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Original Research

Spatial Dynamics Change of Mining Eco-Efficiency in Chinese Provinces: A Novel Assessment Framework Integrating SBM-DEA and Malmquist-Luenberger Models

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Abstract

In the context of global sustainable development goals and heightened environmental awareness, the imperative to evaluate the eco-efficiency of mining becomes paramount. However, the escalated mining activities result in the generation of wastewater, exhaust gas, and solid waste, posing a threat to the environment. This study endeavors to assess the mining eco-efficiency across Chinese provinces by introducing a pioneering assessment index system and framework. The framework incorporates the non-desired output SBM-DEA model and the Malmquist-Luenberger total factor productivity index model. To validate the reliability of the model, it is applied to 27 provinces in China. The findings unveil significant insights: (1) The mining eco-efficiency of Chinese provinces exhibits an overall positive trend but displays notable spatial variations; (2) East China demonstrates superior technical progress and overall technical efficiency, while North, Northeast, and Northwest China lag in technical progress but excel in overall technical efficiency. Notably, non-desired outputs exert an influence on China's level of green mining development, particularly in Northeast and Central China. The study recommends that enterprises shoulder the responsibility of environmental management and mine restoration, enhance their capacity for innovation in green technology, and expedite the construction of green mines to augment mining eco-efficiency. These results furnish valuable perspectives and pertinent information for decision-making related to green mining development, energy structure transformation, and the implementation of large-scale mining projects.

Key Words: ecological efficiency, mining industry, SBM-DEA model, Malmquist-Luenberger productivity index

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Introduction

Amidst increasing economic globalization and industrialization, mining activities have surged [1, 2]. While mineral resources are vital for societal development, excessive mining due to high demand has led to severe environmental and social consequences like land pollution, soil erosion, and ecosystem destruction [3, 4]. Aligned with the United Nations Sustainable Development Goal 7 and the European Union's focus on green development, China has initiated a green development strategy to harmonize environmental protection and mineral resource efficiency [5, 6]. Hence, exploring eco-efficient mining and promoting green mining development is a vital global imperative.

In recent years, the promotion of carbon-neutral strategies has facilitated the development, and practical deployment of renewable energy technologies, including solar, wind, and biomass [7, 8]. This trend suggests that large-scale implementation of new energy sources is possible, and has a significant substitution effect on reducing the demand for coal mining [9]. European countries have already implemented "coal phase-out" energy policies to achieve carbon reduction and sustainable development goals [10]. The implementation of these policies is not only important for the European countries themselves but also has a direct and profound impact on the Chinese energy sector [11, 12]. Under this background, coal mining regions in China should take measures to improve eco-efficiency in order to adapt to the challenges of carbon neutrality, and for better promotion, transformation, and up gradation of the regional economy.

As the largest developing country, China faces challenges in mining development due to economic structural issues, slow growth of alternative industries [13], and ecological concerns [7, 12]. In 2013, the State Council issued a directive urging resource-based cities to shift from the traditional "black development" model to a "green development" model, aiming for sustainable economic, social, and environmental progress through ecological construction and environmental remediation (http://www.gov.cn/zhuanti/2013-12/03/content_2609341.htm). Unlike other industries, mining development can fundamentally damage the original ecosystem, impacting surface stability through open pit excavation, dump occupation, mine exploitation, tailings heap occupation, and mining community construction [14]. This damage may even lead to the disappearance of ecosystems over time [15, 16]. Therefore, evaluating mining eco-efficiency is crucial for transitioning to a "green development" model, enhancing economic efficiency, and ensuring regional sustainability.

In the realm of eco-efficiency evaluation, scholars generally acknowledge its pivotal role in sustainable development [17, 18]. Existing research primarily employs energy value synthesis, ecological footprint analysis, life cycle assessment, and data envelopment analysis for eco-efficiency studies [19, 20]. A growing number of researchers have adopted a combination of methods. One category involves combining data envelopment analysis with energy value analysis, ecological footprint analysis, and life cycle assessment [21-23]. Another category integrates Data Envelopment Analysis (DEA) with econometric models and geographically weighted regression models [3, 24]. However, prior studies often rely on static panel data, conducting quantitative analyses from the perspective of ecological economics, lacking dynamic assessments of industry eco-efficiency [25, 26]. In contrast, this study innovatively integrates the non-expected output Slacks Based Measure-Data Envelopment Analysis (SBM-DEA) model and the Malmquist-Luenberger index to assess the mining eco-efficiency of Chinese provinces.

Many studies have effectively assessed eco-efficiency from different aspects, but diverse findings pertaining to the assessment of eco-efficiency in the mining industry have been reported. For example, Wang et al. (2019a) assessed the eco-efficiency of 28 typical coal mining resource-based cities in China, and their results showed significant regional variability, and that the level of technological innovation and marketization can significantly improve eco-efficiency [6]. Zhang et al. (2020) showed that mining eco-efficiency in China showed a series of changes in stages between 2008 and 2019, mainly due to the redundancy of inputs and outputs, and environmental pollution. In addition [27], Chen et al. (2022) evaluated the eco-efficiency of the circular economy chain in the Longkou coal mining area from 2008 to 2020 by considering the energy-value synthesis of undesirable outputs, and super-efficiency based on relaxed measure data envelopment analysis (SBM-DEA) [28]. Luo et al. (2023) evaluated the green development and eco-efficiency of the mining industry, explored the internal system degree of coupling coordination, and found that the national Green Mining Development Index (GMDI) showed a stable coordination state, but the stage balance relationship was inconsistent and lacked extreme coordination [29]. However, despite the good results of these studies, the effects of spatial heterogeneity, and regional differences were not considered.

Despite the numerous studies suggesting both quantitative and qualitative methods for mining eco-efficiency evaluation, it remains a multi-dimensional decision-making process [30, 31]. The primary challenges lie in the statistical randomness and fuzzy classification, hindering a comprehensive and effective assessment of the ecological efficiency of the mining industry [32]. Hence, existing models and frameworks for mining eco-efficiency assessment require further discussion. Previously, mining eco-efficiency measurements were limited to single-region or single-year data, lacking a holistic view, and neglecting the exploration of changes in eco-efficiency levels. This study addresses these gaps by proposing a novel framework (Fig. 1) that employs mathematical modeling, specifically the non-expected

