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Carbon emissions management efficiency evaluation based on indicator information integration and DEA-Malmquist index

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The completeness of indicator information is a critical issue that requires further investigation in the evaluation of carbon emissions management efficiency. However, this problem has not received adequate attention in existing studies, and there is a dearth of analysis using the total factor productivity method, which has proven effective in evaluating efficiency in various domains. Consequently, this study proposes a model for evaluating carbon emissions management efficiency that integrates indicator information and employs the data envelopment analysis (DEA)-Malmquist index. The integration of indicator information is accomplished through the evidential reasoning (ER) approach, which includes the calculation of indicator weights. The DEA-Malmquist index is utilized to assess the efficiency of carbon emissions management and analyze its total factor productivity based on the integrated indicator information. To demonstrate the efficacy of the proposed model, a case study of 17 corporates in China from 2019 to 2021 is provided to illustrate the analysis of three scopes efficiency distribution, efficiency change and improvement strategy of carbon emissions management. Results discussion show that the proposed model can be used to provide a reference for the improvement effectiveness of carbon emissions management.

KEYWORDS

evidential reasoning, indicator information integration, carbon emissions management, efficiency evaluation, improvement strategy

1 Introduction

As the global economy undergoes rapid expansion, society faces a complex balance between reducing carbon emissions and promoting economic growth. When carbon emissions exceed the environmental capacity, it exacerbates the challenges related to environmental remediation and management, putting the sustainability of economic progress at risk. Consequently, optimizing the strategy for carbon emissions management has emerged as a critical priority in our endeavor to mitigate the adverse effects of climate change and environmental degradation, and to achieve sustainable development.

Existing studies shed light on significant regional discrepancies in the efficiency of carbon emissions management within China, influenced by factors such as GDP, level of industrialization, and technological innovation. Ongoing research endeavors strive to refine methodologies, including various DEA models, to enhance their resilience against uncertainties. However, in the selection of DEA carbon emissions management related indicators, careful consideration must be given to determining the appropriate number of indicators. The DEA theory adheres to the rule of thumb, which suggests that the number of decision-making units should be at least 2 to 3 times greater than the number of evaluation indicators. An excessive number of input-output indicators for decision-making units tends to result in efficiencies converging towards 1, thereby diminishing the distinctiveness among decision-making units. Conversely, an inadequate number of indicators renders the decision-making process susceptible to errors and the loss of vital indicator information.

Simultaneously, it becomes apparent that the evaluation of carbon emissions management efficiency is influenced by various indicators to different extents (Ramón et al., 2016; Chen et al., 2017). Inadequate availability and knowledge limitations have resulted in a constrained selection of output indicators for efficiency assessment that is subject to debate as to its sufficiency (Yu et al., 2016; Costa-Campi et al., 2017). One notable limitation of this indicator selection approach is its inherent failure to encompass the comprehensiveness of output indicators in emissions management. For example, Chen et al. (2017) exclusively considered SO_2 as an output indicator to represent waste gas emissions, thereby overlooking other pertinent indicators such as O_3, smoke, and dust emissions. Furthermore, the majority of studies have ascribed equal significance to diverse input and output indicators within the system modeling of carbon emissions management, despite the evident disparity in their roles. While certain existing research has incorporated weight calculation (Yang et al., 2019), application of these weighting methods within the realm of carbon emissions management has been limited. Consequently, future studies on carbon emissions management must confront numerous challenges that remain unresolved.

Firstly, it is worth noting that the existing body of research on the evaluation of carbon emissions management efficiency has displayed inconsistencies, primarily stemming from variations in the selection of indicators. Different methodologies for indicator selection have yielded divergent outcomes in terms of the chosen indicators. Given that indicator selection plays a pivotal role in the assessment of carbon emissions management efficiency, this inconsistency poses challenges. Notably, previous studies have predominantly relied on experts' experiences or empirical judgment to guide their indicator selection process (Chen et al., 2017). Consequently, the accuracy and objectivity of the evaluation of carbon emissions management efficiency can be significantly affected by this subjective approach to indicator selection; *Secondly*, it is worth noting that the previous studies on evaluating the efficiency of carbon emissions management have overlooked the significance of ensuring the integrity of indicator information. This oversight arises from the potential loss of indicator information and its subsequent impact on the evaluation results. Concurrently, it is imperative to consider the thumb rule within the framework of DEA theory, which necessitates the inclusion of two to three times the number of decision-making units (DMUs) compared to the total number of evaluation indicators. Utilizing an excessive number of indicators in a DEA model can lead to a situation where the efficiency of all DMUs approaches unity, thereby reducing the differentiation among DMUs; Finally, it is worth noting that the prevailing body of research on the evaluation of carbon emissions management efficiency has primarily relied on statistical analyses to assess efficiency levels. However, the evolutionary trajectory of these efficiencies, particularly at the industry or corporate level, has been infrequently examined. As highlighted by Sheng et al. (2015), the examination of efficiency changes offers a valuable means of quantifying the rate of change in carbon emissions management efficiency. This approach proves instrumental in comprehensively assessing issues associated with the input-output structure via the lens of efficiency fluctuations.

To address the aforementioned challenges associated with the evaluation of carbon emissions management efficiency, this study introduces a novel efficiency evaluation model. The key components of this model are as follows: 1) the determination of relative weights for different input, undesirable and desirable output indicators pertaining to carbon emissions management; 2) the integration of the set of undesirable output indicators and desirable output indicators, based on the obtained weights, utilizing the evidential reasoning (ER) approach to generate new combined indicators; 3) the utilization of the integrated indicators in conjunction with the DEA model and Malmquist index to assess the efficiency of carbon emissions management. Consequently, the proposed model makes the following contributions to the evaluation of carbon emissions management efficiency:

1) The Correlation Coefficient and Standard Deviation (CCSD) method is employed to compute the relative weights of diverse input, undesirable, and desirable output indicators that are pertinent to carbon emissions management. This method is specifically designed to allocate appropriate significance to each indicator within the comprehensive evaluation process;
2) The integration of input, undesirable, and desirable output indicators is achieved through the use of the ER approach, thereby circumventing the loss of pertinent information and adhering to the fundamental principles of the DEA model. This integration mechanism enables the comprehensive analysis of the various indicators, ensuring their collective consideration and evaluation within a unified framework;
3) The utilization of integrated indicators plays a pivotal role in facilitating the efficiency evaluation of carbon emissions management through the adept application of the DEA model and the Malmquist index. These analytical tools provide a rigorous methodological framework for comprehensively assessing the efficiency of carbon emissions management founded upon the integrated indicators. By addressing the limitations encountered in prior research, this innovative model aims to contribute to a more precise and holistic evaluation of the efficiency of carbon emissions management.

In order to validate the effectiveness of the proposed model, a comprehensive case study is conducted using input, desirable output, and undesirable output indicators as well as data pertaining to carbon emissions management from 17 corporations in China. The dataset encompasses the period spanning from 2019 to 2021. Through this empirical analysis, multiple efficiency-related outcomes are computed, thereby presenting a research framework for the management of carbon emissions in China. Furthermore, the evaluation results of carbon emissions management efficiency highlight significant disparities between comprehensive efficiency and pure technical efficiency during different management periods. Notably, both overall environmental efficiency and pure technical efficiency demonstrate an upward trajectory within these Chinese corporations. This suggests that the positive impact of the existing input-output structure and technical aspects on the comprehensive efficiency of carbon emissions management becomes increasingly pronounced over time.

2 Literature reviews of carbon emissions management

The escalating issue of carbon emissions necessitates effective scientific management to mitigate its detrimental impact on the global climate and environment. Consequently, an increasing number of scholars have directed their attention towards conducting research on the analysis of influencing factors and addressing the myriad challenges that arise from carbon emissions. Presently, investigations pertaining to carbon emissions predominantly center around exploring the connection between energy consumption and carbon emissions, examining the influencing factors associated with carbon emissions, and developing evaluation model for carbon emissions management.

