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City-level green growth accounting: Evidence from China's thirteen urban agglomerations

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ABSTRACT

Cities play a pivotal role in achieving 'Carbon Peak' and 'Carbon Neutrality' objectives through the implementation of strategies aimed at mitigating environmental risks. While the environmental impacts of industrial production activities have been widely examined, the nuances of their internal structures remain obscure. This study delves into the industrial sector across the 'thirteen urban agglomerations (TUAs)' in mainland China, covering the years 2006–2016, by developing a comprehensive (source-specific and variable-specific) decomposition framework for Malmquist productivity index. The framework is utilized to discern whether efficiency changes or technological advancements drive productivity growth, considering input/output variables such as capital and labor. Findings show that the average annual environmental productivity gain during the examined period was 2.6 %, suggesting a general enhancement in productivity within TUAs' industrial sectors. A detailed breakdown of productivity changes indicates that a combined contribution of 1.8 % to environmental productivity growth stemmed from energy use and pollutant variables, with emissions of industrial sulfur dioxide being the most significant at 0.9 %. Conversely, the 'catch-up effect,' or environmental efficiency change, was negative (−0.2 %), indicating the TUAs' inability to emulate the productivity levels of more advanced areas. Industrial energy use and capital inputs were the primary contributors to this negative trend, each accounting for a −0.2 % impact. The results underscore the importance of facilitating technology transfers from more developed to less advanced regions, especially regarding renewable energy and capital investment, to bolster environmental performance and productivity in the TUAs' industrial sectors.

1. Introduction

Smog has become a critical environmental problem fueled by industrial and urban growth, commanding the focus of academics and policymakers alike [1,2]. The pollution emanating from economic activities inflicts notable environmental damage and economic hazards globally. For example, air quality has a direct correlation with the U.S. housing market [3], and wildfires in Southern Europe account for a GDP contraction of 0.11–0.18 % [4]. [5] stress the immediate requirement to reduce environmental risks to agriculture, employing cross-country panel data. The persistence of sustainability challenges poses risks of deepening inequality as global production networks may redistribute pollution to nations with weaker environmental safeguards. This is of particular concern in developing countries, especially China. For instance, several Chinese cities along the Yangtze River's middle and lower reaches, in Northeast China, and the Beijing-Tianjin-Hebei area suffered intense smog episodes in 2013, 2016, and 2017. Findings from the National Environmental Analysis by the Asian Development Bank and Tsinghua University (2013) show that fewer than 1 % of China's largest 500 cities meet the World Health Organization's air quality standards. Researchers like [6] have pointedly documented the escalation in prolonged smog events to evoke a response from authorities. Echoing these concerns, the Report on Comprehensive Scientific Assessment of Airborne Particulate Matter by the [7] clarifies that atmospheric fine particles attract numerous carcinogens and mutagens with genotoxic potential. The pernicious health impacts of these pollutants are undeniable; they are linked to increases in mortality, the intensification of chronic conditions, as well as respiratory and cardiovascular disorders. Changes in lung function, influences on fertility, and

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Nomenclature

Abbreviations

BAM	Bounded-adjusted measure
CE	Contemporaneous efficiency
CIE	Current inefficiency
CRS	Constant returns to Scale
DDF	Directional distance function
DEA	Data envelopment analysis
DMU	Decision-making unit
EC	Efficiency change
EPT	Environment Production Technology
GHG	Greenhouse gas
GE	Global efficiency
GIE	Global inefficiency
GPEC	Global pure efficiency change
GPTP	Global pure technological progress
GSEC	Global scale efficiency change
GTPSC	Global technological progress of scale change
GVMI	Global variable-specific Malmquist index
IE	Inefficiency
SBM	Slack-based model
TUAs	Thirteen urban agglomerations
TP	Technological progress
TFP	Total Factor Productivity
TR	Technology ratio
VRS	Variable returns to Scale

Symbols

S_p^x	slack of inputs
L_p^x	lower bound for inputs
U_q^e	upper bound for outputs

impairment of the immune system are all associated with these contaminants.

The industrial sector is the primary contributor to smog, which poses significant risks to human health. As one of the key drivers of economic growth, the industrial sector heavily relies on fossil energy consumption [8] and is responsible for emitting carbon dioxide and sulfur dioxide [9]. For example [10], have highlighted that the industrial sector contributes more than 52.89 % to overall sulfur dioxide emissions in certain regions of China [11]. state that the industrial sector in Canada accounts for over 39 % of the country's total greenhouse gas emissions. In contrast to developed countries, China, as the largest developing country, views the industrial sector as a crucial engine for further development. Consequently, the byproducts of industrial activities, such as carbon dioxide and sulfur dioxide emissions, represent the intricate nexus of energy, environment, and the economy in the country. Furthermore, the energy consumption and pollutant emissions from industrial activities also present significant constraints on the process of intensive urbanization. It is evident that a cleaner and more sustainable development approach should be pursued to address the pressures on natural habitats [12,13]. The current production patterns result in various negative externalities, primarily in the form of environmental pollutant emissions due to the extensive use of conventional inputs [14]. argue that investing in innovation and progress could partially offset these costs and benefit the environment. However, Porter's viewpoint has received less attention in developing countries where the conventional approach remains prevalent. In an unsustainable economy, the lack of awareness regarding environmental costs is accompanied by expanding energy consumption, high-density pollutant emissions, and significant technical inefficiencies.

Conducting research on an economy's performance within the Malmquist environmental total factor productivity (*ME-TFP*) framework allows for a comprehensive analysis of both economic growth and environmental protection [15,16]. This framework considers the transformation of multiple inputs into multiple outputs. Through such an approach, it becomes possible to identify trends in productivity change for specific decision-making units and determine avenues for enhancing existing environmental regulations in line with the principles of sustainable development. In conclusion, prioritizing sustainable development requires adopting a cleaner and more sustainable development mode that addresses the pressures on natural habitats. The current production patterns generate negative externalities, including environmental pollutant emissions resulting from the extensive use of conventional inputs. Previous work could benefit from further refinement. A notable limitation is the prevalent focus on composite indicators that encapsulate both environmental efficiency and productivity. While useful for regional comparison, these metrics may obscure the distinct elements or variables driving performance enhancement. A more granular analysis would elucidate the particular dynamics behind environmental achievements. Additionally, the generic classification of all energy consumption as 'dirty' overlooks the increasing integration of renewable sources. An exemplar is Shanghai's stipulation for non-fossil renewable energy to represent 25 % of total energy use. Recognition of renewable energies' burgeoning role is crucial for an accurate assessment of environmental efficiency. In essence, there resides substantial potential for enriching the current body of literature on this topic.

Considering the academic and policy context, this work has the potential to provide valuable insights and contributions in three aspects. First, from a methodological perspective, the work addresses a limitation commonly encountered in previous studies by illustrating the disposability for both input-oriented and output-oriented variables. This consideration allows for a more comprehensive analysis and overcomes a gap in existing literature. Second, the work introduces a novel managerial disposability concept for the Bounded-adjusted measure (BAM), which was introduced by Ref. [17] and is one of the more recent additions to the Data Envelopment Analysis (DEA) family. This concept opens new avenues for exploration and warrants further investigation and application. Lastly, the work proposes a novel global variable-specific Malmquist index and incorporates this index into the DEA-based framework. This approach not only enhances the analytical capabilities of the research but also offers a fresh perspective on evaluating and measuring environmental performance within the context of the study. In the robustness, this work also compares our results with those employing by-production technology [18,19]. Empirically, the work highlights the significance of city-level data from China's "thirteen urban agglomerations (TUAs)." These agglomerations are key regions for regulation, as emphasized in the Plan of Air Pollution Prevention in Key Regions throughout 2011–2015 (12th "Five-Year Plan") issued by the Chinese central government. To capture the environmental impact effectively, the work specifically focuses on industrial sulfur dioxide and dust (soot) emissions as undesirable outputs, aligning with the objectives of the study. More details of Thirteen Urban Agglomerations are given in the Appendix. The aim of this study is to demystify urban growth at the city level, with a particular focus on the boundaries imposed by energy consumption and pollutant emissions. This research has developed a nuanced decomposition framework for the Malmquist productivity index, which considers both variable-specific and source-specific factors, to initially estimate the overarching environmental productivity index. Upon applying this comprehensive framework to China's TUAs, this article gains insights into the green growth status of individual cities. These insights pave the way for establishing targeted 'common but differentiated' industrial environmental regulations. From a variable-specific lens, this article dissects the total environmental productivity index, technological advancements, and efficiency modifications to single out each variable's contributions. This analysis allows us to distinguish the most viable strategies for cities pursuing sustainable development trajectories. Subsequently, this work seeks to categorize various regions based on their environmental achievements, which will inform tailored regulatory measures.

The subsequent sections of the research are structured as follows: Section 2 provides a comprehensive literature review. Section 3 presents the methodology framework in detail. It elaborates on the concept of disposability for both input-oriented and output-oriented variables and introduces the BAM. Furthermore, the section explains how the concept of managerial disposability is applied to the BAM. Additionally, the construction of the global variable-specific Malmquist index is outlined, and its incorporation into the framework is described. In Section 4, an empirical analysis is conducted focusing on the TUAs in China. This analysis utilizes the city-level data and examines the environmental performance of these key regions for regulation. The specific emphasis is placed on industrial sulfur dioxide and dust (soot) emissions as undesirable outputs. The empirical findings provide insights into the environmental efficiency and productivity of the TUAs. In Section 5, a robustness analysis is conducted, while Section 6 concludes the research.

2. Literature review: drivers of environmental productivity

Existing literature that probes the interconnected realms of energy and pollutants is plentiful and varied, featuring several studies of particular significance [20,21]. A segment of studies has honed in on the economic ramifications of energy-centric policies at the national level. For instance Ref. [22], gauge the enduring effects of widespread carbon taxation on energy applications, contrasting with empirical investigation of [23] into energy-efficient housing via a field experiment undertaken in Mexico. In more recent discourse, there has been a growing focus on urban-level pollution mitigation, largely encouraged by the versatility of treatment approaches [24–27]. Prior investigations have thoroughly scrutinized the interplay among energy consumption, pollutant discharge, and the expansive production process. This process duly acknowledges the limitations placed upon economic activity by the parameters of energy and pollution. A favored methodology for modeling this production process and appraising environmental total factor productivity (TFP) is data envelopment analysis (DEA), initially introduced by Ref. [28]. DEA is adept at integrating considerations such as energy utilization and emission levels within its evaluative framework. Moreover, augmenting DEA with productivity indices like the sequential Malmquist-Luenberger productivity index yields more nuanced insights [29]. To clarify, DEA is a tool for quantitative analysis that assesses the relative efficacy by quantifying how closely a particular decision-making entity approximates the efficiency frontier, assigning static scores between zero and one. Contrastingly, productivity change encompasses the temporal shifts of these entities across different time slices. Spatially, investigations into the interrelations among energy consumption, pollutant emissions, and economic prowess can be clustered into three distinct categories. The initial category entails international studies, exemplified by the research of [30], who delves into the impact of heterogeneity on the stability and efficacy of international environmental accords. This category emphasizes decoding the complexities and obstacles inherent in worldwide environmental collaboration. The second category encompasses country-specific analyses, with the work of [31] serving as a telling instance. They dissected the repercussions of energy substitution in China's unique milieu, thus shedding light on the singular economic and ecological narratives of individual nations. The focus here rests on dissecting the nuances of energy policies and their environmental aftereffects within a sovereign boundary. The third category, regional studies, zooms in on discrete locales, as illustrated by Ref. [32] in their probe of Jiangsu province, China. Their investigative lens, the whole process decomposition method, facilitates an intimate appraisal of that region's environmental stewardship. This granular perspective enhances the understanding of locality-specific elements and directives governing energy and emissions. In the sphere of productivity research, scholars have orchestrated a synthesis between productivity analysis and the DEA paradigm [33]. introduce the Range-adjusted Measure alongside the Luenberger Productivity Indicator and adapted these tools for analysis within Chinese energy policy, affording a layered examination of productivity dynamics and efficiency gains in this ambit [34]. intricately weave the framework of the proportional directional distance function (pDDF) into the fabric of the established output-oriented radial efficiency measure. Merging this with the classical CCD (Caves, Christensen, Diewert) Malmquist index, they crafted a productivity gauge that accurately captures both the directional and radial shifts in efficiency. Furthermore [35], implement the DEA-Malmquist modality in their scrutiny of China's real estate domain, thus enabling a discerning evaluation of productivity trajectories and the quest for augmentation in efficiency specific to the property sector.