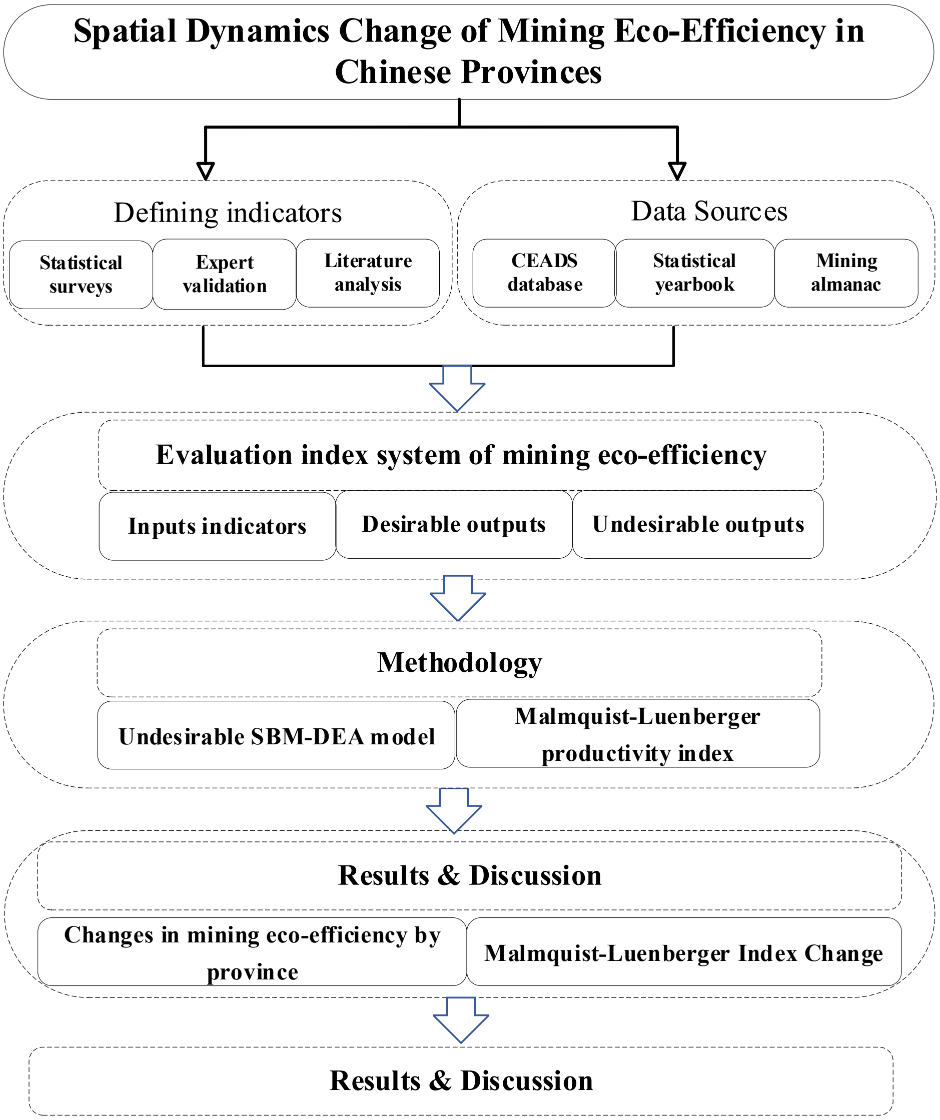

Fig. 1. Research framework for the study.

output SBM-DEA model and Malmquist index. This approach analyzes Chinese provincial panel data to illustrate mining eco-efficiency trends. Additionally, the study delves into spatial differences in green mining development through descriptive statistics and quadrant diagrams, providing empirical analysis-based policy recommendations to enhance green mining in China.

The study introduces key innovations and contributions: (1) A tailored index system is devised for accurate measurement of mining sector ecological efficiency; (2) A pioneering assessment framework is crafted, merging the non-expected output model with the Malmquist-Luenberger index model for mining eco-efficiency evaluation; (3) This framework will holistically assess the evolving trend of mining eco-efficiency in China, offering insights for mining management and planning, fostering the harmonized and sustainable development of the mining industry, ecology, society, and economy.

Indicators and Data Collection

Indicators

Assessing mining eco-efficiency is a multifaceted endeavor, involving various factors like social economy, technological innovation, and ecological environment [33-35]. Interactions exist among factors, such as the environmental impact of mining activities and their economic benefits. To effectively evaluate mining ecological efficiency and gauge its social and environmental impacts, precise indicators must be chosen. Adhering to the principles of subject orientation and index data availability, we comprehensively considered input, expected output, and non-expected output from an input-output perspective. This approach led to the creation of a comprehensive evaluation index system for mining ecological efficiency, enabling the assessment of mining benefits and environmental impacts. The resulting system also aids in identifying measures for enterprises and governments to foster sustainable development in mining activities. Refer to Table 1 for specific details on the index system.

Concerning the input index, we considered the number of mining enterprises, mining employees, annual mine treatment input, and occupied land area in each province. The number of mining enterprises and employees signifies the scale of mining activities and employment conditions [36]. Annual mine governance input reflects the environmental investment by mining enterprises, covering funds for mine environment restoration and governance, sourced from central and local finances, mining enterprises' investments, and private funding [24]. Land occupation area mirrors the use of land resources by mines and serves as a control on mining development intensity [37].

In terms of expected outputs, our focus lies on the rehabilitation and treatment of the mine's geological environment, total industrial output value, comprehensive utilization value of mining, and the proportion of clean energy. The restoration and treatment area in the mine's geological environment indicates the effectiveness of mining enterprises in ecological preservation, covering activities like reclamation, ground collapse control, forest and grass restoration, and construction-ready zones [38]. The total industrial output value showcases the economic contribution of mining activities, representing the economic output of mineral resources, along with inputs like the number of mining enterprises and employees. The comprehensive utilization value of the mining industry reflects the efficient use of mineral resources, encompassing the total value of final industrial products resulting from symbiotic and associated minerals, and the management of "the three wastes" in the total output value [39]. The proportion of clean energy reveals the performance of mining enterprises in terms of energy consumption and environmental protection.

In addition, for evaluating the mining eco-efficiency, undesirable output indicators are also taken into account, such as carbon emissions due to mining activities, and the number of illegal investigations and mining cases. The carbon emissions due to mining reflect the impact of mining activities on climate change, while the number of illegal investigations and mining cases reflects the degree of compliance of the mining enterprises with the laws and regulations [40].

Data Collection

Considering the intensity and extent of mining activities in each province of China, we collected data from 27 provinces, autonomous regions, and municipalities directly under the central government of China, except for Beijing, Tianjin, Shanghai, Tibet, Hong Kong, Macao, and Taiwan, during the period 2008 to 2018. To ensure the reliability and accuracy of the data, we obtained the data pertaining to indicators from several authoritative institutions, the China Environmental Statistics Yearbook, the China Land Resources Statistical Yearbook, the China Energy Statistics Yearbook, and the China Industrial Statistics Yearbook, among others. Additionally, to guarantee that the data was complete and reliable, the statistics related to carbon emissions from the mining industry were gathered from the CEADS database. During data processing, some missing values and outliers were corrected by the linear interpolation method, and intra-group mean method, to ensure precision and accuracy of the data. Finally, the sample data for this study was selected, which provided a solid basis for the assessment of mining eco-efficiency.

Table 1. Ming eco-efficiency assessment index system.