(1) The connection between energy consumption and carbon emissions. The relationship between energy consumption and carbon dioxide emissions has garnered significant attention in light of the pressing issues of climate change and global warming. Researchers have consistently highlighted that carbon dioxide emissions play a crucial role in environmental hazards (Ali et al., 2022). Several studies have underscored the viability of adopting clean and renewable energy as a viable approach to mitigate carbon dioxide emissions (Zarezade and Mostafaeipour, 2016; Samuel et al., 2019). To empirically analyze the impact of energy consumption on environmental degradation, TailonAlisson et al. (2021) proposed the ARDL bounds testing approach, which was applied to G7 countries. Findings revealed that coal, oil, and natural gas consumption had a positive influence on environmental degradation. Similarly, Samuel and Christian, (2019) noted that renewable energy sources contributed more significantly to environmental degradation than nonrenewable energy sources. In an effort to achieve sustainability and energy efficiency goals in China, Zhang et al. (2021a) evaluated the impact of hydroelectric and renewable electricity generation on carbon dioxide emissions while examining the relationship between renewable energy consumption and carbon dioxide emissions. Furthermore, multiple authors have proposed methods for assessing energy-related carbon dioxide emissions and have conducted analyses to outline dynamic low-carbon energy paths towards 2030 (Lin and Agyeman, 2020).

(2) Influencing factors associated with carbon emissions. The analysis of influencing factors related to carbon dioxide emissions has been the focus of previous research. For instance, Wen and Shao (2019) conducted a panel data analysis to investigate the drivers of carbon dioxide emissions in the commercial sector in China. Their findings revealed that diverse influencing factors exerted varying nonlinear effects on carbon dioxide emissions. Additionally, Hang et al. (2019) examined the factors impacting economic growth and carbon dioxide emissions in the manufacturing industry, illustrating that the adjustment of carbon dioxide emissions density falls short of achieving the anticipated reduction outcomes. Reducing carbon emissions and fostering a low carbon economy constitute important objectives, as highlighted by Wang and Ma (2018) who employed the Tobit model to examine influencing factors on the efficiency of carbon dioxide emissions. Furthermore, Liang et al. (2019) emphasized energy intensity as a significant factor influencing carbon dioxide emissions, revealing a consistent upward trend in carbon dioxide emissions from high energy consumption sectors in China.

(3) Efficiency evaluation of carbon emissions management. The examination of carbon emissions management efficiency is a topic that has garnered significant attention within academic circles. An emerging trend in the academic discourse on this subject has been observed in recent years, with the primary focus of research on carbon emissions management being empirical analysis and practical studies (Hong et al., 2016; Makkonen and Repka, 2016; Cheng et al., 2017). Within the specific context of China, the evaluation of carbon emissions management efficiency has been rigorously explored by scholars, with particular emphasis on variances across different sectors and regions. A study by Zhang et al. (2021b) scrutinized the efficiency of carbon emissions in the Chinese construction industry, underlining the substantial impact of factors such as GDP, level of industrialization, and technological innovation. Similarly, Meng et al. (2016) performed an extensive review employing DEA-type models, revealing both stability and regional inconsistencies in energy efficiency and carbon emissions efficiency during the course of China's Five Year Plan.

Building upon previous research, Yan et al. (2017) conducted an analysis of China's power industry, which is responsible for approximately 40% of the nation's carbon emissions. Their findings indicated that the wealthier provinces on the eastern coast demonstrated higher carbon emission efficiency, and that interregional technological collaboration could further enhance this efficiency. In a similar vein, Cheng et al. (2018) employed an enhanced non-radial directional distance function, revealing a substantial opportunity for efficiency improvement across several provinces. Their research underscored the importance of technical advancement in fostering efficiency. Qu et al. (2022) tackled uncertainties related to climate and governmental economic policy through the use of a robust DEA model. They advocated for the adoption of a green and low-carbon lifestyle, a transformation in energy structures, and the promotion of coordinated regional development.

3 ER-based indicator information integration

In this section, Subsection 3.1 presents the methodology for calculating weights for carbon emissions-related indicators, while

Subsection 3.2 introduces the ER approach (Wang et al., 2006) for the integration of indicator information.

3.1 Indicator weight calculation

In the domain of carbon emissions management across diverse enterprises, a variety of distinct indicators exists, each holding its unique degree of importance. To ascertain the importance of these disparate indicators, an esteemed weight calculation mechanism known as the Correlation Coefficient and Standard Deviation (CCSD) method (Wang and Luo, 2010) is utilized. This particular technique enables the determination of indicator weights, underpinned by the collected environmental data, thereby bestowing a rigorous and quantifiable measure of each indicator's contribution to the comprehensive emissions management schema.

Assumes that carbon emissions management contains T related indicators C_t ($t = 1,..., T$) and each indicator has S collected data $v_{s,t}$ ($s = 1,..., S$). Since the collected data is a dimensional representation, it needs to be dimensionless standardized. According to the different characteristics of indicators, the specific standardization is as follows:

$$e_{s,t} = \begin{cases} \dfrac{v_{s,t} - min_{i=1,...,S}\{v_{i,t}\}}{max_{i=1,...,S}\{v_{i,t}\} - min_{i=1,...,S}\{v_{i,t}\}}, if C_t \in \Omega_{benefit} \\ \dfrac{max_{i=1,...,S}\{v_{i,t}\} - v_{s,t}}{max_{i=1,...,S}\{v_{i,t}\} - min_{i=1,...,S}\{v_{i,t}\}}, if C_t \in \Omega_{cost} \end{cases} \tag{1}$$

where $\boldsymbol{\Omega_{benefit}}$ denotes the set of benefit indicators, whose values are always the larger the better; $\boldsymbol{\Omega_{cost}}$ denotes the set of cost indicators, whose values are always the smaller the better; $e_{s,t}$ denotes the tth normalized value of the sth indicator.

Based on the $S \times T$ normalized values, the correlation coefficient of the tth indicator, denoted as R_t, can be calculated when assuming that the weights of T indicators are w_t ($t = 1,..., T$). The specific formula of calculating R_t is as follows:

$$R_t = \frac{\sum_{s=1}^{S} (e_{s,t} - \bar{e}_t)(d_{s,t} - \bar{d}_t)}{\sqrt{\sum_{s=1}^{S} (e_{s,t} - \bar{e}_t)^2 \cdot (d_{s,t} - \bar{d}_t)^2}} \tag{2}$$

where $d_{s,t}$ denotes the overall assessment value of the sth data in the tth indicator when the tth indicator do not consider in the overall assessment; $\bar{e}_t$ and $\bar{d}_t$ denote the mean of normalized values and overall assessment values at the tth indicator. The specific formula of calculating $d_{s,t}$, $\bar{e}_t$ and $\bar{d}_t$ is as follows:

$$d_{s,t} = \sum_{i=1, i \neq s}^{S} e_{i,t} w_t \tag{3}$$

$$\bar{d}_t = \frac{\sum_{s=1}^{S} d_{s,t}}{S} \tag{4}$$

$$\bar{e}_t = \frac{\sum_{s=1}^{S} e_{s,t}}{S} \tag{5}$$

Here, it is worth noting that if R_t is close to one, then the tth indicator has a little influence on carbon emissions management and it can be assigned a small weight; Otherwise, the weight of the tth indicator should be large. Additionally, the standard deviation of the tth indicator, denoted as σ_t, can be calculated by using the following formula:

$$\sigma_t = \sqrt{\frac{\sum_{s=1}^{S} (e_{s,t} - \bar{e}_t)^2}{S}} \tag{6}$$

According to the T correlation coefficients and T standard deviations, a revised weight for each indicator, symbolized as $\bar{w}_t$, can be derived utilizing the subsequent formula:

$$\bar{w}_t = \frac{\sigma_t \sqrt{1 - R_t}}{\sum_{k=1}^{T} \sigma_k \sqrt{1 - R_k}} \tag{7}$$

Ultimately, given that the T initial weights w_t are premised on the assumption of equality with the T new weights $\bar{w}_t$, the weight of T indicators can be computed utilizing the following optimization model:

$$\begin{aligned} &Min\ J = \sum_{t=1}^{T} (w_t - \bar{w}_t)^2 \\ &s.t. \sum_{t=1}^{T} w_t = 1 \\ &w_t \geq 0; t = 1, ..., T \end{aligned} \tag{8}$$

3.2 Indicator information integration

In the context of efficiency evaluation for carbon emissions management, certain numerical conditions must be met pertaining to the counts of inputs, outputs, and DMUs. For instance, the number of DMUs should surpass twice the sum of the quantity of inputs and outputs, as stipulated by Golany and Roll (1989). Consequently, the ER approach (Wang et al., 2006), derived from the Dempster-Shafer theory of evidence and recognized for its robust capabilities in information fusion, is deployed for the integration of indicator information. Thus, in this study, the input related indicators, desirable output related indicators and the three types of carbon emissions are integrated by the proposed ER model for carbon emissions evaluation.

