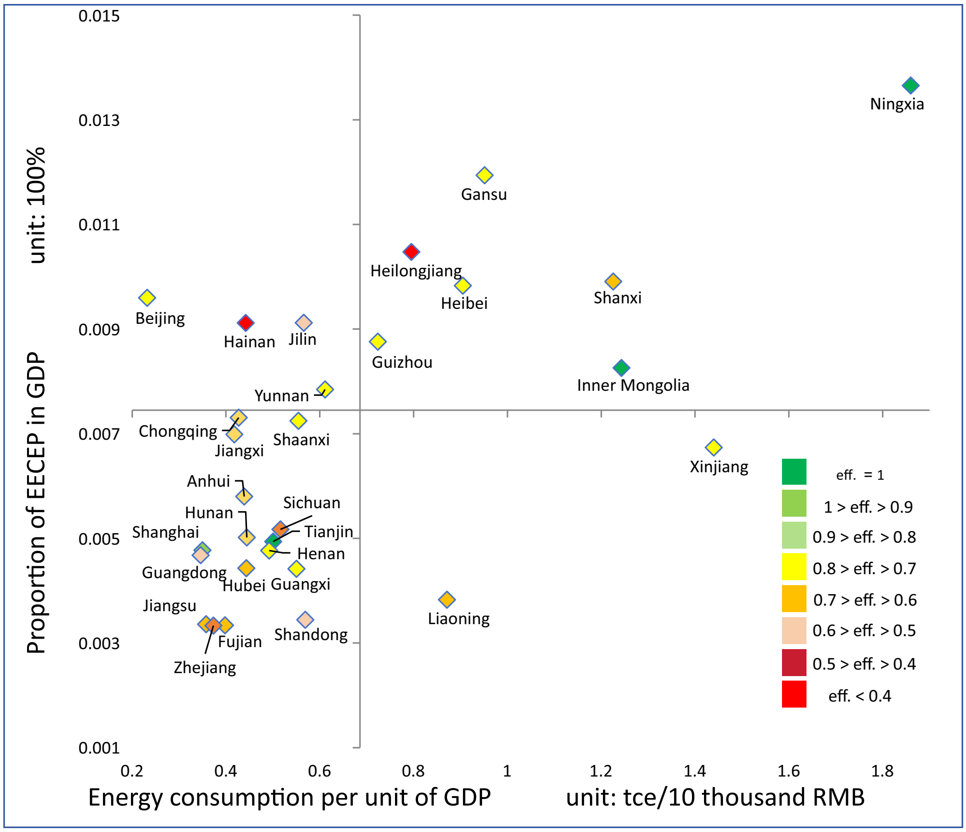

Fig. 5 Relationship between energy consumption, EECEP, and CNTE.

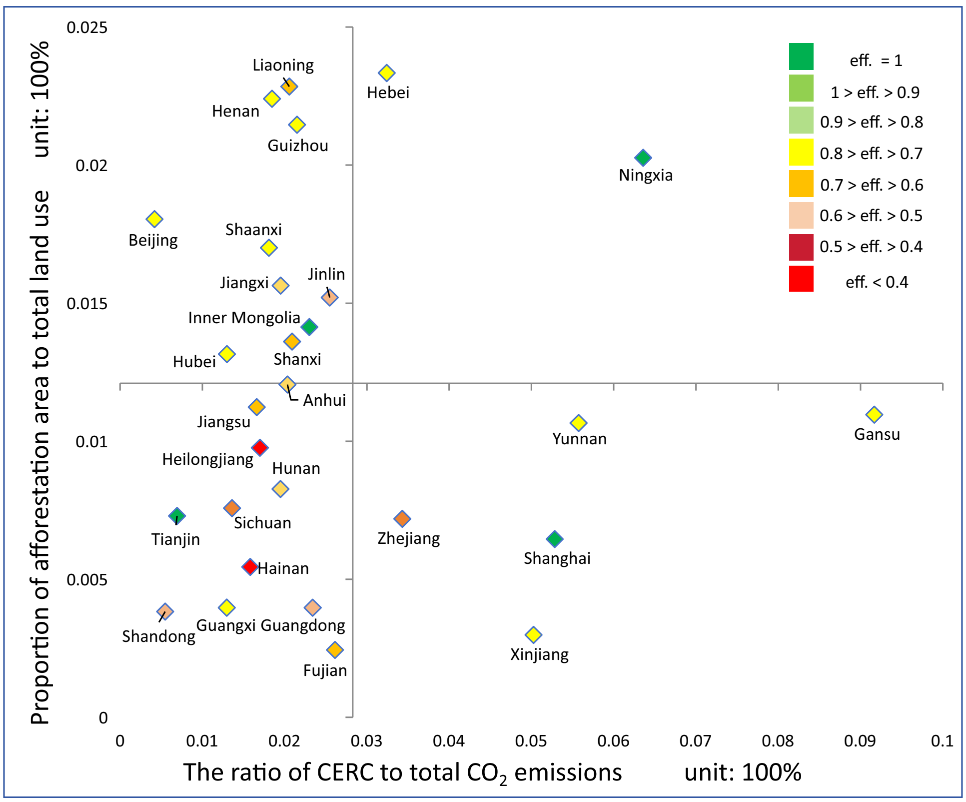

Fig. 6 Relationship between CERC, afforestation, and CNTE.