A multitude of modeling techniques have been applied to gauge environmental efficiency and productivity adeptly. As a case in point [36], harness the power of Malmquist-Luenberger indexes for a deep-dive into China's star-rated hospitality sector, whereas [37] turns the lens towards Korea's manufacturing firms, with an emphasis on carbon neutrality. Meanwhile [38], utilize the Malmquist index to elucidate the environmental productivity landscape within China's metallurgy sector, and [39] quantify the socio-environmental strides made by various enterprises. The by-production environmental technology, brought into the limelight by Ref. [18], has seen increased adoption, particularly due to its innovative double frontier concept, further enhanced by Refs. [40,41]. [42] provide an important extension of this model to the economic sphere. The by-production framework offers a robust mean to dissect environmental efficiency and productivity. Despite these developments, the extant literature predominantly fixates on the gross estimations of environmental efficiency and productivity, often overlooking the inward contributions of each discrete component. Confronting this gap, our article moots a variable-specific decomposition methodology, scaffolded on the comprehensive decomposition technology proposed by Ref. [43]. This scheme disentangles the threads of environmental technological evolution and efficiency variance, spotlighting both frontier shifts and catch-up mechanisms. This methodological stance reverberates with the analytical choices of studies like that by Ref. [39]. It is critical to recognize, however, that the prevailing frameworks have not delineated with absolute clarity whether the concentration should be on modulating energy use or curbing undesirable outputs. Thus, this article presents a distinct gradient in our discourse: a variable-specific decomposition approach, engineered to unmask the intricate pathways through which environmental productivity, coupled with technological and efficiency changes, can be vigorously fostered. By parsing out the input of individual components, this technique sheds light on actionable strategies and bespoke policy interventions poised to bolster environmental stewardship with exacting precision.

The Malmquist Productivity Index and the Luenberger Productivity Indicator, as delineated in scholarly narratives, have garnered substantial interest for their robust analytical capabilities. The Malmquist index, in particular, with its foundation in a multiplicative paradigm, is extensively leveraged across diverse sectors, commanding a robust reputation for appraising efficiency change (*EC*) and technical progress (*TP*). Especially within the Chinese analytical sphere, the Malmquist index remains a topic of considerable utility though there exists potential for more expansive inquiries. For instance, the employment of the output-oriented Malmquist Productivity Index in Ref. [44] provides a detailed review of the Chinese agricultural milieu from 1994 to 2008, enhancing the comprehension of efficiency modifications and technological advancements peculiar to the sector. Similarly [45], proffer an innovative construct for gauging static inefficiencies and the composite

Malmquist-Luenberger productivity index within China's manufacturing landscape, offering valuable perspectives on the sector's comprehensive productivity evolution. Further to this [46], advance the development and application of the DEA-Malmquist methodology to assess urban infrastructure systems. This novel employment elucidates general efficiency changes and technological progress yet does not venture into the intricacies of variable-specific decomposition. The inclusion of such a decomposition avenue could unfurl additional layers, revealing the underlying influences steering productivity metamorphoses within individual sectors or industries.

Recent literature has centered on the global implementation of DEA, Luenberger, and Malmquist methodologies. Notable examples include [47], who introduce an approach using the Malmquist productivity index for a two-stage dynamic system, subsequently applying this framework to Asia-Pacific airlines. Likewise [48], develop a circular DEA framework to evaluate efficient water usage and recycling processes across Spanish regions. This article, however, concentrates on China—a country viewed as the largest developing nation, which has undergone swift industrialization and urbanization, courting significant economic expansion. Nonetheless, this trajectory of development has drawn scrutiny for substantial emissions of pollutants, resulting in environmental dilemmas like smog events [32,49,50]. Consequently, the repercussions of intense energy utilization and its correlated greenhouse gas (GHG) and air pollutant discharges have come under increased observation [51]. Such negative impacts, associating energy consumption with natural hazards, have posed obstacles to China's productivity growth [52]. Despite endeavors from the Chinese central government to impose regulatory measures via Five-Year plans, these policies often fall short of detailed specificity and efficacy at the municipal government level [53].

This article distinguishes itself by utilizing the BAM model, originally introduced by Ref. [17]. This model offers several advantages over alternative approaches. First, its additive structure enables variable-specific decomposition, allowing for a more detailed and nuanced analysis. Second, compared to the Range-adjusted Measure [35], the BAM model exhibits higher discriminatory power, enhancing its ability to differentiate between different units of analysis. Third, unlike methods such as Slack-based models [54] and Directional Distance Functions [55], which require the specification of artificial vector settings that can introduce bias, this non-parametric BAM model avoids such issues. For a more detailed explanation of the Bounded-adjusted Measure, refer to Ref. [17]. The primary contribution of this work lies in the proposal of a variable-specific decomposition approach for the Malmquist Index. While previous literature has focused on the application of this approach, the use of an all-in-one indicator fails to provide detailed policy implications for end-of-pipe regulation or source control. In contrast, this developed decomposition framework allows us to attribute the performance of cities to each specific input/output variable. This provides valuable insights into identifying the most effective strategies for promoting environmental performance. While this

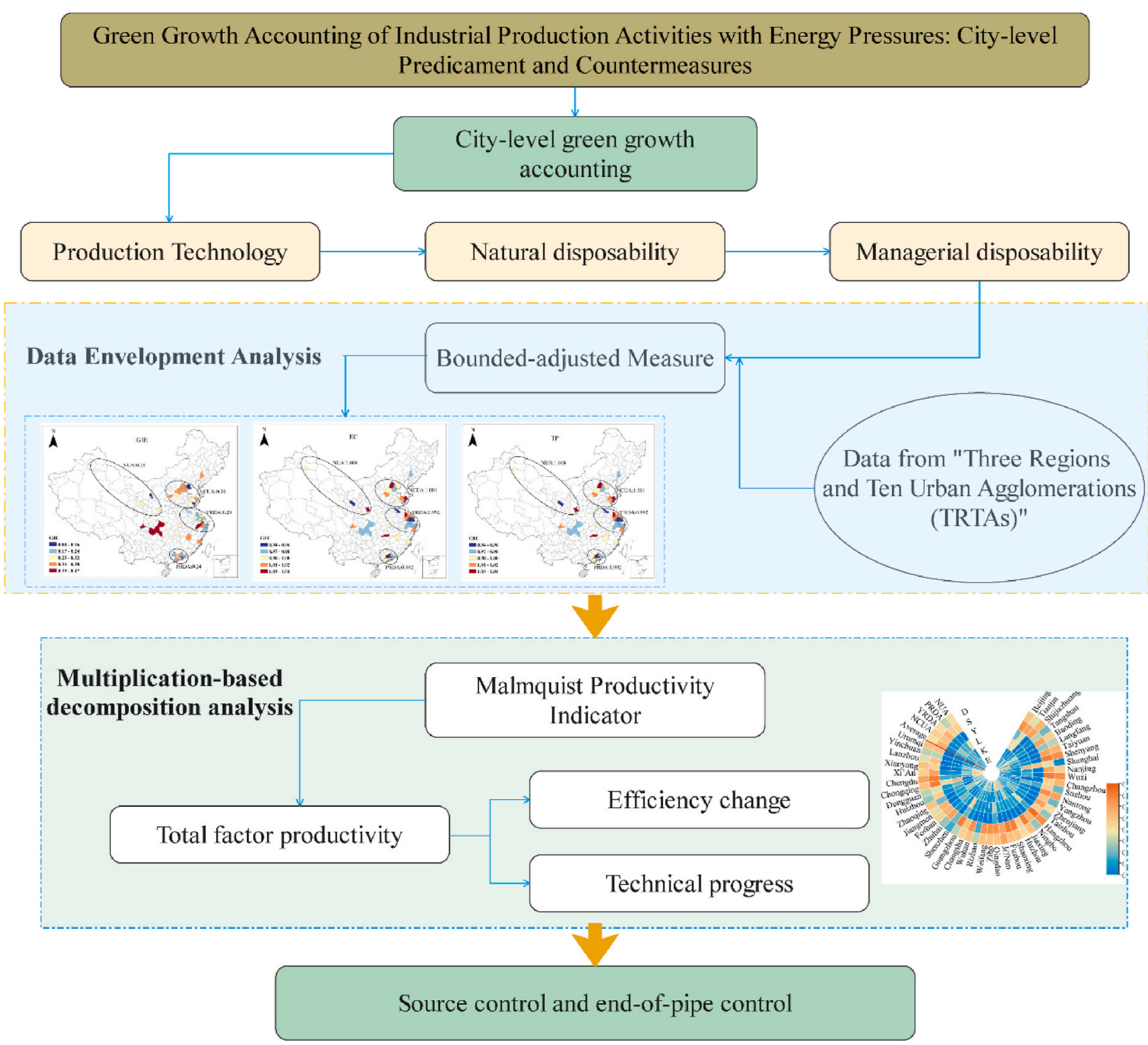

Fig. 1. Methodology framework of this article.

research paradigm can be applied to any region with sufficient input/output datasets, its application to China holds particular significance. China accounts for approximately 22 % of global industrial outputs, underscoring the relevance and implications of this study in this context [56].

3. Methodology framework

In this study, we utilize the methodology introduced by Ref. [34] to develop the Global Variable-specific Malmquist index (GVMI) for China's TUAs. The GVMI assesses the performance of these areas, considering the limitations caused by energy consumption and air pollutant emissions. Initially, in Fig. 1this research establishes a theoretical framework that lays the groundwork for the analysis. This framework is critical for grasping the context and preparing for the empirical investigation. Subsequently, this research explores the disposability of both input-oriented and output-oriented variables, forming conclusions based on the prevailing literature. This research also presents the innovative BAM and incorporate an extended disposability concept into the model. The BAM provides numerous benefits - for instance, its additive nature permits non-radial progress toward the production frontier. Moreover, the BAM exhibits enhanced discriminatory capability when contrasted with other models, such as the Range-adjusted Measure. Notably, in distinction from the Slack-based Measure and the Directional Distance Function), the BAM circumvents the necessity for setting artificial parameters, rendering it a sounder methodological choice.

3.1. The Interdisciplinary theoretical framework

The field of operational research has played a crucial role in addressing environmental economics and management challenges, which are essential for promoting sustainable development and meeting human needs. Researchers in environmental economics have focused on three pressing issues, as highlighted by Ref. [18]. First, there is a need to address the byproducts of desirable outputs, which are represented by greenhouse gas and air pollutant emissions. These undesirable outputs pose significant environmental concerns and require effective management strategies. Second, it is important to consider the further assimilation of undesirable outputs into the environment. Understanding the environmental impact and finding ways to mitigate or minimize their effects are critical for achieving sustainable development. Lastly, the interaction between regulatory policies and the production process related to the environment needs to be examined. The effects of such policies on environmental performance and the overall production process require thorough analysis. While previous theoretical frameworks have made significant progress in quantitatively analyzing these issues, there is still considerable potential for further exploration. It is crucial to develop suitable and reasonable mathematical expressions for production technology that incorporate the generation of undesirable outputs. This will enable us to accurately assess the gap between ideal and actual environmental performance and identify the determinants for narrowing this disparity.

The theoretical framework rests on the production possibility set, allowing flexible quantity fluctuations [57]. The variables in the production possibility set are taken for (x, e, k, y, b), which have particular disposability for themself. Indeed, the production possibility set has been modified for more functions, such as allowing for negative data [58]. The production-possibility frontier, also known as the boundary of the production possibility set, needs to satisfy the properties of convexity and monotonicity, along with minimum extrapolation and represents the efficient production unit [35,59].

3.2. Environmental Production Technology

To accurately estimate energy and environmental performance, it is essential to address the treatment of undesirable outputs. Distinct disposability assumptions can lead to varied policy implications. This subsection will elaborate on the disposability settings for both input-oriented and output-oriented variables.

3.2.1. Disposability for outputs

The integration of undesirable outputs, such as pollutant emissions, into the framework of the Production Possibility Set, also termed Environmental Production Technology, garners considerable attention. Various methods exist for including undesirable outputs, each bearing distinct implications for the intensity of environmental regulations [35,60]. Broadly, two types of disposability are recognized: strong and weak. Strong disposability equates the treatment of undesirable outputs with that of desirable ones, reflecting a degree of environmental deregulation without affecting total output. In this scenario, undesirable outputs may effectively function as specific inputs, leading to an increase in desirable outputs and a simultaneous reduction of undesirable ones. Conversely, weak disposability indicates environmental regulation, where an increase in desirable outputs is feasible with constant inputs. Here, the objective is to augment the production of favorable outputs while curbing environmental impact by controlling the generation of undesirable ones. The choice between strong and weak disposability rests on the environmental and policy context at hand. Strong disposability lends a more adaptable approach, potentially allowing the expansion of desirable outputs with fewer constraints on the creation of undesirable ones. Weak disposability prioritizes stringent environmental regulation, aiming to diminish the production of undesirable outputs while enhancing desirable ones. Determining the most fitting disposability approach necessitates a balanced assessment of environmental objectives against economic factors. A judicious consideration of the consequences of each method is crucial to select the one that best aligns with the unique demands and policy goals of the situation.