Assuming that carbon emissions management incorporates T related indicators, denoted as C_t ($t = 1,..., T$), each indicator carries a weight w_t ($t = 1,..., T$) derived from Section 2.1 and shares a set of mutually exclusive and collectively exhaustive evaluation grades, represented as $H = \{H_1,..., H_N\}$. In accordance with the N grades, the distribution assessment of each indicator, symbolized as $S(C_t)$, can be defined as follows:

$$S(C_t) = \{(H_n, \beta_{n,t}), n = 1, ..., N\} \tag{9}$$

In the above equations (Eq. 9), $\beta_{n,t}$ denotes the belief degree assigned to the nth grade for the tth indicator and it satisfies:

$$\sum_{n=1}^{N} \beta_{n,t} \leq 1 \tag{10}$$

$$\beta_{n,t} \geq 0; n = 1, ..., N \tag{11}$$

Based on the distributed assessments and T weights, the basic probability assignments (BPAs) for each indicator can be calculated by:

$$m_{n,t} = m(H_n) = w_t\beta_{n,t},\ n= 1,...,N;\ t= 1,...,T \tag{12}$$

$$\bar{m}_{H,t} = \bar{m}_t(H)= 1-w_t,\ t= 1,...,T \tag{13}$$

$$\tilde{m}_{H,t} = \tilde{m}_t(H) = w_t\left(1 - \sum_{n=1}^{N}\beta_{n,t}\right), t= 1,...,T \tag{14}$$

where $m_{n,t}$ is the BPA of the nth grade on the tth indicator. $\bar{m}_{H,t}$ is the uncertain BPA caused by the relative weight of the tth indicator; $\tilde{m}_{H,t}$ is the uncertain BPA caused by the incompleteness of the distributed assessment.

According to the analytical ER algorithm (Chen et al., 2017), the BPAs of T indicators can be integrated as the BPAs of a new integrated indicator, namely, indicator information integration. The corresponding formulas are as follows:

$$m_n = k\left[\prod_{t=1}^{T}(m_{n,t} + \bar{m}_{H,t} + \tilde{m}_{H,t}) - \prod_{t=1}^{T}(\bar{m}_{H,t} + \tilde{m}_{H,t})\right], n= 1,...,N \tag{15}$$

$$\tilde{m}_H = k\left[\prod_{t=1}^{T}(\bar{m}_{H,t} + \tilde{m}_{H,t}) - \prod_{t=1}^{T}\bar{m}_{H,t}\right] \tag{16}$$

$$\bar{m}_H = k\left[\prod_{t=1}^{T}\bar{m}_{H,t}\right] \tag{17}$$

$$k = \left[\sum_{n=1}^{N}\prod_{t=1}^{T}(m_{n,t} + \bar{m}_{H,t} + \tilde{m}_{H,t}) - (N-1)\prod_{t=1}^{T}(\bar{m}_{H,t} + \tilde{m}_{H,t})\right]^{-1} \tag{18}$$

Thus, the BPAs of the integrated indicator is then transformed into the distributed assessment $S(C) = \{(H_n, \beta_n), n= 1,...,N\}$, in which the belief degree of the nth grade is calculated by:

$$\beta_n = \frac{m_n}{1 - \bar{m}_H},\ n= 1,...,N \tag{19}$$

Meanwhile, the belief degree of uncertainty is calculated by:

$$\beta_H = \frac{\tilde{m}_H}{1 - \bar{m}_H} \tag{20}$$

Finally, efficaciously represent the integrated indicator information, the distributed assessment should be transmuted into a numeric value. Therefore, when $u(H_n)$ denotes the utility of the n-th grade, the utility value of the integrated distributed assessment is computed using the following equation:

$$u(S(C)) = \sum_{n=1}^{N}\beta_n u(H_n) + \frac{u(H_1) + u(H_N)}{2}\beta_H \tag{21}$$

4 DEA-Malmquist index-based efficiency evaluation

In this section, Subsection 4.1 introduces the concept of efficiency evaluation considering undesirable outputs. Subsequently, Subsection4.2 proposes the dynamic efficiency evaluation utilizing the Malmquist index. It is worth noting that the input related indicators, desirable output related indicators and the three types of carbon emissions of each DMU in DEA undesirable output model and DEA-Malmquist index are integrated based on the Section 3.

4.1 Efficiency measure with undesirable outputs

In the realm of carbon emissions management, undesirable outputs, such as varying degrees of CO_2 in a corporate's carbon emissions, are inevitable and significantly influence efficiency evaluation. To approach carbon emissions management in a more scientifically rigorous manner, this section incorporates a DEA undesirable output model (Seiford and Zhu, 2002). This model facilitates the evaluation of carbon emissions management efficiency considering undesirable outputs. The DEA undesirable output model, a variant of the DEA models employed for efficiency evaluation, holds comparative advantages over other DEA models (Wang et al., 2008; Wang and Wu, 2011; Song et al., 2018). These include the capability to evaluate efficiency for multiple inputs and outputs without the necessity for dimensionless data processing and weight assumption.

Within the framework of the DEA undesirable output model, assuming the existence of n DMUs with m input indicators, s desirable output indicators and h undesirable output indicators, then the input data, desirable output data, and undesirable output data of n DMUs can be denoted as X, Y and Z, respectively.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \tag{22}$$

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1j} & \cdots & y_{1n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{r1} & \cdots & y_{rj} & \cdots & y_{rn} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ y_{s1} & \cdots & y_{sj} & \cdots & y_{sn} \end{bmatrix}_{s\times n} \tag{23}$$

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1j} & \cdots & z_{1n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ z_{f1} & \cdots & z_{fj} & \cdots & z_{fn} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ z_{h1} & \cdots & z_{hj} & \cdots & z_{hn} \end{bmatrix}_{h\times n} \tag{24}$$

Next, according to the input data X, desirable output data Y and undesirable output data Z shown in Eqs 22–24, the following optimization model can be used to evaluate the efficiency of each DMU with consideration of undesirable outputs and the condition of constant returns to scale

$$\begin{aligned} &\theta_0^* = min\,\theta_0 \\ &s.t.\sum_{j=1}^{n}\lambda_j x_{ij} \le \theta_0 x_{i0};\ i= 1,...,m \\ &\sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{r0};\ r= 1,...,s \\ &\sum_{j=1}^{n}\lambda_j b_{fj} \ge b_{f0};\ f= 1,...,h \\ &\lambda_j \ge 0;\ j= 1,...,n \end{aligned} \tag{25}$$

where

$$b_{fj}= -z_{fj} + max_{j=1,...,n}\{z_{fj}\}+min_{j=1,...,n}\{z_{fj}\} \tag{26}$$

Finally, the efficiency value θ_j^* ($j = 1,..., n$) of n DMUs can be obtained. When $\theta_j^* = 1$, it means that the input-output structure of the jth DMU is effective. Conversely, if these conditions are not met, it implies that the input-output structure of the jth DMU necessitates further enhancement.

Additionally, in circumstances where an increase or decrease in inputs or outputs leads to a proportional change in the outputs or inputs, i.e., a phenomenon termed variable returns to scale, is also an extra constraint needs to be integrated into the optimization model outlined in Eq. (25). This adjustment enables the evaluation of each DMU's efficiency considering undesirable outputs under variable returns to scale.