Table 6 Evolution of CERC improvement potential from 2013 to 2022 unit:%.

DMUs	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Beijing	44.4	46.8	41.1	71.0	52.3	40.2	23.8	10.6	60.2	44.9
Fujian	23.9	29.9	12.6	16.1	20.1	16.3	9.1	14.8	24.9	23.7
Guangdong	38.5	33.9	12.1	37.2	27.6	32.2	27.6	26.4	39.8	23.7
Hainan	40.1	42.0	36.7	41.5	42.5	44.3	39.3	41.2	42.4	41.9
Hebei	10.3	4.5	9.1	0	0	0	0	3.6	16.1	4.8
Jiangsu	31.5	30.8	30.3	29.9	27.8	25.0	23.5	21.8	19.1	13.7
Liaoning	19.2	7.6	18.4	18.3	24.5	12.3	16.1	36.5	26.6	22.0
Shandong	39.2	14.5	17.3	30.4	28.6	28.3	25.0	25.8	25.0	21.5
Shanghai	0	0	0	0	0	0	0	0	8.8	6.5
Tianjin	0	0	0	0	0	0	0	0	0	0
Zhejiang	53.6	40.3	36.3	38.8	38.3	35.8	33.9	28.9	38.8	34.5
Eastern region	**27.3**	**22.8**	**19.4**	**25.7**	**23.8**	**21.3**	**18.0**	**19.1**	**27.4**	**21.6**
Anhui	0	0	0	0	0	16.2	21.4	13.7	28.0	28.8
Guangxi	91.5	64.1	77.8	0	0	0	0	0	0	0
Heilongjiang	36.9	34.8	37.6	36.7	39.7	32.0	39.6	39.1	33.5	33.5
Henan	42.6	47.1	34.4	40.4	32.5	31.5	27.4	27.2	24.1	20.4
Hubei	11.3	8.0	20.4	15.8	5.8	16.7	0.0	19.2	17.4	19.2
Hunan	0	0	0	0	0	0	0	0	0	0
Inner Mongolia	0	0	0	0	0	0	0	0	0.1	0
Jiangxi	68.9	8.1	54.7	5.8	8.3	3.6	2.8	3.0	0	0
Jilin	35.5	26.3	21.8	27.1	30.1	28.7	33.6	29.0	7.2	9.8
Shanxi	0	0	2.5	10.4	10.5	0	0	0	0	0
Central region	**28.7**	**18.8**	**24.9**	**13.6**	**12.7**	**12.9**	**12.5**	**13.1**	**11.0**	**11.2**
Chongqing	0	0	0	0	0	0	0	0	0	0
Gansu	0	0	0	0	0	0	0	0	0	0
Guizhou	0	0	0	0	0	0	0	0	0	14.7
Ningxia	0	0	0	0	0	0	0	0	0	0
Qinghai	0	0	0	0	0	0	0	0	0	0
Shaanxi	50.3	22.4	17.2	11.8	20.2	14.1	14.7	12.4	0	0
Sichuan	97.8	90.3	81.9	75.3	57.9	76.5	71.2	66.3	49.8	53.9
Xinjiang	25.2	3.1	0	0	0	0	0	0	0	9.5
Yunnan	0	0	0	0	0	0	0	1.9	13.0	16.9
Western region	**19.3**	**12.9**	**11.0**	**9.7**	**8.7**	**10.1**	**9.5**	**9.0**	**7.0**	**10.6**
Average	**25.4**	**18.5**	**18.7**	**16.9**	**15.6**	**15.1**	**13.6**	**14.0**	**15.8**	**14.8**

A zero value indicates that the DMU has no room for improvement in this indicator relative to the benchmarks.
The data for the eastern region is displayed as the average of the 11 provinces mentioned above, the central region as the average of the 10, and the western region as the average of the 9.

Table 7 Evolution of afforestation improvement potential from 2013 to 2022 unit:%.