Category	Primacy index	Secondary index	Unit	Indicator code
Inputs	Input Indicators	Number of mining enterprises	A	X_1
		practitioner	A	X_2
		Occupied land area	1000 square meters	X_3
		Mine environmental restoration management input	10 thousand yuan	X_4
Outputs	Desired Output Indicators	Mine geological environment restoration treatment area	1000 square meters	y_1
		Comprehensive utilization output	10 thousand yuan	y_2
		Industrial output	10 thousand yuan	y_3
		Clean energy ratio	%	y_4
	Undesirable Outputs	Number of cases filed for exploration and mining violations	Piece	y_5
		Carbon Emissions from Mining	100000 tons	y_6

Methodology

Undesirable SBM-DEA Model

Data Envelopment Analysis (DEA) is an important frontier method for assessing eco-efficiency. Chen et al. (2022) constructed the SBM -DEA of undesirable output to deal with waste in output indicators, so as to reduce pollution emissions in mining ecology [28]. The SBM-DEA method is a non-radial directional distance function that allows the unwanted outputs to cause variance in the output at a different rate than the desired output [29]. Therefore, The SBM-DEA model was introduced to evaluate the ecological benefits of the mining industry in China provinces. It was assumed that there were n decision- making units $DMU_j(j = 1, 2, ..., n)$ in determining the mining eco-efficiency, the number of inputs for DMU_j were p, and the number of output s $y_j(y_{1j}, y_{2j}, ..., y_{qj})$ were equal to q. The relaxation variable s^+, and the residual variable s^-, were introduced to construct the mining eco-efficiency evaluation model, which is illustrated below:

$$\min\ \rho_{rm} = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{ro}}}$$

$$s.t.\begin{cases}\sum_{j=1}^{n}\lambda_j y_{ro} - s_r^+ = y_{ro}\\ \sum_{j=1}^{n}\lambda_j x_{ro} - s_r^- = x_{ro}\\ \forall j = 1,2,\cdots,n, s_r^+, s_r^- \geq 0\end{cases} \tag{1}$$

In order to facilitate the calculation of the non-expected output, on the basis of equation (1), the elements of non-expected output, namely s_1 and s_2, were used to indicate the number of expected output and non-expected output indicators, respectively, and s^g and s^b represented the expected output and non-expected output residual variables, respectively, for constructing the SBM model of non-expected output based on constant returns to scale, which is illustrated below:

$$\min\ \rho_{rm} = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right)}$$

$$s.t.\begin{cases}\sum_{j=1}^{n}\lambda_j y_{ro}^g - s_r^+ = y_{ro}^g\\ \sum_{j=1}^{n}\lambda_j y_{ro}^b - s_r^+ = y_{ro}^b\\ \sum_{j=1}^{n}\lambda_j x_{ro} - s_r^- = x_{ro}\\ \forall j = 1,2,\cdots,n, s_r^+, s_r^- \geq 0\end{cases} \tag{2}$$

Malmquist-Luenberger Productivity Index

The measurement of mining eco-efficiency requires not only static analysis of the non-desired output models but also dynamic analysis of the productivity indices; additionally, the Malmquist-Luenberger (ML) productivity index is one of the indices proposed by Malmquist specifically for measuring the dynamic efficiency [34, 37]. The non-desired output indicators such as the number of exploration and development violation cases, and mining carbon emissions were included for determining the mining eco-efficiency in the 27 Chinese provinces; hence, it was considered appropriate to use the ML productivity index to assess the changes in the mining eco-efficiency of the Chinese provinces. The concept of inter-period dynamics was introduced to construct the ML index based on the SBM directional distance function of non-desired output in period t and period t+1, and the ML index model of mining eco-efficiency was expressed as follows:

$$ML(x^{t+1}, y^{t+1}, s^{t+1}, x^t, y^t, s^t)$$

$$= \sqrt{\frac{E^t(x^{t+1}, y^{t+1}, s^{t+1})}{E^t(x^t, y^t, s^t)} \times \frac{E^{t+1}(x^{t+1}, y^{t+1}, s^{t+1})}{E^{(t+1)}(x^t, y^t, s^t)}} \tag{3}$$

For calculating the ML index, $E^t(x^t, y^t, s^t)$ and $E^t(x^{t+1}, y^{t+1}, s^{t+1})$, were considered as evaluation units for periods t and $t + 1$, respectively, and The ML index can be divided into the technical efficiency variation index (EC) and the technological progress variation index (TC) based on the predicted output of the technical efficiency value, and these two components can be written as follows:

$$EC = \frac{E^{t+1}(x^{t+1}, y^{t+1}, s^{t+1})}{E^{t}(x^{t}, y^{t}, s^{t})} \tag{4}$$

The technical progress index can be described by the following expression:

$$TC = \sqrt{\frac{E^{t}(x^{t}, y^{t}, s^{t})}{E^{t}(x^{t+1}, y^{t+1}, s^{t+1})} \times \frac{E^{t+1}(x^{t}, y^{t}, s^{t})}{E^{t+1}(x^{t+1}, y^{t+1}, s^{t+1})}} \tag{5}$$

If the TC value is greater than 1, it means the frontier moves forward; if it is less than 1, it means that the frontier moves backward; and the moving forward of the frontier represents technical progress.

The quantitative relationship among the ML index, technical efficiency change index, and technological progress change index can be expressed as:

$$ML(x^{t+1}, y^{t+1}, s^{t+1}, x^{t}, y^{t}, s^{t}) = EC \times TC \tag{6}$$

Efficiency is rising if the ML index value is more than 1, reducing if the ML index value is less than 1, and remains stable if the ML index value is equal to 1.

Results & Discussion

Results of Changes in Mining Eco-Efficiency by Province

Results of Regional Differences in Eco-Efficiency of the Mining Industry

For a precise evaluation of non-expected output's influence on the eco-efficiency of China's mining industry across provinces and cities, two efficiency values from the Charnes Cooper Rhodes (CCR) model were separately calculated. These values were compared with and without considering non-expected output in the SBM model, as outlined in Table 2. Notably, the mean mining eco-efficiency, considering non-expected output, was 0.75 (2008-2018), a 0.12 decrease from the CCR model's mean efficiency without considering non-expected output (0.87). This emphasizes the significant impact of illegal cases in exploration, mining, and carbon emissions on China's overall green mining growth. In regions like North, East, Southwest, and Northwest China, the average efficiency values remained above 0.8 even after accounting for non-expected output, indicating lesser impact from strict controls on illegal cases and carbon emissions. However, Northeast and Central China experienced a substantial efficiency decrease – from 0.68 and 0.77 before considering non-expected output to 0.47 and 0.51 after, a decline of 0.21 and 0.26. This highlights the substantial impact of non-expected output on green mining development in these regions.

Using panel data to assess mining eco-efficiency in China (2008-2018), we selected non-expected output SBM models with constant payoff of scale (CRS) and variable payoff of scale (VRS), employing non-radial distance functions. The two non-expected outputs 0 the number of exploration and mining violation cases filed and mining carbon emissions – were introduced to calculate technical efficiency (TE) and pure technical efficiency (PTE). The results are shown in Table 3.

Table 3 reveals that when considering undesired output, the average TE of mining ecological efficiency is 0.75, indicating a low overall level with varying states each year. Regionally, North, East, Southwest, and Northwest China exhibit comprehensive TE values above 0.8, while Northeast and Central China have relatively low TE. Specifically, Northeast China's comprehensive technical efficiency is only 0.47 after accounting for unlawful cases and decreased carbon emissions compared to the national average. Additionally, considering non-desired outputs, the mean value of pure technical efficiency in mining eco-efficiency is 0.84, suggesting a high overall level with non-cyclical variation, consistent with Zhang et al.'s findings (2020) [41]. Regionally, East and Southwest China exhibit pure technical efficiency above 0.90, indicating a positive development despite illegal cases and fewer carbon emissions. However, Northeast and Central China have lower pure technical efficiency values (0.56 and 0.69, respectively) compared to values without considering non-desired outputs, significantly decreasing output.