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{27}$$

4.2 DEA-Malmquist index for efficiency evaluation

The efficiencies derived from Section 4.1 are static in nature and often fail to encapsulate the evolution of comprehensive efficiency and technical efficiency. To effectively implement carbon emissions management, it is essential to consider dynamic efficiencies. To this end, the Malmquist index (Fare et al., 1992) is incorporated to enrich the efficiency evaluation of carbon emissions management.

In the course of dynamic efficiency evaluation, let's assume that the input data, desirable output data, and undesirable output data for the tth period are denoted as X^t, Y^t and Z^t, respectively. The Malmquist index formula, which tracks changes from the tth period to the t+1th period, is defined as follows:

$$M\left(X^{t+1}, Y^{t+1}, Z^{t+1}, X^t, Y^t, Z^t\right) = \left[\frac{D_c^t\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_c^t\left(X^t, Y^t, Z^t\right)} \times \frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_c^{t+1}\left(X^t, Y^t, Z^t\right)}\right]^{1/2} \tag{28}$$

In the above equations (Eq. (28)), D_c^t and D_c^{t+1} denote the distance function estimated with the tth period and the t+1th period under the condition of constant returns to scale, respectively, and their values can be obtained by using the optimization model shown in Eq. 25 to evaluate the efficiency of the DMUs constructed by X^t, Y^t and Z^t, or X^{t+1}, Y^{t+1} and Z^{t+1}. Additionally, $M > 1$ indicates that the comprehensive efficiency level of carbon emissions management is improved; $M = 1$ indicates that the comprehensive efficiency level of carbon emissions management remains unchanged; $M < 1$ indicates that the level of carbon emissions management efficiency decreases. According to (Golany and Roll, 1989), Eq. 28 can be decomposed into the following two components:

$$\begin{aligned} & TFPC\left(X^{t+1}, Y^{t+1}, Z^{t+1}, X^t, Y^t, Z^t\right) \\ & = \frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_c^t\left(X^t, Y^t, Z^t\right)} \times \left[\frac{D_c^t\left(X^t, Y^t, Z^t\right)}{D_c^{t+1}\left(X^t, Y^t, Z^t\right)} \times \frac{D_c^t\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_c^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}\right]^{1/2} \\ & = EC \times TC \end{aligned} \tag{29}$$

In the above equations (Eq. (29)), EC and TC represent the efficiency change and the technical change respectively. An EC value greater than 1 signifies an improvement in the efficiency of carbon emissions management; an EC value equal to 1 indicates that the efficiency of carbon emissions management remains unchanged; and an EC value less than 1 suggests a reduction in the efficiency of carbon emissions management.

When the efficiency evaluation of carbon emissions management is assumed to be variable returns to scale, EC_c can be further decomposed into the following two components:

$$\begin{aligned} EC & = \frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_c^t\left(X^t, Y^t, Z^t\right)} \\ & = \frac{D_v^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_v^t\left(X^t, Y^t, Z^t\right)} \times \left(\frac{D_v^t\left(X^t, Y^t, Z^t\right)}{D_c^t\left(X^t, Y^t, Z^t\right)} \times \frac{D_c^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}{D_v^{t+1}\left(X^{t+1}, Y^{t+1}, Z^{t+1}\right)}\right) \\ & = PTEC \times SEC \end{aligned} \tag{30}$$

In the above equations (Eq. (30)), $PTEC$ and SEC denote the pure technical efficiency change and the scale efficiency change; D_v^t and D_v^{t+1} denote the distance function estimated with the tth period and the t+1th period under the variable of constant returns to scale, respectively, and their values can be obtained by using the optimization model shown in Eq. 25 together with Eq. 27 to evaluate the efficiency of the DMUs constructed by X^t, Y^t and Z^t, or X^{t+1}, Y^{t+1} and Z^{t+1}.

5 Framework of efficiency evaluation model for carbon emissions management

Building on the ER-based indicator information integration delineated in Section 3, and the DEA-Malmquist index-based efficiency evaluation illustrated in Section 4, this section proposes a framework for a carbon emissions management efficiency evaluation model. The main process of this model is depicted in Figure 1.

From Figure 1, the detailed steps for carbon emissions management efficiency evaluation include:

Step 1: ER-based indicator information integration for desirable and undesirable output indicators. Suppose that there are s desirable output indicators and h undesirable output indicators and their data are collected from n corporates and T years, namely, $y_{r,j}^t$ ($t = 1,..., T; j = 1,..., n; r = 1,..., s$) and $z_{f,j}^t$ ($f = 1,..., h$). Hence, based on the indicator weight calculation shown in Section 2.1 and the indicator formation integration shown in Section 2.2, all these data of s desirable output indicators and h undesirable output indicators should be integrated into $T \times n$ new data y_j^t and z_j^t.

Step 2: DEA-Malmquist index-based efficiency evaluation based on the integrated desirable and undesirable output data. Suppose that there are m input indicators and their data collected from n corporates and T years are $x_{i,j}^t$ ($i = 1,..., m$). Hence, based on $T \times n$ integrated desirable and undesirable output data, the corresponding data matrix used for efficiency evaluation can be generated and denoted as $X^{(t)} = (x_{i,j}^t)_{m\times n}$, $Y^{(t)} = (y_j^t)_{1\times n}$, and $Z^{(t)} = (z_j^t)_{1\times n}$. Furthermore, efficiency, TFPC, EC, PTEC, and SEC can be calculated based on the efficiency measure shown in Section 3.1 and the efficiency evaluation shown in Section 3.2.

6 Case study

This section of the study focuses on the preprocessing of carbon emissions management data obtained from a sample of 17 Chinese

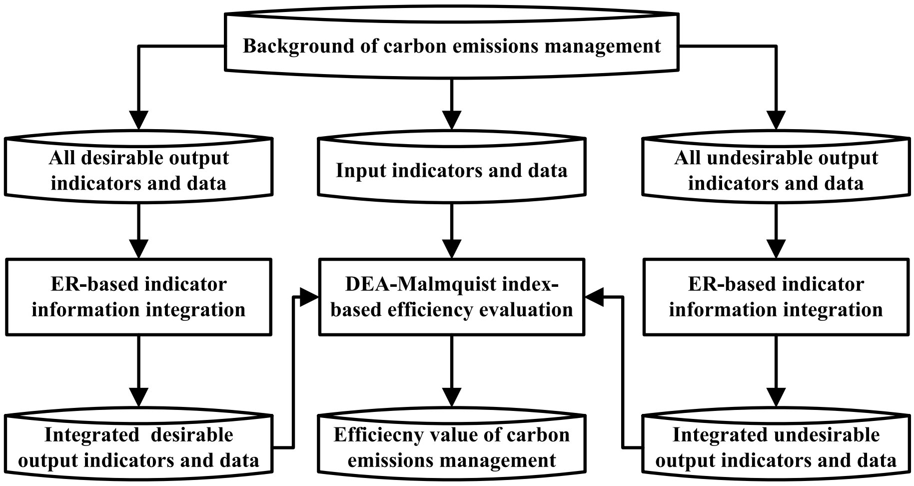

FIGURE 1
Framework of carbon emissions management efficiency evaluation.

corporates, spanning the timeframe of 2019–2021. With the approaching implementation of the "dual-carbon target," the capital market in China is concurrently experiencing an upsurge in carbon investment. To meet this demand, China has taken preliminary steps to establish a green financial system. Accordingly, this article, taking into account the unique characteristics of the Chinese market and companies, has gathered company-level carbon emission data that aligns with the Chinese investment environment. The data sources utilized encompass revenue breakdown data, carbon emission disclosure data, and pollutant emission data. Revenue breakdown data primarily originates from company annual reports and issuance disclosures, carbon emission disclosure data is derived from corporate social responsibility reports, and pollutant emission data is sourced from the National Pollutant Discharge Permit Management Information Platform. The database coverage encompasses A-shares, Hong Kong stocks, Chinese concept stocks, and bond-issuing enterprises, encompassing the time period from 2019 to 2021. Considering the availability of carbon emission data and the associated indicators, and after employing appropriate techniques to address missing data and indicators, this article ultimately derived a comprehensive dataset and indicator set relating to carbon emissions for the 17 selected corporates.