Mathematically, to better characterize the production activities incorporating undesirable outputs, this work needs to define the production set $P(x,e,k)$. Energy use and capital investment play crucial roles in defining the state of energy systems. Upgrading energy technologies and shifting energy-mix can lead to desirable outcomes such as energy conservation, emissions reduction, and increased energy security. Therefore, the analysis focuses on the capital stock and energy use, categorizing inputs into conventional ones, energy use, and capital stock. Assuming the vector $y = \left(y_1, y_2 \cdots y_j\right); b = (b_1, b_2 \cdots b_j)$ which represent the variable set of desirable and undesirable outputs, respectively. Then, the production set $P(x,e,k)$ represents transferring conventional inputs, energy use and capital investment (x,e,k) into desirable and undesirable outputs (y,b). The simplest process can be presented as follow:

$$P(x,e,k) = \{(x,e,k,y,b) \in T; (x,e,k) can\, produce (y,b)\} \tag{1}$$

Further on, the two types of acknowledged disposability for input-oriented variables can be presented as follows.

(1) Strong disposability [61]:firstly proposed the strong disposability for undesirable output variables. If $\begin{cases} (y,b) \in P(x,e,k) \\ (y,b^s) \leq (y,b) \end{cases}$, we have $(y,b^s) \in P(x,e,k)$. Assuming the number of Decision-making Units (DMUs) is N (i.e., the types of undesirable outputs), then the constraints of undesirable outputs can be expressed as:

$$\sum_{n=1}^{N} \lambda_j b_{jn} \geq b_j \tag{2}$$

Note that λ denotes a vector of non-negative variables. Eq. (2) can well define the environmental deregulation (i.e., reducing undesired outputs will do nothing to other output variables).

(2) Weak disposability: undesirable outputs in the framework of Environment Production Technology (*EPT*) can be treated as weak disposability. In detail, we must sacrifice the desirable outputs in the production activities when cutting undesirable outputs [61]. There are also two further assumptions regarding weak disposability. (*i*) null-jointness for desirable and undesirable outputs: $\begin{cases} (y,b) \in P(x,e,k) \\ y = 0 \; if \; b = 0 \end{cases}$, indicating undesirable outputs are the byproducts of desirable ones; (*ii*) single weak disposability for undesirable variable: if $\begin{cases} (y,b) \in P(x,e,k) \\ \lambda \in [0,1] \end{cases}$, we have $(\lambda y, \lambda b) \in P(x,e,k)$, suggesting reducing both the undesirable outputs and the desirable outputs is possible, whereas impossible to reduce the undesirable output while keeping other output fixed. The production set can be expressed as assuming strong disposability, which is not covered for brevity. Then, the constraints of undesirable outputs can be expressed as:

$$\sum_{n=1}^{N} \lambda_j b_{jn} = b_j \tag{3}$$

Fig. 2 displays the related production activities. Assuming the lateral axis represents the number of undesirable outputs while the vertical axis indicates the number of desirable outputs. In Fig. 1, point BCD represents three DMUs, and the following disposability assumptions for desirable & undesirable outputs can be concluded. (1) Strong disposability for both desirable & undesirable outputs: OFCBA holds the production frontier for Decision-making unit B, indicating B can reduce undesirable outputs to zero (i.e., point F) while keeping desirable output fixed (i.e., environment deregulation). (2) Strong disposability for desirable outputs and weak disposability for undesirable outputs: ODCBA represents the production frontier for Decision-making units of C, D. The reduction of undesirable outputs often necessitates a simultaneous reduction in desirable outputs. (i.e., the situation satisfies null-jointness). In addition, point $G \in P(x,e,k)$ indicates weak disposability (i.e., cut desirable & undesirable outputs simultaneously to point G').

The Bounded-adjusted Measure (BAM) employed in the paper will consider undesirable outputs as special inputs through the constrain:

$$\sum_{n=1}^{N} \lambda_j b_{jn} \le b_j \tag{4}$$

The constrain characterizes maximizing desirable outputs while minimizing the undesirable outputs. Also, strong disposability is used for desirable outputs. Generally, the PPS for output-oriented variables can be characterized as:

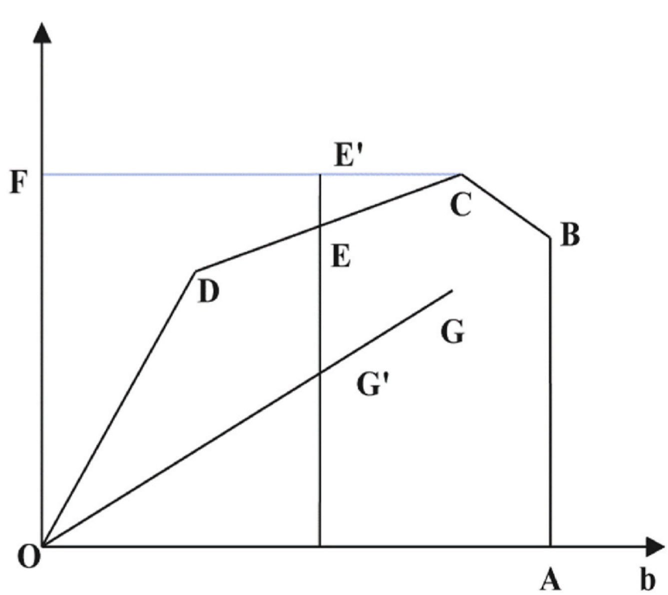

Fig. 2. Illustration of disposability for desirable (F) & undesirable outputs (b).

$$PPS^{output} = \left\{ (y,b); \sum_{m=1}^{M} \lambda_j y_{jm} \ge b_j, \sum_{n=1}^{N} \lambda_j b_{jn} \le b_j \right\} \tag{5}$$

3.2.2. Disposability for inputs

The concept of disposability for input-oriented variables has not been extensively explored in the literature, mainly due to the presumption that disposability is consistent across all inputs [35,62]. Nonetheless, contemporary research has started to delve into the policy ramifications of varied disposability types, particularly natural disposability and managerial disposability [63]. Natural disposability refers to the strategy where a DMU mitigates undesirable outputs by reducing inputs, while simultaneously striving to optimize the production of desirable outputs. This can alternatively be described as a process where the DMU economizes on input usage to decrease negative externalities and, in doing so, enhances positive production outcomes:

$$\sum_{p=1}^{P} \lambda_j x_{pj} \le x_j \tag{6}$$

The concept of managerial disposability posits that through targeted managerial practices, the efficiency of a specific DMU could be elevated. This is achieved by concentrating efforts on the growth of inputs, such as energy consumption, while also seeking to enhance the production of desirable outputs. The mathematical representation of disposability can be expressed as: $\sum_{q=1}^{Q} \lambda_j x_{qj} \ge x_j$ (7)

Fig. 3 provides a detailed illustration of the concept of natural and managerial disposability for input-oriented variables. In the figure, arc ABCD represents the frontier for undesirable outputs, while arc EFGH represents the frontier for desirable outputs. Specifically, arc AB represents the frontier for undesirable outputs under the assumption of natural disposability, while arc BCD represents the frontier for desirable outputs under the assumption of managerial disposability. When we set the input-oriented variable assuming natural disposability, the Decision-making Unit (DMU) j can transform x1 units of inputs into y1 units of desirable outputs and b1 units of undesirable outputs. However, by reducing inputs from x1 to x2, the DMU j can decrease undesirable outputs from b1 to b4, but at the same time, it will also decrease desirable outputs from y1 to y2. Natural disposability can be seen as a negative response to environmental regulation, as it involves sacrificing desirable outputs to reduce undesirable outputs. In contrast, under the novel managerial disposability assumption, when the DMU j expands inputs from x1 to x3, it can simultaneously reduce undesirable outputs from b1 to b2 and increase desirable outputs from y1 to y4. This indicates that managerial disposability allows for a positive response to environmental regulation, as it enables the DMU to effectively control and reduce undesirable outputs while maintaining or even increasing desirable outputs in the long term.

Fig. 3 elucidates the concepts of natural and managerial disposability as applied to input-oriented variables. The figure features arc ABCD, depicting the frontier for undesirable outputs, and arc EFGH, delineating the frontier for desirable outputs. Specifically, the segment AB of the arc demarcates the undesirable output frontier under natural disposability, while the segment BCD represents the desirable output frontier given managerial disposability. With natural disposability assumed for the input-oriented variable, DMU *j*, can convert x1 units of input into y1 units of desirable outputs alongside b1 units of undesirable outputs. If this DMU reduces its inputs from x1 to x2, a correlation is observed: the undesirable outputs decrease from b1 to b4, while, concurrently, the desirable outputs also decline from y1 to y2. Thus, natural disposability is often viewed as a negative consequence of environmental regulation due to the resultant trade-off in decreasing desirable outputs for the sake of mitigating undesirable ones. Conversely, embracing the innovative

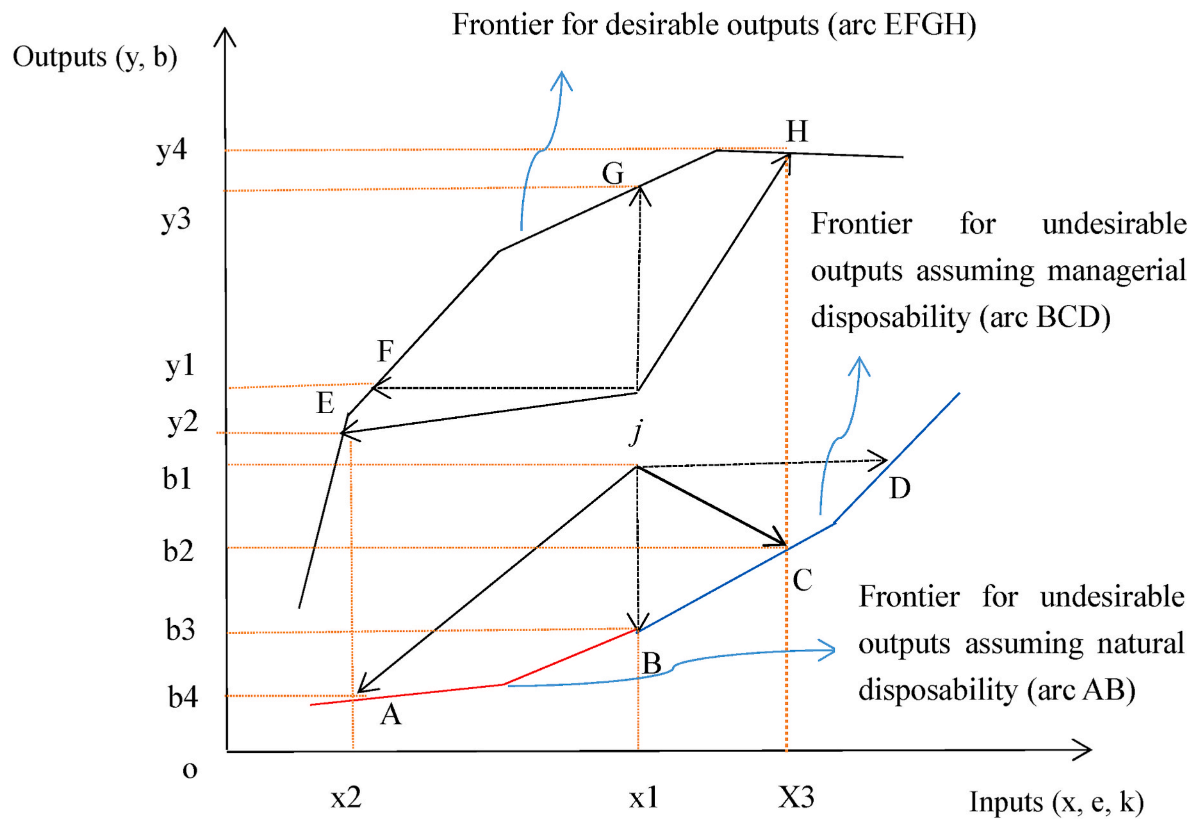

Fig. 3. Illustration of disposability for input-oriented variables (natural & managerial disposability).

concept of managerial disposability, the same DMU j can expand its inputs from x1 to x3. Notably, this expansion concurrently lessens the undesirable outputs from b1 to b2, whilst it escalates the desirable outputs from y1 to y4. This outcome infers that managerial disposability fosters a positive engagement with environmental regulation, empowering the DMU to adeptly manage and curtail undesirable outputs without sacrificing—and potentially even amplifying—desirable outputs over the long haul.