Results of Regional Spatial Characteristics of Mining Eco-Efficiency

Derived from the SBM model's comprehensive technical efficiency (CTE) dimension, considering non-desired outputs (Fig. 2), notable challenges in mining eco-efficiency development emerged in Northeast and Central China from 2008 to 2018. Specifically, both regions exhibited significantly lower total technical efficiency compared to others, factoring in variables like exploration and mining violation cases and mining carbon emissions. The difference in comprehensive technical efficiency values was apparent. Notably, Central China experienced a consistent decline throughout the study period. Although its comprehensive technical efficiency surpassed Northeast China in 2008-2009, it gradually equaled Northeast China's efficiency in subsequent years. This trend persisted despite other regions maintaining a relatively stable level of green mining growth, unaffected by the adverse impact of illegal exploration and mining cases and excessive carbon emissions. This aligns with findings by Wang et al. (2019a) [42].

Table 2. Eco-efficiency of the mining industry based on the CCR model and SBM model for Chinese provinces during 2008-2018.

Region	2008		2010		2012		2014		2016		2018		Average	
	CCR	SBM	CCR	SBM	CCR	SBM	CCR	SBM	CCR	SBM	CCR	SBM	CCR	SBM
Hebei	0.82	0.50	1.00	1.00	0.86	0.40	1.00	1.00	0.70	0.31	0.57	0.34	0.82	0.58
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
Shanxi	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
North China	0.94	0.83	1.00	1.00	0.95	0.80	1.00	1.00	0.90	0.77	0.86	0.78	0.94	0.86
Heilongjiang	0.60	0.29	0.46	0.23	0.47	0.28	0.46	0.28	0.70	0.38	0.56	0.33	0.55	0.30
Jilin	0.76	0.53	0.70	0.39	0.71	0.40	0.86	0.62	1.00	1.00	0.67	0.43	0.76	0.56
Liaoning	0.74	0.49	0.77	0.42	0.62	0.40	0.64	0.48	0.67	1.00	0.69	0.58	0.72	0.54
North East China	0.70	0.44	0.64	0.34	0.60	0.36	0.65	0.46	0.79	0.79	0.64	0.44	0.68	0.47
Anhui	0.84	1.00	0.91	1.00	0.77	0.43	0.99	1.00	0.89	0.59	1.00	1.00	0.87	0.86
Fujian	0.91	0.69	0.77	0.52	0.87	0.64	1.00	1.00	0.98	1.00	0.98	0.65	0.92	0.77
Jiangsu	0.72	1.00	0.77	0.60	0.70	0.50	0.81	1.00	0.79	0.54	0.98	0.64	0.78	0.76
Jiangxi	0.74	0.53	1.00	1.00	1.00	1.00	1.00	1.00	0.77	0.49	0.85	0.57	0.87	0.75
Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.81	0.42	0.98	0.90
Zhejiang	0.88	0.60	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	0.98	1.00	0.97	0.92
East China	0.85	0.80	0.91	0.85	0.89	0.76	0.96	1.00	0.90	0.77	0.93	0.71	0.90	0.83
Henan	1.00	1.00	0.80	0.52	0.82	0.50	0.90	0.64	0.85	0.47	0.54	0.35	0.85	0.60
Hubei	0.81	0.55	0.63	0.45	0.64	0.35	0.78	0.67	0.85	0.52	0.79	0.50	0.73	0.51
Hunan	0.75	0.48	0.71	0.34	0.60	0.31	0.77	0.40	0.80	0.49	0.75	0.47	0.73	0.43
Central China	0.85	0.68	0.71	0.44	0.69	0.39	0.82	0.57	0.83	0.50	0.69	0.44	0.77	0.51
Guangdong	1.00	1.00	0.81	0.55	0.81	0.52	0.94	0.65	0.96	0.79	0.79	0.46	0.89	0.69
Guangxi	0.80	0.61	0.70	0.56	0.69	0.53	0.83	1.00	0.82	0.58	0.74	0.52	0.78	0.64
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89	0.71	0.99	0.97
South China	0.93	0.87	0.84	0.70	0.83	0.69	0.92	0.88	0.93	0.79	0.81	0.56	0.89	0.77
Guizhou	0.93	0.63	0.78	0.52	1.00	1.00	1.00	1.00	0.91	0.49	0.69	0.38	0.91	0.73
Sichuan	0.96	0.74	0.90	0.54	0.98	0.51	1.00	1.00	1.00	1.00	1.00	1.00	0.98	0.89
Yunnan	1.00	1.00	0.96	0.60	0.97	0.49	0.99	1.00	0.74	0.44	0.64	0.37	0.88	0.62
Chongqing	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
Southwest China	0.97	0.84	0.91	0.67	0.99	0.75	1.00	1.00	0.91	0.73	0.83	0.69	0.94	0.81
Gansu	1.00	1.00	0.67	0.64	0.68	0.49	0.70	0.53	1.00	1.00	0.70	0.50	0.84	0.75
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
Qinghai	0.96	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
Shaanxi	0.98	1.00	1.00	1.00	1.00	0.51	0.96	0.57	1.00	1.00	1.00	1.00	0.98	0.87
Xinjiang	0.82	0.56	0.85	0.55	0.84	0.48	1.00	1.00	0.84	0.46	0.79	0.46	0.82	0.55
Northwest China	0.95	0.91	0.90	0.84	0.90	0.69	0.93	0.82	0.97	0.89	0.90	0.79	0.93	0.83
National Average	0.89	0.79	0.86	0.72	0.85	0.66	0.91	0.85	0.90	0.76	0.83	0.65	0.87	0.75

Importantly, inefficiencies in green mining development in Northeast and Central China are not attributed to technical or resource shortcomings but rather stem from significant issues related to exploration and mining violations and carbon emissions. Hence, enhancing management and supervision in these areas is crucial for improving the overall comprehensive technical efficiency of green mining development.

Table 3. Technical efficiency (TE) and pure technical efficiency (PTE) considering undesirable output SBM model, 2008-2018.