Detailed information about these corporates is provided in Table 1. Following the specific procedures outlined in Section 4, the efficiency of carbon emissions management and its corresponding technical change efficiency are analyzed, leveraging integrated indicators. Finally, the strategies to enhance carbon emissions management are also proposed.

6.1 Data resource and variable determination

This study adheres to a well-established framework for corporate carbon emissions indicators, as outlined by Ye et al. (2019a, 2019b). In line with this framework, both undesirable and desirable outputs are considered as significant indicators for carbon emissions management. Building on existing literature, the desirable outputs selected for evaluation include main business income, market capitalization, rate of return on equity, and earnings per share. On the other hand, the evaluation of the efficiency of carbon emissions management focuses on three categories of undesirable outputs, specifically direct carbon emissions, process carbon emissions, and final product carbon emissions.

The input indicators in this study are classified into three distinct categories: labor input, asset investment, and capital input. Labor input is quantified through various metrics, such as the number of employees, average employee salary, rate of salary per share, and salary growth. Asset investment is assessed based on the total assets and net assets per share of the corporations under examination. Capital input, on the other hand, is determined by analyzing the capital expenditure and the ratio of income tax to total profit. It is worth noting that among the 17 corporates selected for analysis, significant disparities exist in terms of both input and output indicators for carbon emission control. Consequently, these variations indirectly imply disparities in carbon emissions and the fiscal advantages of individual corporations.

It is imperative to acknowledge that all the indicators mentioned above, including their historical data, can be derived from various sources. The revenue breakdown data can be primarily obtained from corporate annual reports and issuance disclosures, while carbon emission disclosure data can be acquired from corporate social responsibility reports. As for pollutant emission data, it can be sourced from the National Pollution Discharge License Management Information Platform of China. A comprehensive analysis of the integrated desirable output and undesirable output, derived from the indicator information integration based on the ER approach, alongside the three types of inputs, is presented in Table 2.

To delineate the comprehensive details of both integrated desirable and undesirable outputs, the average values of these outputs across 17 corporations in China for each year are

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TABLE 1 The information of the 17 selected corporates.

Selected corporates	Ticker symbol
China Vanke Co., Ltd.	000002.SZ
China International Marine Containers Group Co., Ltd.	000039.SZ
GF Securities Co., Ltd.	000776.SZ
China Merchants Shekou Industrial Zone Holdings Co., Ltd.	001979.SZ
Sichuan Keelung Pharmaceutical Co., Ltd.	002422.SZ
Bank of Zhengzhou Co., Ltd.	002936.SZ
Bank of Qingdao Co., Ltd.	002948.SZ
CITIC Securities Co., Ltd.	600030.SH
CSSC Offshore & Marine Engineering Group Co., Ltd.	600685.SH
Chongqing Rural Commercial Bank Co., Ltd.	601077.SH
Guotai Junan Securities Co., Ltd.	601211.SH
New China Life Insurance Co., Ltd.	601336.SH
Great Wall Motor Co., Ltd.	601633.SH
Shanghai Electric Group Co., Ltd.	601727.SH
Yangtze Optical Fibre & Cable Joint Stock Co., Ltd.	601869.SH
China Zheshang Bank Co., Ltd.	601916.SH
China Construction Bank Corporation	601939.SH

visually presented in Figure 2. Notably, Figure 2 highlights conspicuous disparities in the desirable and undesirable outputs among different corporations in the same year. However, it is observed that annual variations in both desirable and undesirable outputs among these corporations are relatively modest. Analysis of the publicly available data pertaining to these 17 corporations reveals no discernible transformations in their production and energy technologies from 2019 to 2021. Consequently, it becomes challenging to effectively discern short-term changes in carbon emissions for these enterprises at present.

Consequently, this article aims to assess the carbon emissions of various corporations through a lens focused on the production process. The research outcomes depicted in Figure 3 demonstrate that, in the case of the majority of corporations, both direct carbon emissions and carbon emissions stemming from the production process far surpass those resulting from final products. Notably, many corporations exhibit the highest carbon emissions during the production process, which underscores the strong correlation between this stage of operations and the prevailing deficiency in the adoption of clean technology innovations within the production technologies employed by Chinese corporations.

6.2 Analysis of carbon emissions management efficiency

In an effort to examine the variations in carbon emissions management efficiency across different corporations and to identify the underlying factors driving such efficiency fluctuations, this study employs a proposed model to calculate the annual changes in carbon emissions management efficiency for each individual corporation.

TABLE 2 Statistic analysis of input-output indicators.

Indicator	Average	Std.	Min	Max
Integrated desirable output	1994	907	250	3,729
Integrated undesirable output	1381369	393424	765995	1996742
Labor input	158546	45138	70899	246192
Asset investment	42304	25564	127	84481
Capital input	99	42	4	195

By leveraging a comprehensive dataset obtained over a 3-year period encompassing 17 corporations in China, this paper computes the relative efficiency of each corporation's carbon emissions management. These corresponding efficiencies are visually presented in a clear and comprehensive manner in Figure 4.

Upon evaluating the efficiency of carbon emissions management from 2019 to 2021, it becomes evident that only one corporation has achieved the optimal level of carbon emissions management, as reflected by an efficiency value of 1. Conversely, the remaining 16 corporations consistently fail to attain the threshold of relative efficiency during any given year. The majority of these corporations exhibit management efficiency scores that persistently fall below 0.8, with some corporations even demonstrating a discernible downward trend in efficiency values across the considered period.

From the standpoint of returns to scale, Figure 5 illustrates that the carbon emissions management income of each corporation exhibited an upward trend from 2019 to 2021. This pattern suggests that there is still significant room for improving management efficiency through increasing input factors. However, a subset of corporations experienced diminishing returns to scale, indicating that excessive investments in carbon emissions management resulted in redundant outputs. For these corporations, optimizing input resources becomes a key concern. Furthermore, on a broader scale, the carbon emissions management efficiency among the 17 examined corporations varies significantly, highlighting disparities in management capabilities. Consequently, the carbon emissions management efficiency of individual corporations has not effectively improved over time. These findings underscore the importance of rational allocation of input-output structures and the development of effective carbon emissions management policies as crucial factors in addressing current challenges in carbon emissions management in China.

To highlight the disparities in the efficiency of carbon emissions management, Figure 6 presents the average efficiency across three types of carbon emissions management from 2019 to 2021 for 17 corporates in China. Through an encompassing analysis, it becomes evident that the carbon emissions management efficiency in 2019 surpasses that of subsequent years, with 2021 registering the lowest efficiency.

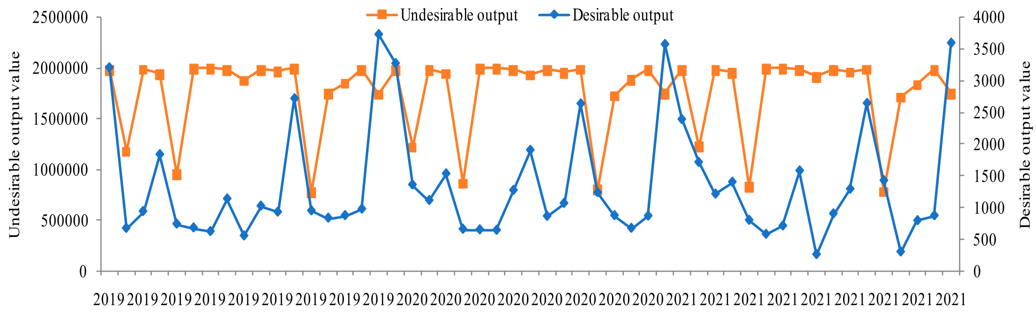

FIGURE 2
Integrated desirable and undesirable output from 2019 to 2021.