In conclusion, the framework incorporates managerial disposability (with natural disposability assumed for other input-oriented variables) specifically for energy and capital inputs. This approach enables the simultaneous growth of desirable outputs and reduction of undesirable outputs. This article considers these changes in production activities as outcomes of managerial efforts. By adopting new technologies that facilitate sustainable production, such as capital investments, firms can achieve this desired direction of changes. This managerial disposability allows for the optimization of resource allocation and the adoption of environmentally friendly practices.:

$$PPS^{input} = \left\{(x,e,k); \sum\nolimits_{p=1}^{P}\lambda_j x_{pj} \geq x_j, \sum\nolimits_{q=1}^{Q}\lambda_j e_{qj} \leq e_j, \sum\nolimits_{q=1}^{Q}\lambda_j k_{ij} \leq k_j,\right\} \tag{8}$$

3.3. Bounded-adjusted measure

The BAM emerges as a recent contribution to the spectrum of additive models in data envelopment analysis, delivering an all-encompassing measure for inefficiencies. It captures all variables discerned by the model's slacks, as affirmed by Ref. [17]. By integrating lower input bounds with upper output bounds and accommodating any imposed production technology returns to scale, the BAM ameliorates the constraints of traditional DEA models. A principal benefit of the BAM is its adept handling of variable returns to scale (VRS) with greater adaptability than conventional models, which typically presuppose VRS. Instead, the BAM acknowledges the scope for enhancement via a rudimentary linear program, a perspective shared by Refs. [17,64], thus facilitating a more precise efficiency evaluation and a truer production process depiction. Moreover, the BAM rectifies certain DEA models' shortcomings. For instance, the directional distance function measure suggested by Ref. [65] falls short in pinpointing variable-specific inefficiencies, a gap bridged by the BAM's comprehensive slacks examination. Concurrently, the Range-adjusted Measure, introduced by Ref. [66], suffers from attenuated discrimination capability, an issue the BAM adeptly manages through the integration of bounds, yielding a notably enhanced inefficiency evaluation.

3.3.1. Basic BAM model

Let λ represents a vector of non-negative variables. There are bounds for inputs and outputs so that the minimum quantity of each input is the lower bound for inputs and the maximum quantity of each output is the upper bound [17]. Assume a particular DMU consumes P types of inputs $x = (x_1, \ldots, x_p) \in R_p^+$, to produce Q types of outputs $y = (y_1, \ldots, y_m) \in R_M^+$. The number of inputs and outputs is incorporated into $\left(x_j^t, y_j^t\right)$, and the slack of inputs and outputs is incorporated into $\left(S_p^x, S_m^y\right)$. Hence, this article can characterize the production possibility set (PPS) for the BAM-DEA assuming VRS as:

$$PPS = \left\{(x,y) \in R_p^+ \times R_M^+ : (x,-y) = \sum_{j=1}^{J}\lambda_i(x_i,-y_i), \lambda_i \geq 0; x_p \geq min(x_p); \right. \\ \left. y_m \leq max(y_m); \forall i,p,m\right\} \tag{9}$$

Given technology defined by Eq. (1): the operational inefficiency for a certain DMU can be obtained as follows:

$$\max \frac{\sum_{p=1}^{P} \frac{S_p^x}{L_p^x} + \sum_{m=1}^{M} \frac{S_m^y}{U_m^y}}{P+M} \tag{10}$$

s.t.

$$\sum_{i=1}^{I} x_{pi}\lambda_i + S_p^x = x_{pi'}, \sum_{i=1}^{I} y_{mi}\lambda_i - S_m^y = y_{mi'};$$
$$\sum_{i=1}^{I} \lambda_i = 1, \lambda_i \geq 0; \quad \forall p, m; \quad S_p^x, S_m^y \geq 0$$

where $\sum_{i=1}^{I} \lambda_i = 1$ indicates VRS. Note that any returns of scale can be assumed in BAM model, see Ref. [17] for more details.

3.3.2. BAM model assuming managerial disposability

Assume a particular unit uses ordinary inputs of P types $x = (x_1, \ldots, x_p) \in R_P^+$; energy inputs of Q types $e = (e_1, \cdots, e_q) \in R_Q^+$; and capital inputs of I types $k = (k_1, \ldots, k_i) \in R_I^+$. In the production plan, the inputs can be transformed into M types of desirable outputs $y = (y_1, \ldots, y_m) \in R_M^+$ and N types of undesirable outputs $b = (b_1, \ldots, b_n) \in R_N^+$. In the t-th period, the conventional input, energy use, capital stock, desirable output and undesirable output quantities for the j-th DMU are arranged into the vector $\left(x_j^t, e_j^t, k_j^t, y_j^t, b_j^t\right)$, and their respective slack is incorporated into the vector $\left(S_p^x, S_q^e, S_i^k, S_m^y, S_n^b\right)$. According to subsection 2.2, this article sets energy use and capital input into managerial disposability. As for energy use, this article assumes using cleaner energy instead of coal, oil and other fossil energy-related pollutant emissions. Turning to capital stock, this can be explained that capital investment improves production technology. Therefore, the BAM model assuming managerial disposability can be introduced as:

$$\max \frac{\left[\sum_{p=1,\neq 0}^{P} \frac{S_p^x}{L_p^x} + \sum_{q=1}^{Q} \frac{S_q^{e+}}{U_q^e} + \sum_{i=1}^{I} \frac{S_i^{k+}}{U_i^{k+}} + \sum_{m=1}^{M} \frac{S_m^y}{U_m^y} + \sum_{n=1}^{N} \frac{S_n^b}{L_n^b}\right]}{P+Q+I+M+N} \tag{11}$$

$$\text{s.t.} \sum_{j=1}^{J} x_{pj}\lambda_j + S_p^x = x_{pj'}, \sum_{j=1}^{J} e_{qj}\lambda_j - S_q^{e+} = e_{qj'} \sum_{j=1}^{J} k_{ij}\lambda_j - S_i^{k+} = k_{ij'};$$
$$\sum_{j=1}^{J} y_{mj}\lambda_j - S_m^y = y_{mj'}, \sum_{j=1}^{J} b_{nj}\lambda_j + S_j^r = b_{nj'}, \sum_{j=1}^{J} x_{pj}\lambda_j \geq \min x_{pj};$$
$$\sum_{j=1}^{J} e_{qj}\lambda_j \leq \max e_{qj}, \sum_{j=1}^{J} k_{ij}\lambda_j \leq \max k_{ij}, \sum_{i=1}^{I} y_{mj}\lambda_j \leq \max y_{mj};$$
$$\sum_{j=1}^{J} b_{nj}\lambda_j \geq \min b_{nj}; \lambda_i \geq 0; \forall p, q, i, m, n \geq 0; \; S_p^x, S_q^{k+}, S_i^{e+}, S_m^y, S_n^b \geq 0$$

Note that the vector $\left(L_p^x, L_n^b\right)$ denotes gaps between the observed values of conventional inputs and undesirable outputs and the lower bounds of the corresponding variables. While that distance between the observed values of the desirable outputs, energy and capital inputs and the upper bounds of the corresponding variables are arranged into vector $\left(U_q^{e+}, U_i^{k+}, U_m^y\right)$. Specifically, the differences are characterized as follows:

$$\begin{aligned}
L_{pj'}^x &= x_{pj'} - \min x_{pj}, p \in P, j' \in J; \\
U_{qj'}^{e+} &= \max e_{qj} - e_{qj'}, q \in Q, j' \in J; \\
U_{ij'}^{k+} &= \max k_{ij} - k_{ij'}, i \in I, j' \in J; \\
U_{mj'}^y &= \max y_{mj} - y_{mj'}, m \in M, j' \in J; \\
L_{nj'}^b &= b_{nj'} - \min b_{nj'}, n \in N, j' \in J
\end{aligned} \tag{12}$$

As [17] pointed out, when the amount of the j-th conventional input equals its minimum level there will be no room for improvement, i.e., $x_{pj'} = \min(x_{pj})$, we have $S_p^{*x}/L_p^x = 0$. Therefore, if we have:

$$\begin{aligned}
x_{pj'} &= \min x_{pj} \\
\max e_{qj} &= e_{qj'} \\
\max k_{ij} &= k_{ij'} \\
\max y_{mj} &= y_{mj'} \\
b_{nj'} &= \min b_{nj}
\end{aligned} \tag{13}$$

Then, the following relationships can be obtained:

$$\begin{aligned}
S_p^{*x} \big/ L_p^x &= 0 \\
S_q^{*e} \big/ U_q^e &= 0 \\
S_i^{*k} / U_i^k &= 0 \\
S_m^{*y} / U_m^y &= 0 \\
S_n^{*b} / L_n^b &= 0
\end{aligned} \tag{14}$$

3.3.3. Variable-specific decomposition

This study builds upon the components of the BAM model discussed in the previous sections to further investigate the contribution of specific variables to the overall operational inefficiency in an environmental context. Specifically, we focus on the energy consumption and capital inputs, which are maximized under the assumption of managerial disposability, while conventional inputs are minimized assuming natural disposability. To assess the contribution of these variables, we analyze the slacks, which represent the gaps between actual and optimal energy and capital use under the respective disposability assumptions. Insufficient or excessive energy and capital use are captured by the slacks, reflecting the inefficiencies associated with the managerial or natural disposability assumptions. Based on this analysis, this article decomposes the overall operational inefficiency into its components, following the framework established by Refs. [17,67]. This decomposition allows us to quantify and evaluate the specific contributions of energy consumption and capital inputs to the environmental total operational inefficiency:

$$\text{inefficiency relying on conventional inputs} : IE_x = \frac{\sum_{p=1,\neq 0}^{P} S_p^{x-} \Big/ L_p^x}{P+Q+I+M+N} \tag{15}$$

$$\text{inefficiency relying on energy use} : IE_e = \frac{\sum_{q=1,\neq 0}^{Q} S_q^{e+} \Big/ U_q^e}{P+Q+I+M+N} \tag{16}$$

$$\text{inefficiency relying on capital inputs} : IE_k = \frac{\sum_{i=1,\neq 0}^{I} S_n^{k+} \Big/ U_n^k}{P+Q+I+M+N} \tag{17}$$

$$\text{inefficiency relying on desirable outputs} : IE_y = \frac{\sum_{m=1,\neq 0}^{M} S_m^y \Big/ U_m^y}{P+Q+I+M+N} \tag{18}$$

$$\text{inefficiency relying on undesirable outputs} : IE_b = \frac{\sum_{r=1,\neq 0}^{R} S_n^b \Big/ U_n^b}{P+Q+I+M+N} \tag{19}$$

3.4. The global variable-specific Malmquist Index

For better proceeding with the analysis of TUAs' atmospheric environmental productivity level, in the production activities of industrial sector, the energy uses (E), the labor force (L) and capital stock (K) are regarded as inputs. Whereas the production value (Y) of the sector is considered an expected outcomes, the SO_2 (S) and the dust (soot) emissions (D) of the sector are taken as unexpected outputs. On this basis, variable-specific components of inefficiency outlined in Eqs. (15)–(19) can be further broken down in terms of individual variables as follows:

$$IE = IE_E + \underbrace{IE_L + IE_K}_{IE_x} + IE_Y + \underbrace{IE_S + IE_D}_{IE_b} \tag{20}$$

Based on the static inefficiencies according to BAM assuming managerial disposabilty, this article further constructs a novel economy-energy-environment productivity index (i.e., GVMI) for measuring the dynamic setting. To begin with, we need to construct the global and contemporaneous frontiers according to the data for a single time period (i.e., one year) and the pooled data for the entire period under analysis, respectively [68]. Thus, the inefficiency (IE) is presented in the two forms, i.e., global inefficiency (GIE) and current inefficiency (CIE). Then, the performance gap across the time periods is obtained by calculating the variable-specific inefficiency scores (in terms of both the global & contemporaneous frontier) of the adjacent time periods. What is more, the corresponding efficiency can be obtained by:

$$GE_c(t) = 1 - GIE_c(t); CE_c(t) = 1 - CIE_c(t) \tag{21}$$

Different from the technology gap stated in Ref. [2] (i.e., additive-based technical gap), the quotient between GE and CE comprises the technology ratio (TR). This research uses subscript index v to denote the VRS estimators, whereas subscript index c relates to the CRS estimators. Then, the relationship corresponding to the two measures associated with the global and contemporaneous frontiers can be defined as follows:

$$TR_c(t) = \frac{1 - GIE_c(t)}{1 - CIE_c(t)}, \tag{22}$$

$$TR_v(t) = \frac{1 - GIE_v(t)}{1 - CIE_v(t)}, \tag{23}$$

Eq. (21) denotes the global and contemporaneous efficiency scores based on the variable-specific inefficiencies. Under the assumption that data for multiple time spans are available for a certain DMU, global efficiency scores across different time periods (as measured against the global technical frontier) can be compared to measure the environmental total factor productivity in the framework of the global variable-specific Malmquist index ($GVMI$). The $GVMI$ be obtained by the product of individual variables. For example, $METFP = \prod(METFP_{e,k,x,y,b})$

$$METFP_t^{\ t+1} = \frac{GE_c(t+1)}{GE_c(t)} = \frac{1 - GIE_c(t+1)}{1 - GIE_c(t)}, \tag{24}$$

The $METFP_t^{t+1}$ reflects the environmental productivity change across adjacent years. The subscribe c and v denotes constant and variable returns to scale respectively. Then, TR and CIE comprise global variable-specific Malmquist index ($GVMI$), namely efficiency change ($ME\text{-}EC$) and technical progress ($ME\text{-}TP$):

$$\begin{aligned} METFP_t^{\ t+1} &= \frac{GE_c(t+1)}{GE_c(t)} = \underbrace{\frac{CE_c(t+1)}{CE_c(t)}}_{MEEC_t^{\ t+1}} \times \underbrace{\frac{GE_c(t+1)/CE_c(t+1)}{GE_c(t)/CE_c(t)}}_{METP_t^{\ t+1}} \\ &= \underbrace{\frac{CE_c(t+1)}{CE_c(t)}}_{MEEC_t^{\ t+1}} \times \underbrace{\frac{TR_c(t+1)}{TR_c(t)}}_{METP_t^{\ t+1}} \end{aligned} \tag{25}$$

Note that TP_t^{t+1} denotes the relative change of ratio between global efficiency and contemptuous efficiency across adjacent years assuming CRS technology. According to Eqs. (22) and (23), TR represents the ratio of the static efficiencies associated with the global and contemporaneous frontiers, representing the ratio between these two DEA technical frontiers. Therefore, $METP$ can also be obtained by comparing the change of TR.