Region	2008		2010		2012		2014		2016		2018		Average	
	TE	PTE	TE	PTE	TE	PTE	TE	PTE	TE	PTE	TE	PTE	TE	PTE
Hebei	0.50	0.51	1.00	1.00	0.40	0.46	1.00	1.00	0.31	0.31	0.34	0.45	0.58	0.64
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
Shanxi	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
North China	0.83	0.84	1.00	1.00	0.80	0.82	1.00	1.00	0.77	0.77	0.78	0.82	0.86	0.88
Heilongjiang	0.29	0.31	0.23	0.23	0.28	0.29	0.28	0.28	0.38	0.40	0.33	1.00	0.30	0.43
Jilin	0.53	0.53	0.39	0.39	0.40	0.42	0.62	0.62	1.00	1.00	0.43	0.59	0.56	0.59
Liaoning	0.49	0.51	0.42	1.00	0.40	0.42	0.48	0.51	1.00	1.00	0.58	1.00	0.54	0.65
North East	0.44	0.45	0.34	0.54	0.36	0.38	0.46	0.47	0.79	0.80	0.44	0.86	0.47	0.56
Anhui	1.00	1.00	1.00	1.00	0.43	0.47	1.00	1.00	0.59	1.00	1.00	1.00	0.86	0.90
Fujian	0.69	1.00	0.52	1.00	0.64	1.00	1.00	1.00	1.00	1.00	0.65	1.00	0.77	1.00
Jiangsu	1.00	1.00	0.60	1.00	0.50	1.00	1.00	1.00	0.54	1.00	0.64	1.00	0.76	1.00
Jiangxi	0.53	0.53	1.00	1.00	1.00	1.00	1.00	1.00	0.49	0.56	0.57	1.00	0.75	0.80
Shandong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.42	0.56	0.90	0.96
Zhejiang	0.60	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.96
East China	0.80	0.92	0.85	1.00	0.76	0.91	1.00	1.00	0.77	0.93	0.71	0.93	0.83	0.94
Henan	1.00	1.00	0.52	1.00	0.50	0.53	0.64	0.64	0.47	0.59	0.35	0.37	0.60	0.70
Hubei	0.55	1.00	0.45	1.00	0.35	0.38	0.67	1.00	0.52	1.00	0.50	1.00	0.51	0.87
Hunan	0.48	0.48	0.34	0.35	0.31	0.32	0.40	0.41	0.49	0.54	0.47	1.00	0.43	0.50
Central China	0.68	0.83	0.44	0.78	0.39	0.41	0.57	0.68	0.50	0.71	0.44	0.79	0.51	0.69
Guangdong	1.00	1.00	0.55	0.58	0.52	0.56	0.65	0.65	0.79	1.00	0.46	0.63	0.69	0.78
Guangxi	0.61	1.00	0.56	0.60	0.53	0.57	1.00	1.00	0.58	0.62	0.52	1.00	0.64	0.86
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.71	1.00	0.97	1.00
South China	0.87	1.00	0.70	0.73	0.69	0.71	0.88	0.88	0.79	0.87	0.56	0.88	0.77	0.88
Guizhou	0.63	1.00	0.52	0.53	1.00	1.00	1.00	1.00	0.49	1.00	0.38	1.00	0.73	0.96
Sichuan	0.74	0.79	0.54	1.00	0.51	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89	0.98
Yunnan	1.00	1.00	0.60	0.63	0.49	0.52	1.00	1.00	0.44	0.54	0.37	0.49	0.62	0.72
Chongqing	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
Southwest Region	0.84	0.95	0.67	0.79	0.75	0.88	1.00	1.00	0.73	0.88	0.69	0.87	0.81	0.91
Gansu	1.00	1.00	0.64	1.00	0.49	0.49	0.53	0.53	1.00	1.00	0.50	0.73	0.75	0.89
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
Qinghai	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
Shaanxi	1.00	1.00	1.00	1.00	0.51	1.00	0.57	0.58	1.00	1.00	1.00	1.00	0.87	0.96
Xinjiang	0.56	0.58	0.55	0.56	0.48	0.50	1.00	1.00	0.46	0.47	0.46	0.49	0.55	0.56
Northwest China	0.91	0.92	0.84	0.91	0.69	0.80	0.82	0.82	0.89	0.89	0.79	0.84	0.83	0.88
National Average	0.79	0.86	0.72	0.85	0.66	0.74	0.85	0.86	0.76	0.85	0.65	0.86	0.75	0.84

Examining the pure technical efficiency dimension from the SBM model, considering non-desired outputs (Fig. 3), reveals distinctive patterns in the mining eco-development process for Northeast and Central China from 2008 to 2018. Northeast China demonstrates a notable upward trend, albeit still significantly lower than other regions – a positive signal. Conversely, Central China's pure technical efficiency in green

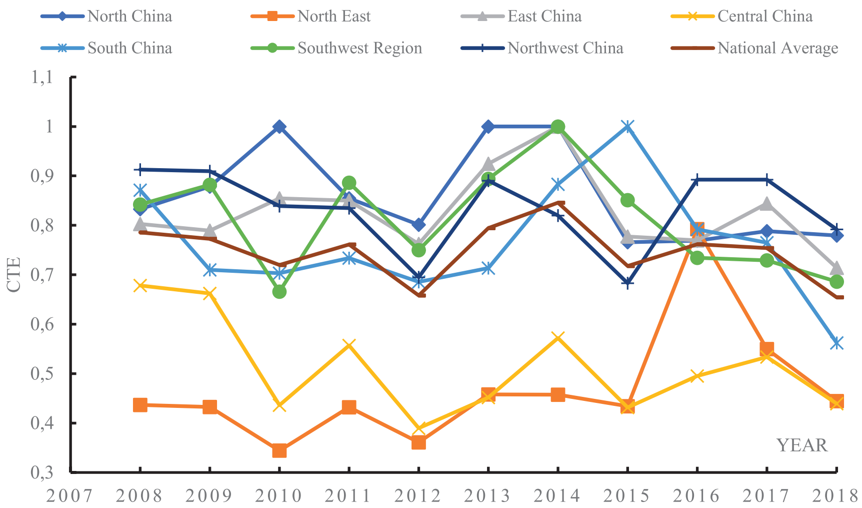

Fig. 2. Trends in the combined technical efficiency (TE) considering the non-expected output SBM model.

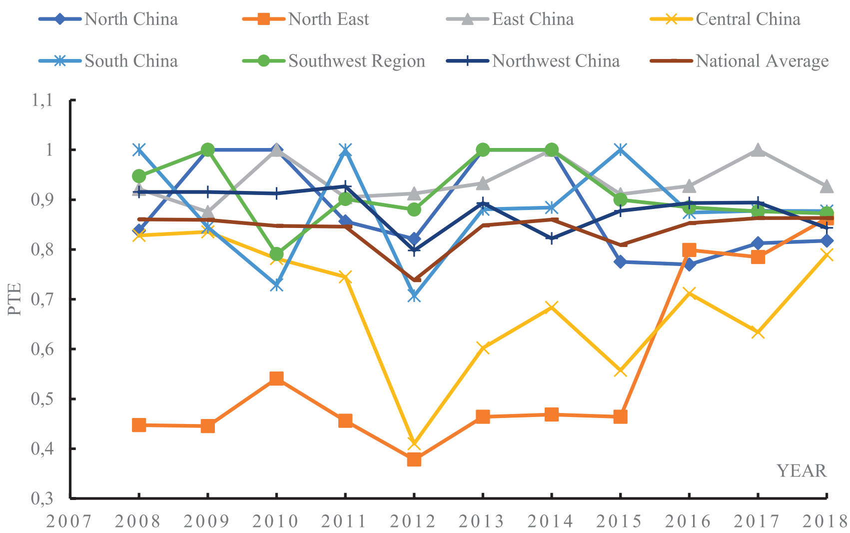

Fig. 3. Trends in pure technical efficiency(PTE)considering the non-expected output SBM model.

mining, accounting for exploration and mining violation cases and carbon emissions, exhibits a V-shaped trend, increasing from 2008 to 2013 but decreasing from 2014 to 2018. Excluding Northeast and Central China, other regions maintain a pure technical efficiency exceeding 0.8 during 2008-2018, indicating a relatively high level of pure technical efficiency and experience in achieving higher mining eco-efficiency.

Analyzing the pure technical efficiency level from the SBM model, considering non-expected output (Fig. 3), reveals that although Northeast China's pure technological efficiency remains lower than other areas during 2008-2018, a clear increasing tendency is observed when accounting for exploration and mining violation cases and mining carbon emissions. In contrast, Central China displays a V-shaped trend in pure technical efficiency, while the remaining regions consistently maintain a level above 0.8. To enhance the pure technical efficiency of mining ecological development, regions should invest more, improve technological innovation management, optimize resource utilization, strengthen environmental governance, and enhance policy enforcement and regulations on mining carbon emissions to reduce negative impacts and elevate the level of pure technical efficiency in mining ecological development.