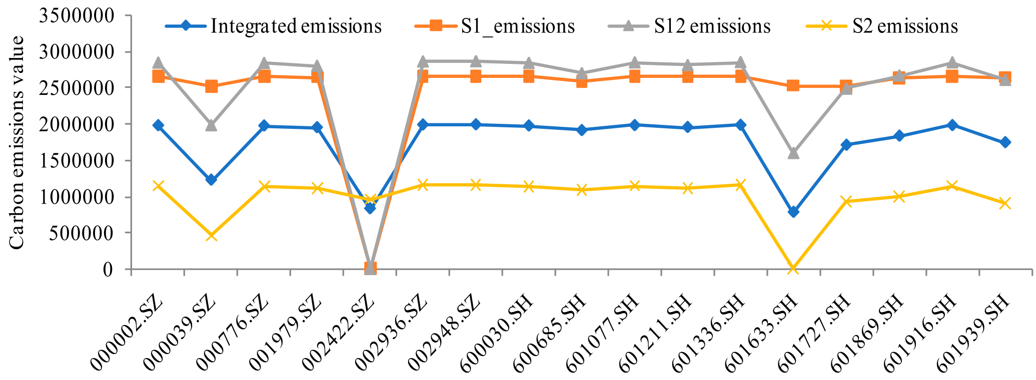

FIGURE 3
Different Scopes of Carbon Emissions of 17 corporates in 2021.

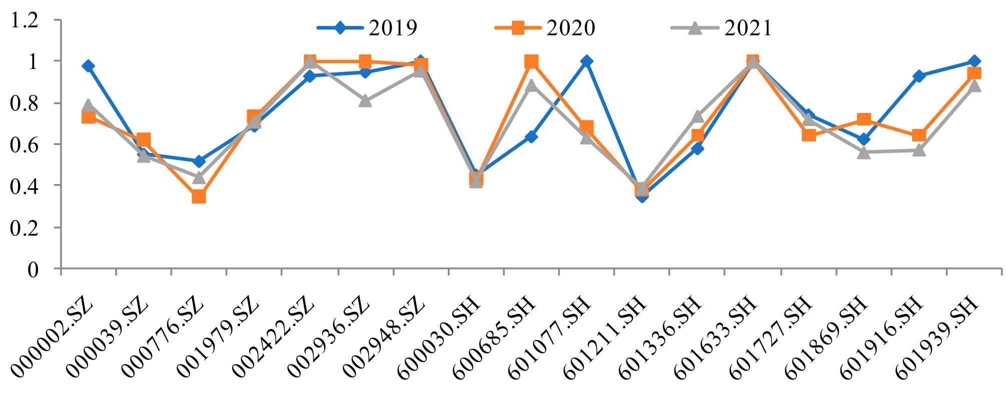

FIGURE 4
Comprehensive efficiency of different corporates from 2019 to 2021.

In addition to the impact of economic and resource endowment shifts over the years, substantial discrepancies are observed in the pure technical efficiency of carbon emissions management across different years for these 17 corporates. This is largely attributable to variations in the level of economic development and policy changes. The pure technical efficiency and scale efficiency in 2019 and 2020 are notably higher than those in 2021 across the 17 corporates. This underscores the significant challenge of balancing economic development with sustainable environmental protection within the industrial production processes in China.

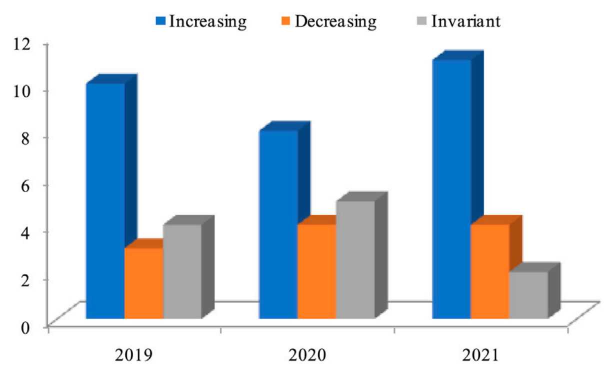

FIGURE 5
Number of corporates in different returns to scale from 2019 to 2021.

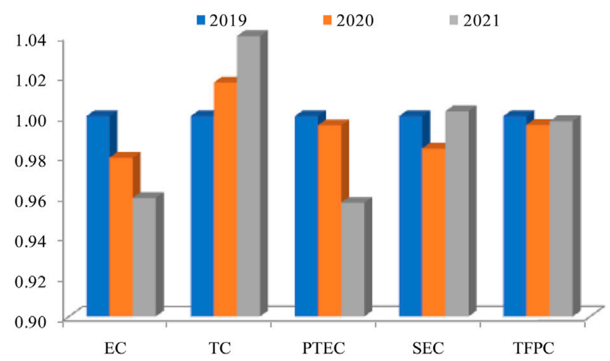

FIGURE 7
Carbon emissions management efficiency change from 2019 to 2021.

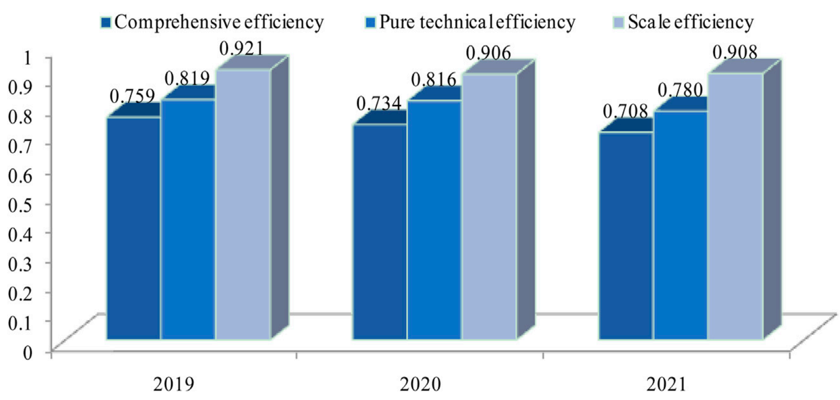

FIGURE 6
Efficiency distribution of different regions in China.

6.3 Time changes of carbon emissions management efficiency

In the subsequent section, this study delves into the temporal dynamics of carbon emissions management efficiency. Figure 6 presents the results obtained from the assessment of efficiency using the DEA-Malmquist index. Subsequently, Figure 7 demonstrates the variables EC, PTEC, EC, and TFPC, all indicating a decline in the efficiency of carbon emissions management.

A close examination of these figures reveals a discernible downward trajectory in the overall efficiency of carbon emissions management among the 17 included corporations over time. Despite notable fluctuations, the prevailing trend unequivocally points towards a decrease in efficiency. Considering the rapid expansion of these 17 corporations, the issue of carbon emissions necessitates continued attention and heightened significance.

Subsequently, Figure 8 illustrates the variations in carbon emissions management efficiency across different corporates. A perusal of Figure 8 reveals that the efficiency of carbon emissions management in the majority of corporates lacks stability. Despite the numerous shortcomings in China's current carbon emissions management, there is a conspicuous absence of institutional standardization in the carbon emissions management process. This lack of standardization impedes industrial coordination and the stability of carbon emissions management.

Furthermore, a comparative analysis conducted between the SEC and EC reveals that the integration of Pure Technical Efficiency Change (PTEC) into the framework yields enhanced efficiency and greater stability in the realm of carbon emissions management. In fact, the inclusion of PTEC facilitates a more intricate examination of the technical processes involved in the management of carbon emissions, enabling a more targeted identification of areas for improvement, such as resource optimization or the adoption of innovative technologies. Moreover, this approach not only augments the efficiency value but also imparts increased stability to the carbon emissions management efficiency. Stability, within this context, denotes the ability to consistently maintain high levels of efficiency over time. This aspect is of utmost importance in the realm of carbon emissions management, as a stable efficiency level signifies a corporation's capacity to consistently and effectively handle its carbon emissions, thereby making noteworthy contributions towards sustainable development objectives.