What is more, incorporating the VRS technology into the framework allows performing further decomposition. Specifically, the Malmquist environmental efficiency change ($MEEC$, also known as catch-up effects) term can be further broken into Malmquist environmental pure efficiency change ($MEPEC$, also known as pure catch-up effects) and Malmquist environmental scale efficiency change ($MESEC$, also known as scale catch-up effects). Furthermore, Malmquist environmental technical progress ($METP$, also known as frontier movements) can be further decomposed into Malmquist environmental pure technical progress ($MEPTP$, also known as pure frontier movements) and technical progress of scale change ($GTPSC$, also known as scale frontier movements). Fig. 4 displays the detailed decomposition process. The underlying calculation process is presented below:

$$MEEC_{i,t}^{t+1} = MEPEC_t^{t+1} \times MESEC_t^{t+1} = \underbrace{\frac{CE_v(t+1)}{CE_v(t)}}_{MEPEC_t^{t+1}} \times \underbrace{\frac{\frac{CE_c(t+1)}{CE_c(t)}}{\frac{CE_v(t+1)}{CE_v(t)}}}_{MESEC_t^{t+1}}, \tag{26}$$

$$\begin{aligned} METP_t^{\ t+1} &= MEPTP_t^{\ t+1} \times METPSC_t^{\ t+1} = \frac{TG_v(t+1)}{TG_v(t)} \times \frac{\frac{TG_c(t+1)}{TG_c(t)}}{\frac{TG_v(t+1)}{TG_{i,v}(t)}} \\ &= \underbrace{\frac{\frac{GEE_{i,v}(t+1)}{GEE_{i,v}(t+1)}}{\frac{GEE_{i,v}(t)}{CEE_{i,v}(t)}}}_{MEPTP_t^{\ t+1}} \times \underbrace{\frac{\left(\frac{\frac{GE_c(t+1)}{CE_c(t+1)}}{\frac{GE_c(t)}{CE_c(t)}}\right)}{\left(\frac{\frac{GE_v(t+1)}{CE_v(t+1)}}{\frac{GE_v(t)}{CE_v(t)}}\right)}}_{METPSC_t^{\ t+1}} \end{aligned} \tag{27}$$

These indicators carry distinct theoretical meanings and provide valuable insights into different aspects of energy conservation and pollutant mitigation efficiency. Eqs. (26) and (27) discuss each indicator in more detail: $MEEC$ (Malmquist Environmental Efficiency Change) represents catch-up effects and measures the proximity to the production frontier, $METP$ (Malmquist Environmental Technological progress) represents frontier movements. When $MEEC$ is larger than 1, it indicates progress in city-level energy-conservation and pollutant mitigation efficiency. Conversely, a value less than 1 indicates a decline in efficiency.

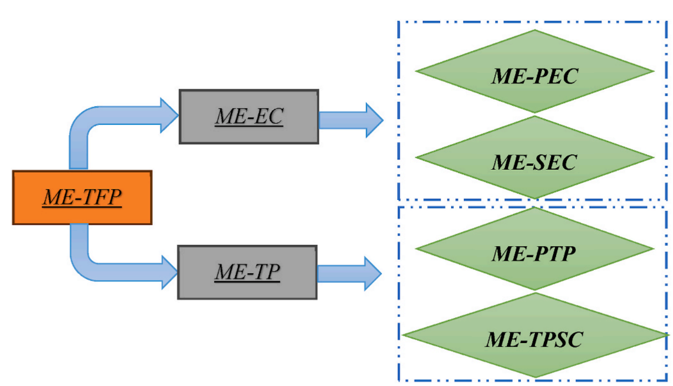

Fig. 4. decomposition of Malmquist productivity index.
Notes: *ME-TFP* denotes the Malmquist environmental total productivity, *GE-TP* is environmental technological progress, *ME-EC* represents Malmquist environmental efficiency change, *ME-PEC* is environmental pure efficiency change, *MS-EC* is the global environmental scale efficiency change, *ME-PTP* is the global environmental pure technological progress, *ME-TPSC* is the environmental technical progress of scale change.

MEEC reflects the extent to which a city is approaching the optimal level of energy efficiency and pollution reduction. *METP* greater than 1 signifies technological progress, indicating that the production frontier is expanding. Alternatively, *METP* less than 1 denotes comparative technological regress, suggesting a deviation from the production frontier. *METP* captures changes in overall productivity and reflects advancements or setbacks in technology and practices. *MEEC* can be further decomposed into two components: *MEPEC* (Malmquist Environmental Pure Efficiency Change) and *MESEC* (Malmquist Environmental Scale Efficiency Change). *MEPEC* captures efficiency changes for different groups operating with various frontiers under variable returns to scale assumptions. *MEPEC* greater than 1 indicates efficiency growth under variable returns to scale assumptions, while a value less than 1 represents a decline. *MESEC* denotes the difference in efficiency change between constant returns to scale and variable returns to scale. *MESEC* greater than 1 signifies efficiency growth from period t to t+1, while a value less than 1 indicates a decline. *MEPTP* represents the technological gap (efficiency under current frontier and global frontier) under the variable returns to scale assumption. *MEPTP*>1 represents technological progress under different frontiers (global and current) and decrease otherwise. *METPSC* is the difference of technological gap between global and current frontiers. *METPSC*>1 denotes technological progress across t-t+1 and decline otherwise.

As the current research focuses on environmental performance, this research decomposes the overall productivity change in Eq. (25) (and its terms in Eqs. (26) and (27)) regarding the input/output variables presented in Eq. (20). On this basis, one can identify the productivity change relevant to energy consumption and capital stock or other variables of interest.

4. Data and empirical analysis

4.1. Data

This study evaluates the environmental performance of cities on the Chinese mainland by employing crucial input-oriented and output-oriented variables. It concentrates on 45 cities comprising the TUAs designated as DMUs. To appraise environmental performance, selected variables encompass energy and capital employment, as well as air pollution indicators. In particular, the industry sector's primary environmental pressures, such as SO_2 and dust (soot) emissions, are incorporated. These parameters facilitate the computation of inefficiency scores and productivity shifts for TUA cities. Concerning input-oriented variables, the investigation accounts for the labor force (*L*), capital stock (*K*), and industrial energy intake (*E*), reflecting the resources and inputs engaged in the industrial ambit. Output variables treat sectoral production value (*Y*) as a positive outcome, emblematic of the economic yield from industrial undertakings. Conversely, SO_2 (*S*) and dust (soot) emissions (*D*) are treated as negative outputs, denoting the environmental toll of industrial operations - specifically air quality degradation. The simultaneous consideration of favorable and unfavorable outputs underscores the economic-environmental nexus, encapsulating the balancing act between industrial output and environmental integrity. In 2012, the Chinese Central Authority promulgated the *Prevention of Air Pollution in Key Regions*, which clustered thirteen key areas for preventing and controlling air pollution. Spatially, this article clusters main TUAs cities (39 cities) into four groups in terms of administrative area and geographical proximity for illustration purposes, including North China urban agglomeration (NCUA), Yangtze River Delta urban agglomerations (YRDA) and Pearl River Delta urban agglomerations (PRDA) and Northwest urban agglomeration (NUA) in turn. To provide a concise presentation of the cities included in the thirteen key areas and four urban agglomerations, the specific details can be found in Appendix A of the Supplementary materials.

The data utilized in this study covers the period from 2006 to 2016 (panel data). The results presented herein are reflective of the period from 2006 to 2016. This interval is commensurate with the most recent data accessible from official governmental records. The sources of the data include the China City-level Statistical Yearbook for variables such as pollutant emissions, labor force, production value in the industrial sector. Energy consumption data for the industrial sector is obtained from either the Statistical Yearbook of the respective city or the website of the City Statistics Bureau. It is important to note that there is a special treatment required for the capital stock variable. In this study, the province-level industrial capital stock is estimated using the perpetual inventory method, as proposed by Ref. [69]. This estimation method allows for the approximation of the capital stock at the provincial level. To allocate the capital stock to the corresponding city, it is distributed based on the production value share of the industrial sector in each city. To ensure consistency, the study deflated both the capital stock and production values of individual cities to constant 2000 prices. This adjustment is made to account for inflation, enabling meaningful comparisons over time. By utilizing these data sources and applying appropriate methodologies for capital stock estimation and deflation, the study aims to provide accurate and reliable insights into the relationship between various variables and environmental performance in the selected cities.

Summary statistics for the inputs/outputs during the sample period are presented in Table 1. In 2016, on average, the industrial sector of 45 key cities used 35.31 million tons of standard coal energy, 0.59 million adult employees, and 32.99 million CNY capital to produce 1112.30 billion CNY outputs, together with 3.87 million tons SO_2 and 3.96 million tons NOx.

4.2. BAM inefficiencies

4.2.1. BAM inefficiencies assuming managerial disposability

The BAM model, described in Equations (11)–(20), was used to calculate the industrial atmospheric environmental inefficiency values for 45 cities in TUAs over the time of 2006–2016. Fig. 5 illustrates the average scores of *GIE* for the four urban agglomeration groups and the 45 cities in TUAs, assuming the use of VRS (Variable Returns to Scale) technology. For brevity, this article only reports results and analysis under VRS technology, unless noted otherwise.

Fig. 5 presents the average *GIE* scores across 2006–2016 in TUAs cities and its principal urban agglomerations. Inefficiency scores associated with the TUAs industrial production value (*Y*, as measured by GDP) is 0.01. According to the additive model assuming managerial disposability, there is limited potential for further growth in production value, considering the current levels of energy use, capital investments, as well as SO_2 and dust (soot) emissions from the industrial sector. Therefore, the focus is on prioritizing structural adjustments, such as increasing the use of cleaner energy sources and advanced technologies, rather than pursuing extensive growth or reducing inputs. Comparatively lower inefficiency scores are observed for industrial capital stock (*K*) and the labor force (*L*). Analyzing the capital stock, with a *GIE* of 0.02 assuming technically managerial disposability, there is evidence of an advanced and reasonable investment pattern in the industrial sector, although there is still room for improvement. As for the industrial labor force, a *GIE* of 0.03 suggests that there is excess or redundant labor in the industrial sector. The average levels of SO_2 emissions (*S*), dust (soot) emissions (*D*), and energy use (*E*) are 0.04, 0.11, and 0.08, respectively, which are relatively high. These three factors together contribute to a total of 0.23 inefficiency score, accounting for 79.31 % of the overall inefficiencies of 0.29. This indicates a significant potential for reducing emissions and introducing cleaner energy inputs in the cities of TUAs. Under the natural disposability assumption, energy conservation performance can be concluded, whereas the performance of advanced technologies and cleaner energy inputs can be obtained assuming managerial disposability. The highest inefficiency scores observed for sulfur dioxide emissions (0.11) may be attributed to lagged policy in China. China has not put regulations on sulfur dioxide emissions until

Table 1
Summary statistics for selected years across 2006–2016.

Variable	Year	Notation	Unit	Max	Min	Mean	S.D
Input							
Industrial energy use	2006	*E*	Million tons standard coal	82.07	4.58	27.57	21.35
	2010			119.53	6.06	34.73	28.10
	2016			144.89	4.20	35.31	31.31
Industrial labor force	2006	*L*	Million active adults	1.23	0.05	0.39	0.28
	2010			1.46	0.08	0.45	0.31
	2016			2.36	0.11	0.59	0.53
Capital	2006	*K*	Million CNY	58.33	1.82	12.47	11.51
	2010			83.17	5.46	23.44	17.53
	2016			88.53	0.31	32.99	20.93
Output							
Industrial SO2 emissions	2006	*S*	Million tons	0.37	4.23	0.13	0.08
	2010			0.50	3.23	0.11	0.09
	2016			0.17	0.00	0.04	0.04
Industrial dust (soot) emissions	2006	*D*	Million tons	0.14	0.00	0.04	0.03
	2010			0.10	0.00	0.03	0.02
	2016			0.45	0.00	0.04	0.07
Industrial production	2006	*Y*	Billion CNY	1846.24	70.00	413.95	381.34
	2010			3016.24	149.13	756.56	622.43
	2016			3340.08	161.49	1112.30	810.80

Notes: The summary statistics in this table are based on a balanced panel of 45 China's cities covering 2006, 2010 and 2016 (total sample size = 473).