Analyzing the quadrants of the CCR model efficiency values and SBM model efficiency values (Fig. 4) unveils the influence of illegal exploration and mining cases and mining carbon emissions on the mining industry's ecological development level. Northeast and Central China are positioned in the third quadrant, indicating a low level of green mining development in these regions, regardless of considering the impact of mining violations and carbon emissions. Although Northeast China shows an upward trend in pure technical efficiency after considering these factors, the overall level remains modest. Conversely, North, Northwest,

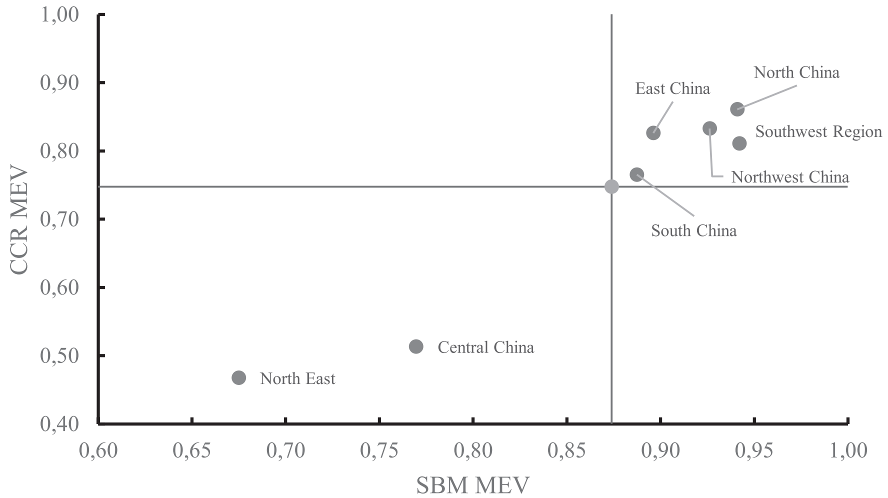

Fig. 4. Regional CCR model efficiency values and SBM model efficiency values quadrant diagram.

Southwest, East, and South China are located in the first quadrant, signifying a high level of ecological development in mining across these regions, regardless of the aforementioned factors.

Further analysis reveals that North China and Southwest China exhibit higher levels of total ecological development in mining when considering the impact of illegal exploration and mining cases and mining carbon emissions. Meanwhile, East and Northwest China perform well in green mining development without considering these factors. The overall level in South China approaches the national average, regardless of considering these factors or not. In conclusion, the impact of mining violations and carbon emissions varies significantly across regions in the development stages of green mining. Northeast and Central China need to enhance control measures and management of these factors to improve their mining ecological development levels. In other regions, promoting green mining development and advancing efficiency and technology levels is essential for achieving sustainable development.

Analysis of Malmquist-Luenberger Index Change Results

Results of the Temporal Characteristics of the ML Index of Mining Eco-Efficiency

The outcomes presented in Table 4 and Fig. 5 suggest that mining eco-efficiency development has generally been sustained. While significant fluctuations occurred during 2008-2009 and 2016-2018, the ML productivity index for mining eco-efficiency remained within a fluctuation range of about 1.1. The average ML productivity index value for the 27 provinces, cities, and autonomous regions during 2008-2018 was 1.0924, indicating an average increase of 9.24%. Among these, the technical efficiency index exhibited a mean change of 1.0334, with an average increase of 3.34%, while the technical progress efficiency index had a mean change of 1.1042, with an average increase of 10.42%. Therefore, it's evident that the ML productivity index for mining eco-efficiency in China from 2008 to 2018 was influenced by both combined technical efficiency and the technical progress index. However, the change in the technical progress index had a more substantial impact on mining eco-efficiency, aligning with the findings of Qiu et al. (2021) [43].

A significant improvement in mining eco-efficiency was noted during 2008-2009 and 2017-2018, with ML index values at 1.2167 and 1.2148, respectively, marking a 21.67% and 21.48% increase compared to previous years. However, the ML indices for 2009-2010 and 2015-2016 were 0.9381 and 0.9762, respectively, indicating a contraction in China's overall green mining development between 2010 and 2016. The composite technical efficiency index showed a decreasing trend for half of the time during 2010-2016. Although the overall situation improved, the change in the integrated technological efficiency was only 0.8714. Notably, during 2017-2018, the technical advancement index mean reached 1.4148, emphasizing the need to significantly enhance mining industry eco-efficiency in terms of business management and production scale optimization.

Results of the Spatial Characterization of the ML Index of Mining Eco-Efficiency

As per Table 5, the eco-efficiency of China's major mining regions consistently exceeds 1, signifying overall improvement in the green mining sector across administrative regions. Notably, East China demonstrated the most significant enhancement in mining eco-efficiency from 2008 to 2018, with an average annual increase of 15.82%, as reflected in its MML total factor productivity indicator reaching 1.1582. From 2008 to 2018, East China experienced continuous improvement in mining eco-efficiency due to technological progress and equipment introduction.

Table 4. China's green mining development ML index and its decomposition from 2008 to 2018.

YEAR	ML	EC	TC
2008-2009	1.2167	0.9909	1.2257
2009-2010	0.9381	0.9561	1.0198
2010-2011	1.0813	1.1289	0.9692
2011-2012	1.1037	0.8906	1.2954
2012-2013	1.0988	1.3102	0.8589
2013-2014	1.0386	1.1363	0.9207
2014-2015	1.1084	0.8687	1.3445
2015-2016	0.9762	1.1515	0.8727
2016-2017	1.1472	1.0293	1.1202
2017-2018	1.2148	0.8714	1.4148
AVERAGE	1.0924	1.0334	1.1042

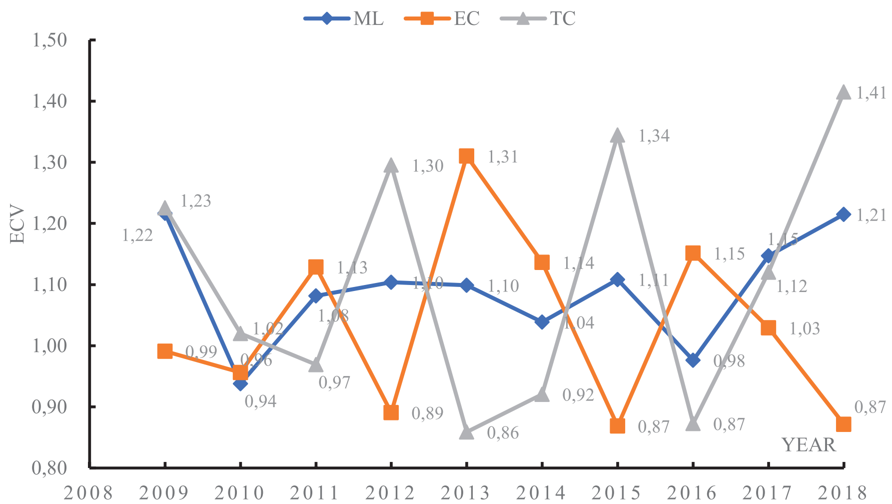

Fig. 5. ML index and its decomposition in China for the period 2010-2018.

However, both production scale and human management still offer untapped potential.