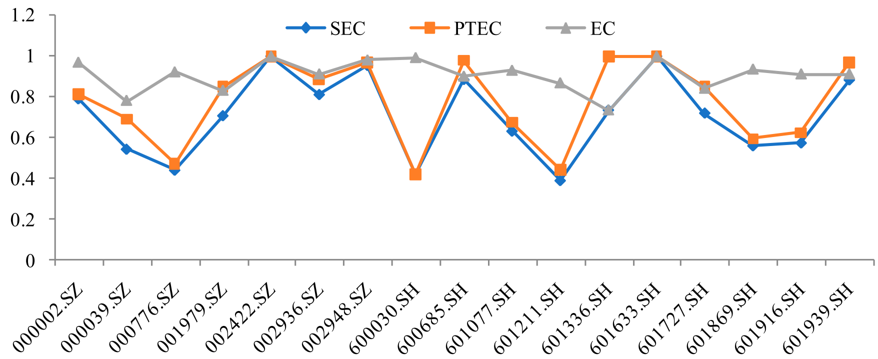

FIGURE 8
Carbon emissions management efficiency change in different corporates.

6.4 Improvement strategy of regional carbon emissions management efficiency

In this section, this paper analyzes the comprehensive efficiency of carbon emissions management of 17 corporates in China from 2019 to 2021, which forms 51 analysis samples, and then analyzes the input and output indicators of the samples that fail to reach the effective efficiency according to these data, and obtains the number of provinces with unreasonable input-output indicators, which provides reference for the design of carbon emissions management efficiency improvement scheme, as shown in Figure 9. From the perspective of input redundancy, the situation of investment redundancy in environmental pollution control is more serious, which indicates that there are unreasonable investment resources and excessive investment in the implementation process of carbon emissions management in these corporates production process. The redundancy degree of the three input indicators is basically similar, and the number of provinces occupied by the three excessive investments is relatively large. However, from the perspective of output from 2019 to 2021, it can be found that the output is not reasonable.

Simultaneously, to dissect the structural disparities in regional carbon emissions management inputs and outputs, this study uses the carbon emissions management efficiency assessment for each corporate in 2021 as a representative example. Additionally, an adjustment scheme for each region's input-output structure is proposed, the results of which are outlined in Table 3.

Table 3 offers a clear illustration that the crux of enhancing the efficiency of carbon emissions management is addressing the issues of input redundancy and the insufficiency of desirable output. Among the corporates, a scant few do not necessitate any adjustments to their inputs and outputs in 2021. The majority, however, must prioritize reducing input in carbon emissions management and tackle the issue of excessive emission of undesirable output.

With regard to the redundancy of the three input indicators—labor, capital, and environmental pollution control investment—labor input redundancy emerges as the most significant issue. The data suggest that one corporate's labor input needs to be reduced by a considerable amount, specifically 25,566 units. This startling figure underscores the critical need for corporates to reassess their use of labor in the context of carbon emissions management.

This redundancy can often be attributed to an overabundance of input and the excessive consumption of resources, which is a symptom of sub-optimal planning and execution in the corporates' production processes. Such an imbalance in the input structure can lead to substantial wastage of resources, both human and material. This is particularly concerning in a world where resource conservation and efficient usage are paramount to sustainable development and environmental protection.

Furthermore, this escalation in input, particularly in relation to environmental pollution control investment, does not correspond to a commensurate decrease in pollution levels. This disconnect implies that despite increased efforts and resources being directed towards managing carbon emissions, the desired results—in this case, reduced pollution—are not being achieved. This situation leads to a serious redundancy of pollution emissions.

In essence, the current state of affairs indicates a pressing need for these corporates to revisit their strategies and operational processes. The goal should be to optimize their use of labor and other resources, and ensure that investments in environmental pollution control are effective in actually reducing pollution. This could involve a range of measures, from implementing more efficient technologies to restructuring labor practices, all aimed at improving the overall efficiency of carbon emissions management.

6.5 Robust analysis

To validate the efficiency of the carbon emission governance evaluation results presented in this article, Figure 10 illustrates the varying ranges of carbon emissions management efficiency. This delineation takes into account the inclusion of carbon emissions at distinct stages as undesirable outputs. By examining the research findings, notable discrepancies in the efficiency values, predicated on different carbon emission measurements, become apparent. This further substantiates the influence of the diverse indicators proposed in this article on the outcomes of efficiency evaluations. As a result, conducting assessments of carbon emission governance based on indicator integration becomes crucial to prevent any potential loss of pertinent information.

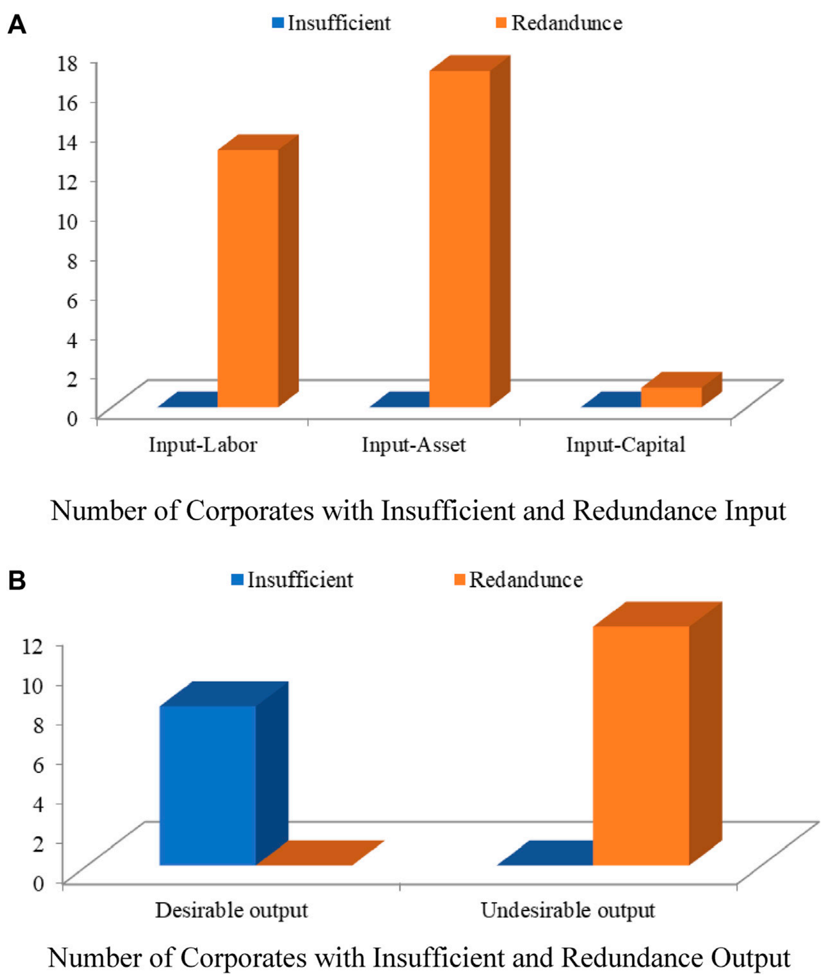

FIGURE 9
Number of corporates with redundant input and insufficient output.

Furthermore, to validate the thumb principle of the DEA model and assess the indispensability of indicator fusion, Figure 11 demonstrates the efficiency evaluation outcomes obtained through indicator integration. The graphic represents that carbon emission efficiency values for all corporations predominantly cluster around 1 without indicator integration. Nonetheless, a distinct divergence in efficiency values emerges after employing indicator integration, leading to a heightened level of differentiation. This enhanced differentiation is advantageous for decision-makers conducting efficiency evaluations and analysis, as it provides a more nuanced understanding of the performance variations among the corporations.