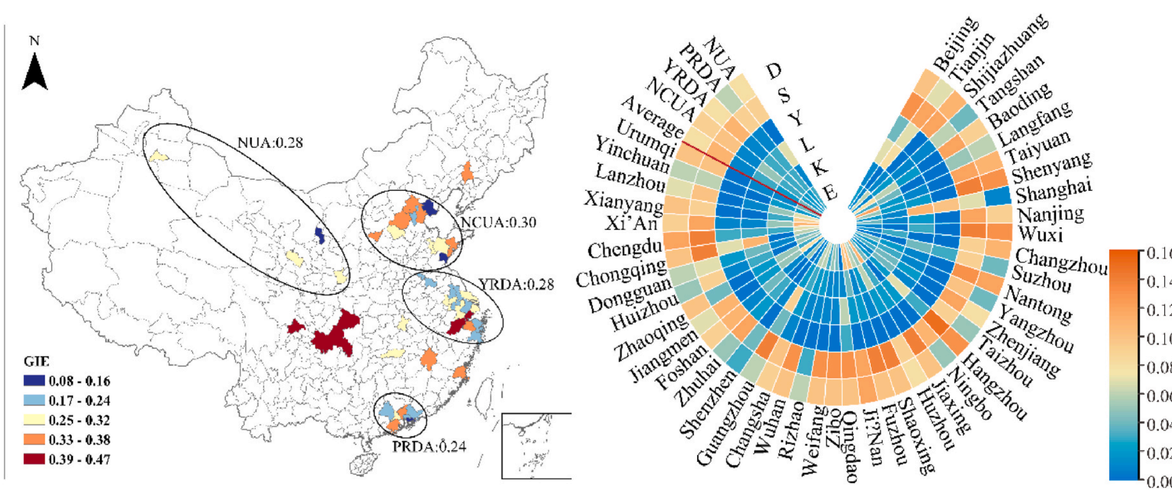

Fig. 5. the average *GIE* scores across 2006–2016 in TUAs cities.
Notes: The left map shows the total *GIE*, and the right figure shows the *GIE* scores associated with individual variables.

2006.

Regarding regional variations, the environmental inefficiency scores related to energy use and pollutant emissions exhibit discrepancies across the cities in the TUAs from 2006 to 2016. Specifically, Ji'Nan, located in NCUA, Hangzhou, and Jiaxing (YRDA), as well as Chongqing and Chengdu in southwest China, have comparatively high inefficiency scores of 0.40, 0.40, 0.47, and 0.41 respectively. To be more specific, Taiyuan has the highest inefficiency score for energy use (0.12), followed by Xi'an and Jiaxing (both 0.11). These cities, when considering managerial disposability for energy use, have potential for adopting advanced technologies and promoting cleaner energy sources. Hangzhou shows the highest inefficiency scores for SO_2 and dust (soot) emissions (0.15 and 0.13 respectively), followed by Wuxi and Shenyang (0.14 and 0.13 respectively). Higher inefficiency scores for the labor force can be observed in Shanghai and Chongqing (both 0.11). Thus, it is crucial for these cities to prioritize the elimination of outdated industrial capacity. It is worth noting that Shenzhen, as one of the first-tier cities, has the lowest inefficiency score (0.08). This indicates that the city has successfully coordinated the integration of cleaner energy inputs, technology upgrades and pollutant emission reduction. By comparison, first-tier cities Beijing and Shanghai have demonstrated limited progress in implementing energy conservation and pollution reduction measures within the sector. Their inefficiency scores remain relatively high at 0.36 and 0.32 respectively. Accordingly, upgrading technologies and transitioning to less polluting energy sources are necessary steps to address these inefficiencies.

Based on the urban agglomeration clusters discussed in Section 4.1, this article conducted further analysis of the disparities in inefficiencies related to energy use and environmental variables. Fig. 6 presents a line chart illustrating the inefficiency disparities of six variables across four urban agglomerations from 2006 to 2016. Among these agglomerations, PRDA demonstrates the best performance across all energy and environmental variables, while NCUA exhibits the worst performance. It is important to note that the distribution pattern of inefficiencies closely resembles that of energy use, industrial production, and industrial pollutant emissions. However, there are variations in the inefficiencies related to the industrial labor force. This suggests a higher level of redundancy in the industrial labor force within NCUA and NUA, with inefficiency scores of 0.05 and 0.07 respectively.

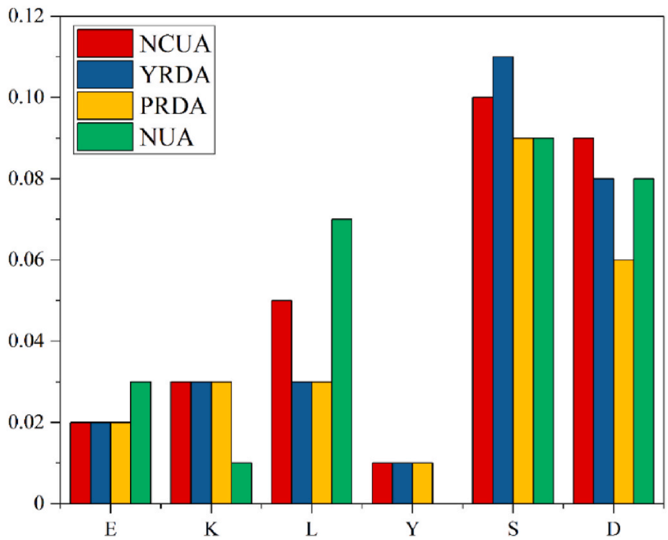

Fig. 6. Inefficiency disparities of six variables in four urban agglomerations, 2006–2016.
Notes: The left map indicates the total *GIE*, and the right shows the *GIE* scores associated with individual variables. *GIE*: global inefficiency. *D*: Industrial dust (soot) emissions; *S*: Industrial SO_2 emissions; *Y*: Industrial production; *L*: Industrial labor force; *K*: Capital stock; *E*: Industrial energy use.

4.3. Environmental productivity

4.3.1. Variable-specific environmental productivity decomposition of global Malmquist Index

Using Eqs. (21)–(26), the productivity change can be estimated. Table 2 shows the environment productivity performance in TUAs cities of China from 2006 to 2016 per annum. The global Malmquist index allows for the decomposition of environmental productivity change into individual variables.

The country-level analysis, represented by the geometric mean in Table 2, demonstrates that between 2006 and 2016, the environmental productivity gain reached 2.6 % per annum. Specifically, the geometric mean for energy consumption and pollutant emissions was 1.8 % (with 0.8 % attributed to other variables), revealing that environmental factors accounted for 69.2 % of the total productivity increase. A noteworthy aspect is the distinct contribution of SO_2 emissions at 0.9 % to productivity enhancement, resonating with the observed high Growth Index of Environmental Productivity (GIE) scores, signifying enhanced improvement prospects. The compulsory SO_2 reduction directives enacted since 2006 have ostensibly been instrumental in achieving these results. In contrast, the higher inefficiency linked with industrial dust (soot) emissions underscores the existing scope for refinement, although their influence on productivity alteration is negligible when juxtaposed with industrial SO_2. The rapid rise in dust (soot) emissions during the 11th Five-Year Plan period, predominantly from the burgeoning of small-scale industrial ventures, accounts for this. Nevertheless, the absence of stringent regulations for dust (soot) has stunted productivity advancements in subsequent phases. It is vital to isolate the origins of these outcomes to inform efficacious policy interventions. Lastly, regarding production values, the latitude for enhancement in production amplification is restrained. Its impact on productivity has demonstrated minimal fluctuation. Ascertain the contributory factors to this consistency is imperative in devising policies that maximize efficiency.

When analyzing productivity change at the regional level, distinct patterns can be observed. Negative productivity change is evident in Dongguan (−2.0 %), Suzhou (−1.9 %), Foshan (−1.1 %), and Wuxi (−0.2 %). It is worth noting that their poor performance is primarily attributed to their industrial energy use and industrial capital inputs, with scores of −2.0 % for Dongguan, 0.0 % for Suzhou, −2.0 % for Foshan, and −0.9 % for Wuxi, respectively. Therefore, considering the managerial disposability for energy (*E*) and capital (*K*), promoting cleaner energy sources and adjusting investment structure will play a crucial role in enhancing productivity in these regions. Additionally, stricter regulations should be imposed on sulfur emissions (*S*) in Dongguan (−0.5 %). Conversely, the highest productivity growth is observed in Changsha (5.6 %), Urumqi (5.5 %), Xi'An (5.5 %), Taizhou (5.4 %), and Yinchuan (5.4 %). Importantly, the contribution of industrial energy use to overall productivity growth remains relatively stagnant in these cities, with scores of 0.3 % for Xi'An, 0.2 % for Urumqi, 0.1 % for Changsha, 0.0 % for Taizhou, and 0.0 % for Yinchuan. By comparison, SO_2 and dust (soot) emissions make substantial contributions to overall productivity growth, with scores of 3.6 % for *S* and *D* in Changsha, 3.4 % for *S* and *D* in both Taizhou and Yinchuan, and 3.3 % for both Xi'An and Urumqi. Therefore, policy options should prioritize addressing

Table 2
the average *GE-TFP* values for TUAs cities, 2006–2016.

City (region)	*GE-TFP*[a]	*E*	*K*	*L*	*Y*	*S*	*D*
Beijing	1.049	1.001	1.014	1.000	1.009	1.017	1.008
Tianjin	1.017	1.017	1.000	1.001	0.991	1.008	1.000
Shijiazhuang	1.045	1.016	1.006	1.005	1.001	1.014	1.003
Tangshan	1.018	1.000	1.006	1.002	1.001	1.014	0.996
Baoding	1.020	1.000	1.000	1.010	1.000	1.002	1.007
Langfang	1.001	1.001	1.001	0.995	1.000	1.002	1.002
Taiyuan	1.053	1.018	1.006	1.006	1.001	1.011	1.009
Shenyang	1.014	1.000	1.000	1.004	1.000	1.004	1.006
Shanghai	1.039	1.000	1.018	0.997	1.018	1.012	0.992
Nanjing	1.051	1.018	1.006	1.006	1.000	1.012	1.008
Wuxi	0.998	1.000	0.991	1.000	0.999	1.009	1.000
Changzhou	1.031	1.000	1.000	1.012	1.000	1.016	1.003
Suzhou	0.987	1.000	1.000	0.994	0.989	1.005	0.999
Nantong	1.034	1.000	0.998	1.015	1.000	1.006	1.015
Yangzhou	1.053	1.000	1.000	1.018	1.000	1.018	1.016
Zhenjiang	1.039	1.000	1.000	1.018	1.000	1.013	1.007
Taizhou	1.054	1.000	1.000	1.018	1.000	1.018	1.016
Hangzhou	1.011	1.018	1.002	1.007	0.999	0.994	0.991
Ningbo	1.025	1.009	0.998	1.004	1.000	1.014	1.000
Jiaxing	1.016	1.012	1.002	1.010	1.000	0.996	0.995
Huzhou	1.014	1.000	1.000	1.011	1.000	1.001	1.002
Shaoxing	1.019	1.000	1.000	1.012	1.000	1.002	1.005
Fuzhou	1.013	1.000	0.998	1.012	1.000	1.003	1.000
Ji'Nan	1.008	1.000	1.000	1.006	1.000	1.004	0.998
Qingdao	1.053	1.018	1.016	1.000	1.008	1.010	1.000
Zibo	1.020	1.000	0.996	1.005	1.000	1.014	1.004
Weifang	1.036	1.000	1.001	1.014	1.000	1.017	1.003
Rizhao	1.012	1.000	1.000	1.007	1.000	1.006	0.999
Wuhan	1.034	1.018	1.002	1.010	1.000	1.010	0.994
Changsha	1.056	1.001	1.000	1.018	1.000	1.018	1.018
Guangzhou	1.047	1.000	1.002	1.010	1.000	1.018	1.016
Shenzhen	1.028	1.000	1.001	1.000	1.002	1.017	1.009
Zhuhai	1.026	1.000	0.999	1.007	1.000	1.018	1.002
Foshan	0.989	0.998	0.982	1.005	0.992	1.006	1.006
Jiangmen	1.012	1.000	1.000	1.009	1.000	1.000	1.003
Zhaoqing	1.012	1.000	1.001	1.008	1.000	1.001	1.002
Huizhou	1.023	1.000	0.997	1.008	1.000	1.010	1.008
Dongguan	0.980	0.998	0.982	1.018	0.984	0.995	1.004
Chongqing	1.006	1.000	1.000	1.006	1.003	0.996	1.000
Chengdu	1.026	1.010	1.002	1.013	0.994	0.999	1.007
Xi'An	1.055	1.003	1.000	1.018	1.000	1.017	1.016
Xianyang	1.044	1.004	1.001	1.010	1.000	1.013	1.015
Lanzhou	1.022	1.000	1.000	1.007	1.000	1.009	1.005
Yinchuan	1.054	1.000	1.000	1.018	1.000	1.018	1.016
Urumqi	1.055	1.002	1.000	1.018	1.000	1.017	1.016
Geometric mean	1.026	1.004	1.001	1.008	1.000	1.009	1.005
NCUA	1.028	1.006	1.004	1.004	1.001	1.010	1.002
YRDA	1.026	1.004	1.001	1.009	1.000	1.008	1.004
PRDA	1.015	1.000	0.995	1.008	0.997	1.008	1.006
NUA	1.046	1.002	1.000	1.014	1.000	1.015	1.014

[a] Noteworthy, the overall *GE-TFP* is obtained from the production values of individual variables and then averaged. In addition, *GE-TFP*>1 (*GE-TFP*<1) indicates productivity growth (decline).

industrial energy use variables to further enhance productivity gains.