Table 5 results indicate that the ML total factor productivity index of mining eco-efficiency in each Chinese province generally ranged between 1.0 and 1.1. Notably, the Anhui and Jiangsu provinces exhibited the most substantial changes, with both the ML TFP and technical progress index hovering around 1.3, while comprehensive technical efficiency changes remained around 1.1. Conversely, in Jiangxi, Zhejiang, and other provinces, the change in overall technical efficiency increased dramatically compared to the change in technical advancement. This suggests that the efficiency improvement in Anhui and Jiangsu was predominantly influenced by changes in the technical progress index, whereas in Jiangxi and Zhejiang, comprehensive technical efficiency played a more significant role in driving eco-development efficiency.

Analysis of the Overall Difference Results of Mining Eco-Efficiency

From the perspective of total factor productivity (Fig. 6), the ML productivity index of mining ecology fluctuates considerably in different regions. Except for 2010, the ML total factor productivity index was higher than 1 in all the years and has remained relatively stable, indicating that the level of development of mining ecology is improving steadily. The total factor productivity varies significantly across different locations as well, and the trend varies from place to place. For example, the overall mining ecosystem factor productivity in North China reached 1.45 in 2009, but declined continuously during 2010 and 2011, with the total factor productivity below 1. However, after 2011, the total factor productivity gradually increased again, indicated by a "W-shaped" curve representing the overall trend. The total factor productivity of mining

Table 5. Mining eco-development ML index and its decomposition by regions in China 2010-2018.

Region	ML	EC	TC
Hebei	1.0634	1.1046	1.0974
Inner Mongolia	1.0521	1.0000	1.0521
Shanxi	1.1059	1.0000	1.1059
North China	1.0738	1.0349	1.0851
Heilongjiang	1.0552	1.0233	1.0434
Jilin	1.0727	1.0501	1.0645
Liaoning	1.1206	1.0593	1.1248
North East	1.0828	1.0442	1.0776
Anhui	1.2702	1.1213	1.3403
Fujian	1.0481	1.0336	1.0768
Jiangsu	1.1938	1.0506	1.2783
Jiangxi	1.2684	1.2048	1.0739
Shandong	1.0673	0.9329	1.1693
Zhejiang	1.1014	1.0784	1.0316
East China	1.1582	1.0703	1.1617
Henan	1.0256	0.9292	1.1389
Hubei	1.1522	1.0326	1.1636
Hunan	1.1466	1.0370	1.1413
Central China	1.1081	0.9996	1.1479
Guangdong	1.0184	0.9705	1.0737
Guangxi	1.0621	1.0262	1.0692
Hainan	0.9892	0.9709	1.0296
South China	1.0233	0.9892	1.0575
Guizhou	1.1014	0.9998	1.1203
Sichuan	1.1227	1.1213	1.0254
Yunnan	0.9367	0.9644	1.0168
Chongqing	1.0616	1.0000	1.0616
Southwest Region	1.0556	1.0214	1.0561
Gansu	1.1541	1.0322	1.1783
Ningxia	1.0084	1.0000	1.0084
Qinghai	1.0264	1.0000	1.0264
Shaanxi	1.1576	1.0975	1.2112
Xinjiang	1.1126	1.0610	1.0903
Northwest China	1.0918	1.0382	1.1029
National Average	1.0924	1.0334	1.1042

ecology in Northeast China remained around 1 from 2009 to 2014, indicating that there was not much change in the development of mining ecology. However, during (2015-2016), its total factor productivity increased significantly, reaching 1.29 and 1.38, respectively, which means that the mining eco-efficiency increased by 29% and 38%, respectively, during these two years. This is the main reason why the non-expectation SBM model for the central and northeastern regions, described in the previous section, improved significantly in the latter

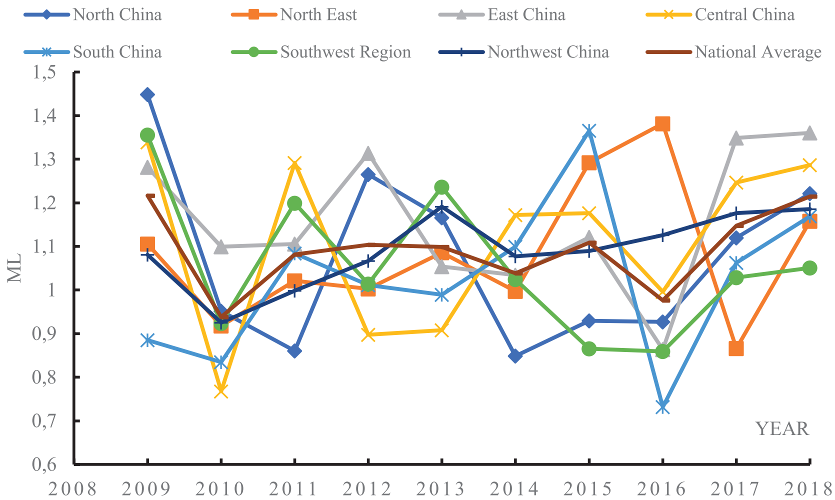

Fig. 6. Trends in total factor productivity by region in China.

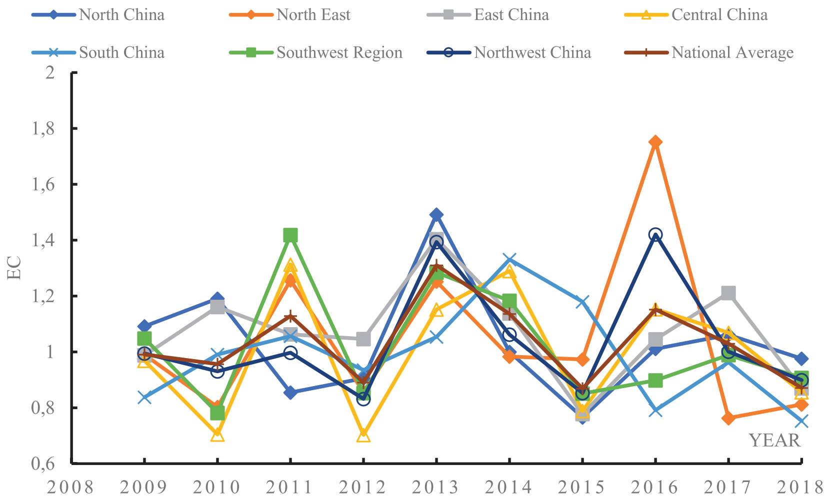

Fig. 7. Trends in the change in integrated technical efficiency(EC) by region in China.

years and was essentially at par with the rest of the country.

In terms of the variation of comprehensive technical efficiency, the variation value of comprehensive technical efficiency in all regions is basically around 1, and the overall trend is basically the same (Fig. 7). These changes show an up-and-down trend, with peaks in 2011, 2013 and 2016, and troughs in 2010, 2012 and 2015. It is noteworthy that the performance of the northeast region was the most significant in 2016, with a value of 1.75 for the change in its combined technical efficiency, which is one of the main reasons why the northeast reached a total factor productivity of 1.38 in 2016 in the green mining sector. However, in 2017, the Northeast region once more had the lowest value of the change in integrated technical efficiency, which was 0.76. This might have attributed to the northeast region's ML TFP index of only 0.87 in 2017.