7 Conclusion and implications

Based on the carbon emissions management data from 2019 to 2021, the efficiency evaluation of carbon emissions management in 17 corporates of China was performed on the basis of indicator information integration by the ER approach with weight calculation method and DEA-Malmquist index. Additionally, the efficiency of different corporate-level carbon emissions management was further evaluated from the three scopes of efficiency evaluation and dynamic efficiency change. The main conclusions are summarized as follows:

Firstly, the analysis of carbon emissions management in various corporations in China revealed a lower level of comprehensive efficiency in this aspect. The examination of data further indicated that the comprehensive efficiency of carbon emissions management in these corporations has not witnessed significant improvement and remains unstable. The fluctuations in comprehensive efficiency are closely correlated with changes in pure technical efficiency, thereby suggesting a strong relationship between them. Furthermore, the analysis of scale benefits reveals an ongoing existence of an unsustainable input-output structure within each corporation, primarily stemming from inadequate investments in carbon emissions management, resulting in insufficient output.

Secondly, when examining the input-output structure, it becomes evident that redundancy exists within the majority of corporations, particularly in terms of labor input in carbon emissions management. Moreover, an analysis of the output reveals that the structure of desirable output is predominantly reasonable, but there exists significant redundancy in undesirable

TABLE 3 Values of input-output adjustments in different corporates.

	Emissions management input			Emissions management output	
	Labor	Asset	Capital	Desirable output	Undesirable output
000002.SZ	0	−25319	0	0	−331746
000039.SZ	0	−37168	0	0	−323349
000776.SZ	0	0	0	0	0
001979.SZ	0	0	0	0	0
002422.SZ	0	0	0	0	0
002936.SZ	0	0	0	0	−548900
002948.SZ	0	0	0	0	−135925
600030.SH	0	0	0	285	0
600685.SH	−10321	0	0	67	0
601077.SH	−25566	0	0	627	0
601211.SH	−3,278	0	0	524	0
601336.SH	0	0	0	0	−565659
601633.SH	−7,829	0	0	0	−210513
601727.SH	0	0	0	0	0
601869.SH	0	0	0	0	0
601916.SH	0	−4,072	−14	0	0
601939.SH	0	−5,459	0	0	−66238

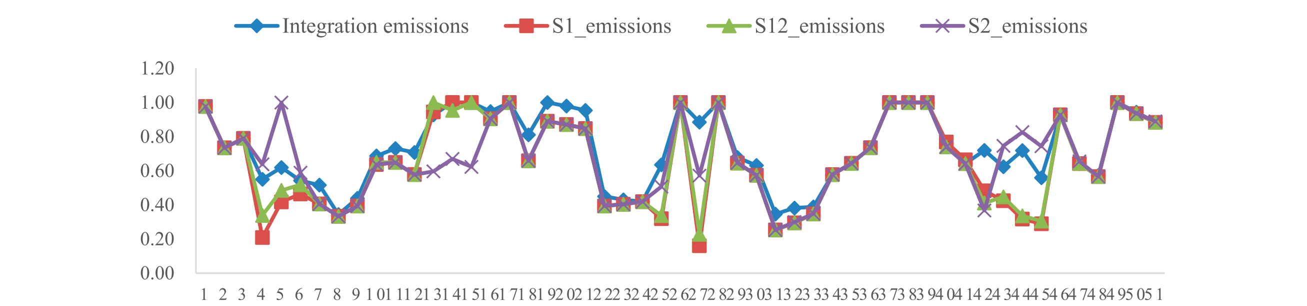

FIGURE 10
Different scopes of carbon emissions management efficiency.

output. Besides optimizing input allocation, it is crucial to implement measures aimed at effectively reducing the emission of undesirable pollution output while ensuring a reasonable output structure.

Thirdly, in order to accurately assess the changes in comprehensive efficiency and pure technical efficiency of carbon emissions management over various time periods, the findings indicate notable distinctions between these two metrics. However, despite these variations, neither the overall efficiency nor the pure technical efficiency demonstrate a significant upward trend within these corporations in China. In other words, the positive impact of the current input-output structure and technical factors on the comprehensive efficiency of carbon emissions management has not yielded significant results over time.

Drawing upon the aforementioned conclusions, the study's outcomes constitute a significant asset for scholars, corporations, and policymakers alike, as they strive collectively towards enhancing carbon emissions management, advancing sustainable development, and addressing the challenges posed by climate change. The identified imperative for critically reassessing and adapting current strategies becomes self-evident, with the overarching objective of optimizing efficiency, fostering sustainable growth, and making substantial contributions to broader endeavors aimed at mitigating climate change:

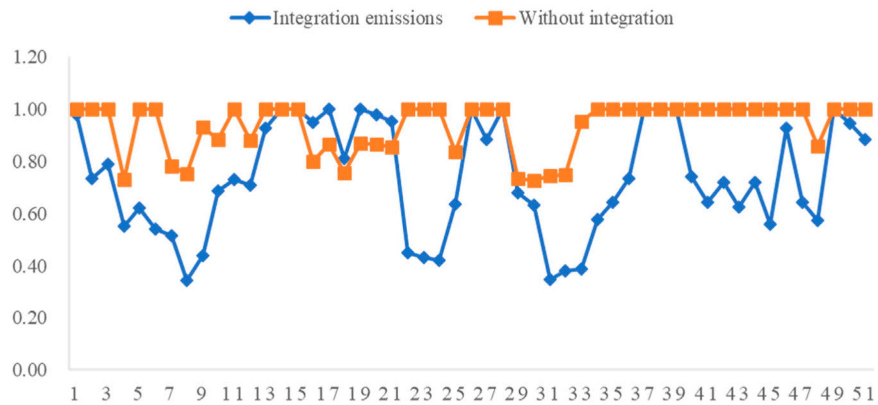

FIGURE 11
Different scopes of carbon emissions management efficiency.

(1) From an academic standpoint, these findings shed light on the intricate dynamics among the input-output structure, technical efficiency, and comprehensive efficiency in the domain of carbon emissions management. This enriches the existing scholarly knowledge base and enables scholars to enhance their comprehension of carbon emissions management, particularly within the unique economic landscape of China. To deepen this understanding, future research can explore these relationships in greater detail, employing sophisticated econometric techniques or conducting longitudinal studies to track and analyze these patterns over an extended timeframe.
(2) From the policy perspective, these findings provide corporations and policymakers with valuable insights to identify areas for improvement and formulate more impactful strategies for carbon emissions management. The noticeable absence of a significant upward trend in both overall and pure technical efficiency signifies ample opportunities for enhancement in these domains. Potential avenues to pursue this enhancement could involve leveraging cutting-edge technologies, optimizing operational processes, or allocating resources to capacity development initiatives. By capitalizing on these opportunities, policymakers and corporations can effectively address the challenges posed by carbon emissions and make substantial strides towards achieving sustainability objectives.
(3) From the corporations perspective, the study also emphasizes the significance of maintaining a balanced input-output structure, presenting explicit guidance in this regard. An overemphasis on investment, particularly in labor, may lead to the inefficient utilization of resources and suboptimal outcomes. Conversely, underinvestment may result in insufficient output. Consequently, corporations must strive for an optimal equilibrium, ensuring the efficient allocation of resources while aligning output with sustainability goals. The identified redundancy in undesirable output serves as a clear indication for the implementation of stricter pollution control measures. This may involve the adoption of more advanced pollution control technologies, improvements in waste management practices, or the enforcement of more stringent internal policies pertaining to pollution control. Such measures would contribute towards achieving greater environmental stewardship and sustainable business practices.

This study is limited by the fact that data on corporate carbon emissions is available only for a relatively short time span. Consequently, the analysis primarily focuses on the efficiency of corporate carbon emissions in the past 3 years. However, future research could expand to encompass long-term assessments of carbon emission efficiency and the exploration of carbon emission prediction studies.

Data availability statement

The datasets presented in this article are not readily available because the owner of the data repository expressly prohibits the dissemination of the data beyond the authors. Unauthorized distribution, transmission, or any form of circulation of the data is strictly forbidden under the terms of the data repository agreement. Requests to access the datasets should be directed to for further inquiries, please get in touch with S-RH (Email: sirui.han@polyu.edu.hk). S-RH will be pleased to provide additional information or clarification as necessary.

Author contributions

F-FY: Conceptualization, Formal Analysis, Writing–original draft. S-RH: Investigation, Methodology, Validation, Writing–original draft, Writing–review and editing. H-TL: Supervision, Validation, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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