Region-wise, different patterns in the overall productivity change can be found. For example, negative productivity change is observed for Dongguan (−2,0 %), Suzhou (−1.9 %), Foshan (−1.1 %), and Wuxi (−0.2 %). Note that their worse performance is associated with their industrial energy use and industrial capital inputs (−2.0 %, 0.0 %, −2.0 % and −0.9 % for Dongguan, Suzhou, Foshan and Wuxi resp.). Thus, considering the setting of managerial disposability for the *E* and *K*, the promotion of further cleaner energy and investment structure adjustment plays a leading role in their productivity gains. Also, *S* for Dongguan (−0.5 %) should receive further stringer regulations. On the contrary, the highest productivity growth is observed for Changsha (5.6 %), Urumqi (5.5 %), Xi'An (5.5 %), Taizhou (5.4 %) and Yinchuan (5.4 %). Noteworthy, the contribution of industrial energy use to the overall productivity growth remains stagnant in the cities (0.3 %, 0.2 %, 0.1 %, 0.0 % and 0.0 % for Xi'An, Urumqi, Changsha, Taizhou and Yinchuan resp.). In contrast, industrial SO_2 emissions and industrial dust (soot) emissions contribute most to the overall productivity growth (3.6 % for *S* and *D* in Changsha, 3.4 % for *S* and *D* in both Taizhou and Yinchuan for *S* and *D,* 3.3 % for both Xi'An and Urumqi, resp.). Therefore, policy options should be partial to industrial energy use variables in the latter direction for further gains.

Further on, certain differences can be observed. For example, the highest productivity growth is found in NUA (4.6 %), whereas smooth productivity change is observed in PRDA (1.5 %). The productivity changes relevant to industrial energy use in NCUA and YRDA is 0.6 % and 0.4 % resp., which exceeds that in PRDA and NUA (0.0 % and 0.2 % resp.). The productivity change associated with industrial dust (soot) emissions in NCUA is 0.2 %, much lower than other urban agglomerations. Thus, due attention to these variables is urgent for policy regulations. Note that NUA has comparatively lower efficiency scores and substantial productivity gains, whereas PRDA holds relatively higher efficiency scores and slower productivity change (0.72 and 4.6 % for NUA resp.; 0.76 and 1.5 % for PRDA resp.). Efficiency scores is obtained from 1-*IE*.

4.3.2. Variable-specific decomposition of environmental efficiency change and technological change

The productivity change under the GVMI framework is further broken down concerning its sources, i.e., efficiency change (*GE-EC*) and technical progress (*GE-TP*) effects. This analysis allows us to identify the key factors driving environmental productivity change across cities in mainland China's TUAs. To uncover these driving factors, this article employs the decomposition method outlined in Eq. (24). Figs. 7 and 8 display the average annual productivity growth rates resulting from efficiency change and technical progress, and further attribute this growth to individual variables.

The average annual *MEEC* (Malmquist Environmental Efficiency Change) for the TUAs cities from 2006 to 2016 is −0.2 %. However, when considering the *MEEC* associated with two environmental variables, it is observed to be 0.2 %. This indicates that efficiency gaps, particularly in pollutant emissions, tend to shrink over time. Therefore, the catch-up effects observed in these cities are primarily driven by improvements in pollutant emissions inefficiency. Conversely, the negative efficiency changes related to energy use and capital stock, both at −0.2 %, suggest that backward industrial capacity has significantly hindered overall growth. Among the cities analyzed, Suzhou (−6.4 %), Dongguan (−5.5 %), Foshan (−4.5 %), and Wuxi (−4.4 %) exhibit the highest decline rates. The decline in *MEEC* in these cities can be attributed to both industrial energy use and pollutant emissions, with scores of −2.8 %, −2.2 %, −2.0 %, and −1.3 % for Suzhou, Dongguan, Foshan, and Wuxi, respectively. In contrast, Xi'An (4.7 %), Qingdao (4.3 %), Changsha (4.3 %), and Guangzhou (4.0 %) demonstrate relatively robust annual gains in *MEC*. These cities have successfully improved the use of cleaner energy in their industries, enhanced environmental performance, and eliminated backward industrial capacity. When considering urban agglomerations, minor gains in technical *MEEC* are observed for NCUA (0.1 %), while significant gains are observed for NUA (0.8 %). However, both YRDA and PRDA experience a steep decline in technical efficiency, with scores of −0.8 % for both regions. Notably, substantial gains in technical efficiency change related to the two environmental variables are observed for NCUA (0.2 % for S and D) and NUA (0.4 % for S and D). However, industrial energy use in NCUA (−0.1 %) and PRDA (−0.4 %) hampers the overall growth of *MEEC*.

The average annual technical progress associated with the industrial energy use, industrial capital inputs, industrial labor force, industrial production and industrial environmental pollution are 2.9 %. This indicates productivity gains (2.6 %) are mainly driven by technical progress. Frontier shifts relevant to industrial energy use, industrial labor force, and industrial sulfur dioxide emissions contribute to overall environmental technological growth by 1.7 %. Though significant differences exist among all input-oriented and output-oriented variables, their frontier movements contribute to the gains of overall technical progress. Mild growth in technical progress is observed for Zhuhai (0.6 %), whereas Shanghai (7.8 %), Lanzhou (6.1 %), Suzhou (5.5 %) and Urumqi (5.5 %) enjoy the highest levels of frontier shifts. Specifically, *E*, *K* and *Y* in Shanghai (both 2.0 %), *Y*, *S* and *D* in Lanzhou (2.5 %, 1.8 % and 1.6 % resp.), *K, S* and *E* in Yinchuan (1.8 %, 1.4 % and 1.3 % resp.) and *K*, *S* and *D* in Urumqi (1.8 %, 1.7 % and 1.6 % resp.) contribute most the overall technical progress. As for four urban agglomerations,

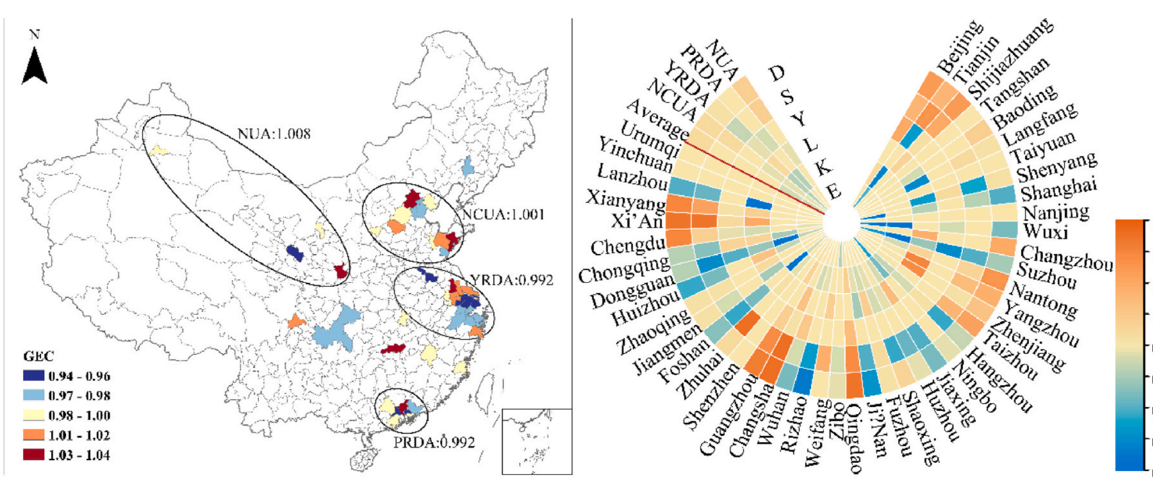

Fig. 7. the average efficiency change (GE-*EC*) across 2006–2016 in TUAs cities.
Notes: The left map presents the total *GEC*, and the right figure shows the *GEC* scores associated with individual variables.

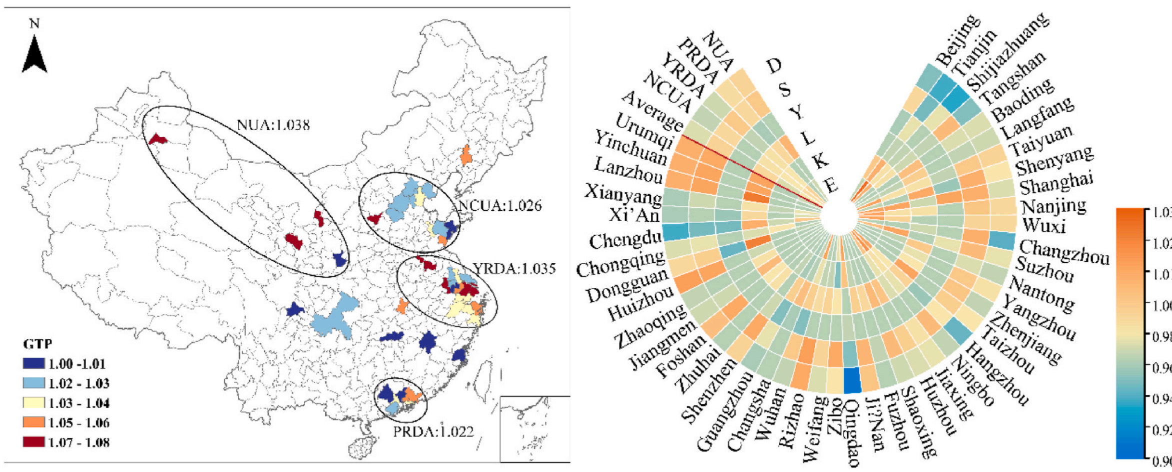

Fig. 8. the average environmental technological progress (*TP*) across 2006–2016 in TUAs cities.
Notes: The left map presents the total *GTP*, and the right figure shows the *GTP* scores associated with individual variables.

positive technical progress prevails through disparities. The NUA demonstrates the highest environmental productivity growth at 3.8 % per annum, closely followed by the YRDA at 3.5 % per annum. In contrast, the NCUA and PRDA exhibit only marginal technological progress, with rates of 2.6 % and 2.2 % per annum, respectively. Specifically, the contribution to the overall technical progress of *E* in NCUA (0.7 %) and YRDA (0.9 %), *S* for NUCA, YRDA, PRDA and NUA (0.8 %, 1.1 %, 0.8 % and 1.1 % resp.) is prominent. Lower values of *MTP* associated with industrial dust (soot) emissions are observed, which corresponds to the lack of regulations for practically mitigating dust emissions.

4.4. Source control or end-of-pipe control

The assumption of managerial disposability permits the decomposition of productivity into different sources, including industrial energy consumption and capital inputs (*E* and *K*), as well as pollutant emission variables (*S* and *D*). Recognizing the significant role of *S* and *D* in driving productivity change, along with the managerial setting of *E* and *K*, it is essential to identify the most effective channels through which cities can enhance their efficiency and productivity. Therefore, we focus on comparing the contributions associated with energy consumption (*E*) and capital input (*K*) from an input perspective, and emissions-related variables (*S* and *D*) from an output perspective to devise the most effective strategies for promoting efficiency and productivity in these cities. Table 3 provides a detailed classification of the results. Regions I and II demonstrate productivity gains in selected input-oriented variables (*E* and *K*) and output-oriented variables (*S* and *D*). In region I, the productivity growth associated with *E* and *K* exceeds that of *S* and *D*. Consequently, long-term efforts should prioritize emission reduction and end-of-pipe control. Conversely, in region II, authorities should prioritize cleaner energy promotion and strengthen source control policies. Region III shows positive productivity gains in *E* and *K*, while negative productivity gains are observed for *S* and *D*. Therefore, cleaner energy promotion has performed better than emission reduction in this region. Strict implementation of end-of-pipe treatment is necessary. In contrast, region IV exhibits negative (or zero) productivity gains in *E* and *K*, but positive productivity gains in *S* and *D*. Thus, it is crucial to focus on preventing, curbing, and controlling air pollution in this region. Region V stands out with negative (or zero) productivity gains in both *E* and *K*. Cities in this region require a win-win strategy that promotes cleaner energy and reduces emissions simultaneously.