As far as the changes in the technological progress index are concerned, a consistent trend was observed across regions, similar to that of the overall technical efficiency, showing the form of up and down. However, the volatility of the technology progress index showed a more obvious consistency and peaked in 2009, 2012, 2015 and 2018 respectively (Fig. 8), which reflected the small differences in technological progress among different regions, indicating that technological improvement and communication played an important role. It can be seen from the fluctuation of the technical progress index that the technological improvement of China's green mining industry is not smooth sailing, but needs constant exploration and efforts. Although the trend of technological progress is upward, technological change and innovation are also influenced by the upgrading of industrial structure, government policy support and other aspects [44]. Therefore, the regions need to continuously strengthen their communication, and cooperation for technological innovation and progress, to facilitate sustainable development of green mining in China [45, 46].

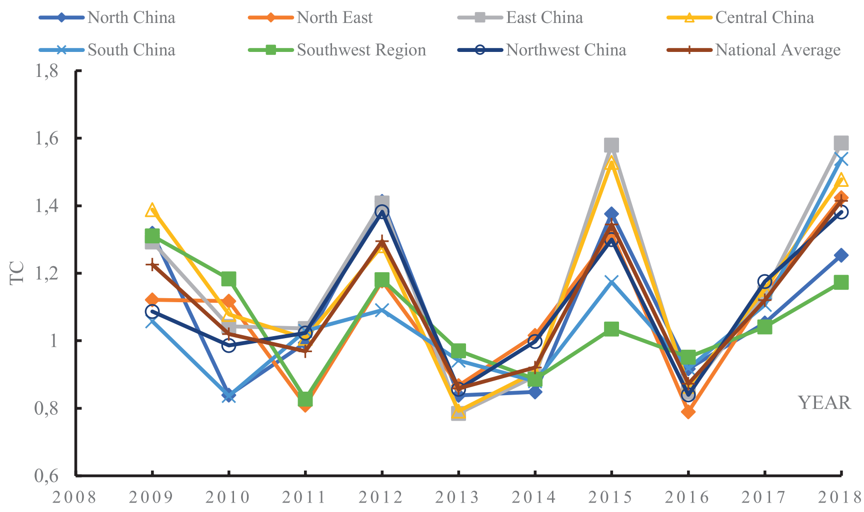

Fig. 8. Trends in regional technological progress index change (TC).

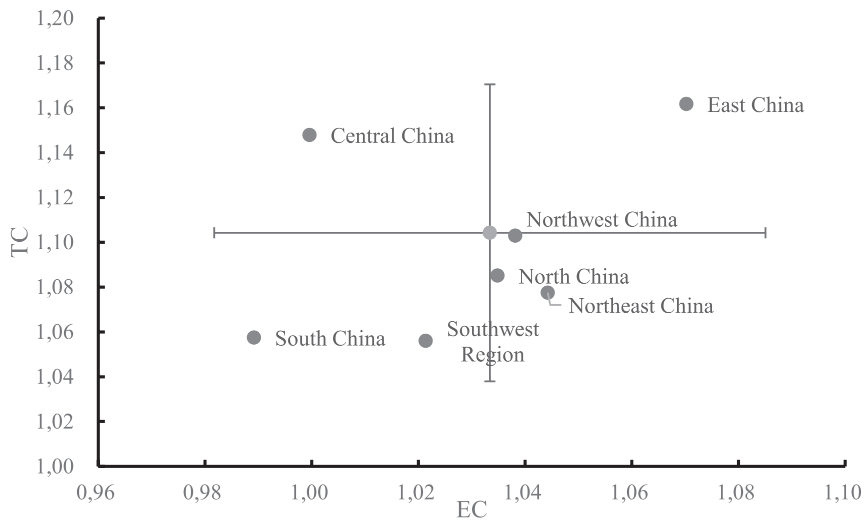

Fig. 9. Regional quadrant of the value of change in integrated technical efficiency and the value of change in technical progress.

Utilizing the ML total factor productivity index model to decompose changes in comprehensive technical efficiency and technological progress, a quadrant diagram (Fig. 9) illustrates the technical performance of the seven regions in green mining development. East China stands out in the first quadrant, showcasing excellent technical development and efficiency. Central China is positioned in the second quadrant, displaying noticeable improvements in technological progress but still leaving room for enhancing comprehensive technical efficiency. South and Southwest China fall in the third quadrant, indicating the need for further improvement despite having a higher technological advancement index. North, Northeast, and Northwest China reside in the fourth quadrant, suggesting slower technological progress but better comprehensive technical efficiency, highlighting untapped potential. The quadrant distribution reveals the strengths and weaknesses of different regions in green mining technology development, offering valuable insights. For instance, East China's success in technological innovation and production efficiency serves as a valuable model for other regions [47]. Simultaneously, the northern region, while experiencing slower technological progress, demonstrates promising comprehensive technological efficiency, providing an opportunity for improvement through technology adoption.

Conclusions

Conclusions and Recommendations

The assessment of mining eco-efficiency is necessary to achieve sustainable development goals. The development of mining industry leads to the generation of large amounts of wastewater, exhaust gas and solid waste, which are likely to cause uncontrollable damage, and pollution to the environment. For effective assessment of the mining eco-efficiency of the Chinese provinces, this study provides a novel mining eco-efficiency assessment framework, which integrates the non-expected output SBM-DEA and Malmquist-Luenberger total factor productivity index models, in order to encourage the green development of the mining sector, to assess the mining eco-efficiency of 27 Chinese provinces and investigate the evolutionary characteristics of mining eco-efficiency in various locations.

Key findings of this study include: (1) The overall trend in the mining eco-efficiency of Chinese provinces is positive, but notable spatial disparities exist. (2) East China displays superior technical progress and comprehensive technical efficiency, while North, Northeast, and Northwest China lag in technical progress but excel in comprehensive technical efficiency. (3) Results from the non-expected output SBM model and Malmquist-Luenberger total factor productivity index indicate that non-desired outputs, such as exploration and mining violation cases and mining carbon emissions, notably influence China's overall green mining development, particularly in Northeast and Central China. (4) Future challenges in China's green mining development include addressing issues like improving economies of scale, enhancing the level of green mining development, restoring environmental systems in mining areas, and advancing energy conservation and emission reduction efforts.

To sum up, improvement in the level of eco-efficiency of China's mining industry, and promotion of the development of green mining can be achieved in the following ways: (1) To urge enterprises to fulfill their responsibilities for environmental restoration in mines. Formulation of relevant policies for promoting the systematic treatment and restoration of the ecological and geological environment in mines, in addition to the adoption of specific measures to prevent soil erosion, restore vegetation, and reclaim land in mines, is required. (2) The ability to achieve green technology innovation should be developed. The government should encourage mines to invest more, make efforts to achieve technological innovation through the introduction of technologies, and thus facilitate comprehensive utilization of resources, reduce the emission of waste rocks, waste gas, and wastewater, reduce energy consumption and carbon emissions; (3) The development of green mines should be strengthened. The government can accelerate the establishment of green mines through the implementation of relevant policies and by providing support and promoting the creation of demonstration zones for green mining development from "point to surface", so as to facilitate the development of green mining on a large scale.

Outlook

In conclusion, our study introduces a robust and comprehensive framework to assess the ecological efficiency of the mining industry. This framework offers fresh perspectives for green mining development and serves as a valuable reference for government planning decisions. Meanwhile, the results of this study can provide some lessons for green mining development in developing countries. Nevertheless, further discussions are needed on two fronts: firstly, achieving efficient development of mining ecological efficiency amidst changing scales, and secondly, understanding the impact of regional innovation differences on the evolution of mining eco-efficiency.

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Conflict of Interest

All authors declare that no conflict of interest exists.

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