DMUs	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Beijing	8.5	22.5	28.4	26.6	10.8	16.4	13.4	10.6	5.7	39.0
Fujian	23.9	29.9	12.6	16.1	20.1	16.3	9.1	14.8	24.9	23.7
Guangdong	38.5	33.9	12.1	21.9	27.6	27.2	27.6	26.4	39.8	23.7
Hainan	40.1	42.0	36.7	41.5	42.5	44.3	39.3	41.2	42.4	41.9
Hebei	10.3	4.5	9.1	0	0	0	0	3.6	16.1	16.9
Jiangsu	35.8	30.8	47.8	69.4	62.4	67.9	67.8	60.9	98.0	98.6
Liaoning	11.3	7.6	18.4	18.3	24.5	12.3	16.1	13.1	32.6	25.6
Shandong	19.3	14.5	17.3	30.4	28.6	28.3	25.0	25.8	94.3	93.5
Shanghai	0	0	0	0	0	0	0	0	57.1	99.5
Tianjin	0	0	0	0	0	0	0	0	0	0
Zhejiang	49.3	40.3	36.3	38.8	38.3	35.8	33.9	28.9	66.1	86.7
Eastern region	**21.5**	**20.5**	**19.9**	**23.9**	**23.2**	**22.6**	**21.1**	**20.5**	**43.4**	**49.9**
Anhui	0	0	0	0	21.7	16.2	21.4	13.7	44.3	47.9
Guangxi	0	0	0	0	0	0	0	0	0	0
Heilongjiang	36.9	34.8	37.6	36.7	47.0	60.8	43.3	39.1	33.5	52.9
Henan	15.4	10.5	27.9	33.1	32.5	31.5	27.4	27.2	24.1	33.8
Hubei	11.3	8.0	20.4	15.8	5.8	16.7	0	19.2	17.4	19.2
Hunan	0	0	0	0	0	0	0	0	0	0
Inner Mongolia	0	0	0	0	0	0	0	0	5.7	0
Jiangxi	8.9	4.8	6.0	5.8	8.3	13.0	29.3	3.0	0	0
Jilin	35.5	26.3	21.8	27.1	30.1	28.7	33.6	29.0	7.2	9.8
Shanxi	0	0	2.5	10.4	10.5	0	0	0	0	0
Central region	**10.8**	**8.4**	**11.6**	**12.9**	**15.6**	**16.7**	**15.5**	**13.1**	**13.2**	**16.4**
Chongqing	0	0	0	0	0	0	0	0	0	0
Gansu	0	0	0	0	0	0	0	0	0	0
Guizhou	0	0	0	0	0	0	0	0	0	7.2
Ningxia	0	0	0	0	0	0	0	0	0	0
Qinghai	0	0	0	0	0	0	0	0	0	0
Shaanxi	3.7	6.4	17.2	11.8	20.2	14.1	14.7	12.4	0	0
Sichuan	39.6	39.6	23.0	0	16.8	18.7	20.8	25.1	26.2	32.8
Xinjiang	23.8	39.5	0	0	0	0	0	0	0	32.3
Yunnan	0	0	0	0	0	0	0	3.9	13.0	16.9
Western region	**7.5**	**9.5**	**4.5**	**1.3**	**4.1**	**3.6**	**3.9**	**4.6**	**4.4**	**9.9**
Average	**14.0**	**13.7**	**13.1**	**13.5**	**14.9**	**14.9**	**14.1**	**13.3**	**21.6**	**26.7**

A zero value indicates that the DMU has no room for improvement in this indicator relative to the benchmarks.
The data for the eastern region is displayed as the average of the 11 provinces mentioned above, the central region as the average of the 10, and the western region as the average of the 9.

Research limitations and prospects. This study develops an evaluation framework using Chinese provinces as DMUs to assess the efficiency of carbon neutrality transition at the provincial level. Government-level design of input-output indicators lacks explanatory power regarding the technological and industrial pathways necessary to achieve carbon neutrality goals. Future research should refine evaluation frameworks to quantify CNTE across the following dimensions.

i. Focus on key technological pathways toward carbon neutrality, using R&D investment and green patents as input indicators to evaluate the effectiveness of CCUS, DAC, BECCS, and hydrogen energy technologies in reducing carbon emissions.
ii. Refine the evaluation scope to the city level, focusing on special types of cities (such as resource-based or coastal cities), and evaluate different carbon neutrality paths by accounting for variations in key factors such as ecological carrying capacity and grid connectivity requirements.
iii. Given that the industrial sector is the primary source of carbon emissions, its evaluation should incorporate labor, AI technology, and sustainable investment as input indicators to assess low-carbon process reengineering pathways toward carbon neutrality.
iv. Future research can employ Tobit regression and the DID method to examine how factors such as Russia-Ukraine war-induced energy price volatility and carbon emissions trading influence CNTE.

However, the optimization of the aforementioned unexplored directions depends on the availability of precise data. Establishing a carbon neutrality evaluation database through national or authoritative research institutions will facilitate future research.

Data availability
All data obtained/ generated has been provided.

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The authors declare no competing interests.

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Not applicable.

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