Table 3
Classification of 45 TUAs cities across 2006–2016.

Type	Description	Region
I	$METFP_E \times METFP_K > METFP_S \times METFP_D > 1$	Tianjin, Shijiazhuang, Taiyuan, Shanghai, Nanjing, Qingdao, Wuhan and Chengdu (8 cities)
II	$1 < METFP_E \times METFP_K < METFP_S \times METFP_D$	Beijing, Tangshan, Langfang, Ningbo, Weifang, Changsha, Guangzhou, Shenzhen, Zhaoqing, Xi'An, Xianyang and Urumqi (12 cities)
III	$METFP_E \times METFP_K > 1$ $METFP_S \times METFP_D \leq 1$	Huangzhou and Jiaxing (2 cities)
IV	$METFP_E \times METFP_K \leq 1$ $METFP_S \times METFP_D > 1$	Baoding, Nantong, Shenyang, Wuxi, Changzhou, Suzhou, Yangzhou, Taizhou, Shaoxing, Fuzhou, Huzhou, Ji'Nan, Zibo, Rizhao, Zhuhai, Foshan, Jiangmen, Huizhou, Lanzhou Yinchuan and Zhenjiang (21 cities)
V	$METFP_E \times METFP_K \leq 1$ $METFP_S \times METFP_D \leq 1$	Dongguan and Chongqing (2 cities)

5. Robustness

Due to the presence of various alternative production technologies and the selections for pollutant emissions, these estimates may be subject to bias. To address this concern, this work have devised two alternative strategies to verify the robustness of the article. First, this work has taken a separate approach to analyze the emissions of SO_2, dust (soot), and CO_2 individually. Further, this article simultaneously considers these pollutant emissions as undesirable outputs to compare the results. By considering these pollutants as outputs, this work aims to assess the reasonableness of the output variables selected in the baseline estimates. Additionally, in response to the suggestion provided by the reviewer, this article has incorporated more recent approaches for measuring environmental efficiency. Specifically, this work has employed the by-production technology to test the robustness of the BAM model, assuming managerial disposability.

5.1. Alternative outputs selection

This work presents four alternative specifications for assessing the robustness of findings in this article, as summarized in Table 4. In columns (1) and (2), this research focuses on SO_2 emissions as the sole undesirable output. Column (1) reports the environmental inefficiency, while column (2) provides the ranking for the overall *GIE*. To maintain conciseness, this article presents the overall *GIE* scores in main text, while the inefficiencies for individual variables are provided in the Online Appendix F. Columns (3) and (4) examine dust (soot) emissions as the undesirable output, with column (3) displaying the *GIE* and column (4) presenting its corresponding ranking. Similarly, columns (5)

Table 4
the average *GIE* values for TUAs cities using various undesirable outputs, 2006–2016.

City	*S*	*Rank*	*D*	*Rank*	*C*	*Rank*	*SDC*	*Rank*
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Beijing	0.34	35	0.28	26	0.39	38	0.40	28
Tianjin	0.37	37	0.27	24	0.40	41	0.48	40
Shijiazhuang	0.27	15	0.25	19	0.34	27	0.47	37
Tangshan	0.23	10	0.12	2	0.05	3	0.04	2
Baoding	0.33	34	0.34	40	0.27	18	0.38	24
Langfang	0.15	2	0.24	17	0.28	22	0.32	18
Taiyuan	0.32	31	0.34	41	0.01	1	0.04	1
Shenyang	0.31	27	0.32	35	0.43	44	0.54	45
Shanghai	0.44	44	0.30	32	0.39	37	0.35	23
Nanjing	0.27	16	0.19	6	0.27	20	0.28	15
Wuxi	0.28	20	0.25	20	0.43	43	0.52	44
Changzhou	0.16	4	0.30	31	0.43	42	0.51	43
Suzhou	0.29	22	0.14	4	0.35	29	0.32	16
Nantong	0.27	17	0.28	27	0.40	40	0.50	41
Yangzhou	0.21	8	0.20	7	0.39	36	0.42	34
Zhenjiang	0.25	13	0.28	28	0.35	30	0.42	35
Taizhou	0.17	6	0.23	13	0.36	31	0.40	30
Hangzhou	0.37	38	0.31	33	0.38	35	0.46	36
Ningbo	0.31	26	0.13	3	0.27	17	0.18	9
Jiaxing	0.39	41	0.32	38	0.24	15	0.33	20
Huzhou	0.28	21	0.33	39	0.26	16	0.33	19
Shaoxing	0.29	24	0.28	25	0.39	39	0.48	39
Fuzhou	0.38	39	0.32	36	0.28	21	0.40	29
Ji'Nan	0.35	36	0.36	44	0.23	14	0.34	21
Qingdao	0.32	32	0.24	18	0.36	32	0.40	31
Zibo	0.31	29	0.21	8	0.30	23	0.41	32
Weifang	0.27	18	0.23	16	0.37	34	0.47	38
Rizhao	0.15	3	0.22	11	0.15	7	0.13	7
Wuhan	0.32	30	0.23	15	0.36	33	0.42	33
Changsha	0.26	14	0.27	23	0.32	26	0.39	27
Guangzhou	0.39	43	0.26	21	0.35	28	0.38	25
Shenzhen	0.23	9	0.06	1	0.27	19	0.12	6
Zhuhai	0.30	25	0.26	22	0.07	4	0.11	5
Foshan	0.25	12	0.23	14	0.44	45	0.51	42
Jiangmen	0.33	33	0.31	34	0.18	12	0.23	11
Zhaoqing	0.17	5	0.34	42	0.13	6	0.14	8
Huizhou	0.31	28	0.18	5	0.09	5	0.05	4
Dongguan	0.24	11	0.22	12	0.30	24	0.32	17
Chongqing	0.49	45	0.40	45	0.15	8	0.25	13
Chengdu	0.39	42	0.34	43	0.31	25	0.39	26
Xi'An	0.38	40	0.32	37	0.17	9	0.20	10
Xianyang	0.27	19	0.29	30	0.17	10	0.28	14
Lanzhou	0.29	23	0.28	29	0.18	11	0.25	12
Yinchuan	0.14	1	0.21	9	0.02	2	0.05	3
Urumqi	0.20	7	0.21	10	0.20	13	0.34	22
Correlation	0.81	0.85	0.81	0.77	0.17	0.14	0.39	0.27

and (6) consider CO_2 emissions as the undesirable output, with column (5) showing the *GIE* and column (6) indicating its ranking. When all three emissions are treated as undesirable outputs, the *GIE* scores are reported in column (7), while column (8) introduces their respective rankings. In the last row of the table, this article provides the correlation coefficient, comparing it with baseline *GIE* and its ranking. These results demonstrate the robustness and comparability of estimates across the various alternative specifications.

5.2. The by-production technology

The measurement of environmental efficiency in this paper is based on the premise that bad outputs are treated as inputs. However, there are more recent approaches for the measurement of environmental efficiency, such as the by-production model [18,70]. To verify whether these results are robust against more advanced approaches, Table 5 compares the inefficiency scores between natural/managerial production technology (Column 1) and by-production technology (Column 3). Their rankings for each city are provided in Column 2 and 4, respectively. For brevity, this article does not report detailed formulas, which can be found in Ref. [70]. The difference lies in that they employ directional function while the BAM is employed in this article. The correlation coefficients for both inefficiency scores and rankings are comparable, indicating that the by-production technology also adds credibility to this article.

6. Conclusion and policy implications

6.1. Conclusion

This paper leverages the advantages of disposability in relation to input-oriented and output-oriented variables and applies appropriate disposability to individual variables. Additionally, this research introduces a global Malmquist variable-specific index (GMVI) based on the additive BAM model. Empirically, this study analyzes the environmental performance of 45 cities in TUAs from 2006 to 2016. Environmental inefficiency scores and productivity changes are computed for individual variables. Decomposition analysis for the environmental productivity growth is conducted to identify the effective regulatory pathways for TUAs cities, specifically in terms of source control or end-of-pipe control. The BAM approach discloses that from 2006 to 2016, the predominant contributors to inefficiency in TUAs cities were industrial

Table 5
the average *GIE* values for TUAs cities using various production technologies, 2006–2016.

City	*Baseline-VRS*	*Rank*	*By-production VRS*	*Rank*
	1	*2*	*3*	*4*
Beijing	0.36	37	0.22	33
Tianjin	0.34	34	0.11	21
Shijiazhuang	0.31	25	0.26	36
Tangshan	0.15	3	0.34	40
Baoding	0.36	38	0.26	37
Langfang	0.18	5	0.05	15
Taiyuan	0.38	40	0.61	45
Shenyang	0.36	36	0.22	32
Shanghai	0.32	27	0.00	1
Nanjing	0.28	17	0.15	28
Wuxi	0.32	28	0.11	22
Changzhou	0.24	12	0.02	9
Suzhou	0.21	8	0.04	13
Nantong	0.32	30	0.09	19
Yangzhou	0.20	7	0.03	11
Zhenjiang	0.29	18	0.08	17
Taizhou	0.20	6	0.03	10
Hangzhou	0.40	43	0.21	30
Ningbo	0.22	9	0.20	29
Jiaxing	0.40	42	0.24	35
Huzhou	0.30	23	0.08	18
Shaoxing	0.34	33	0.12	24
Fuzhou	0.37	39	0.11	20
Ji'Nan	0.40	44	0.21	31
Qingdao	0.33	32	0.13	25
Zibo	0.29	19	0.14	26
Weifang	0.29	20	0.12	23
Rizhao	0.15	2	0.00	1
Wuhan	0.32	29	0.43	43
Changsha	0.30	24	0.14	27
Guangzhou	0.35	35	0.00	1
Shenzhen	0.08	1	0.00	1
Zhuhai	0.27	16	0.01	7
Foshan	0.27	15	0.01	6
Jiangmen	0.33	31	0.02	8
Zhaoqing	0.24	11	0.00	1
Huizhou	0.23	10	0.05	16
Dongguan	0.24	13	0.03	12
Chongqing	0.47	46	0.36	41
Chengdu	0.41	45	0.38	42
Xi'An	0.38	41	0.44	44
Xianyang	0.31	26	0.24	34
Lanzhou	0.30	22	0.33	38
Yinchuan	0.16	4	0.04	14
Urumqi	0.27	14	0.34	39
Correlation	–	–	0.51	0.54

energy use (0.04), industrial sulfur dioxide emissions (0.11), and dust (soot) emissions (0.08). Combined, these factors constitute 79.31 % of the aggregate inefficiency score (0.29). Considering urban agglomerations, the PRDA in South China is marked by notable inefficiency with a score of 0.24, while the NCUA exhibits the most substantial deficiency in environmental performance with a score of 0.30.

The average annual productivity gains in the industrial sector observed for TUAs cities across 2006–2016 are 2.6 %. Results suggest the joint contribution of industrial energy use and pollutants were 1.8 % (with the performance of sulfur dioxide emissions prominent, 0.9 %). As regards the source-decomposition, productivity growth is mainly driven by technical progress. Specifically, the overall average catch-up rate was −0.2 % in China's TUAs but lagged behind frontier movements (*TP*, 2.90 %). This suggests frontier shifts are superior to catch-up effects. Furthermore, the technical productivity change tended to stagnate (0, on average), indicating that production possibilities are limited with fixed inputs and outputs. This indicates further structural shifts are required in the economies of China's 45 TUAs from 2006 to 2016 to increase production. The results show that the catch-up effect (*EC*, −0.2 %) in TUAs cities across 2006–2016 is negative, which can be attributed to industrial energy use (*E*) and industrial capital inputs (*K*) (both −0.2 %). Thus, technology transfer from the frontier to lagged regions is encouraged for *E* and *K*. In addition, efficiency change (*EC*) can further be broken into pure efficiency change (*PEC*) and scale efficiency change (*SEC*). As for source-decomposition, *PEC* contributes to the *EC* gains (0.3 %), whereas *SEC* pushes the *EC* regression (−0.6 %). The results show that frontier movement (*TP*) in TUAs cities across 2006–2016 is 2.9 %, which can be attributed to industrial SO_2 (*E*, 0.9 %) and industrial labor force (*L*, 0.8 %). Rapid technical progress can be attributed to pure technical progress (*PTP*, 2.2 %), exceeding scale change of environmental technological progress (*SCTP*, 0.6 %).

Regarding regional analysis, NUA demonstrates significant productivity gains of 4.6 %, while PRDA shows comparatively milder productivity growth of 1.5 %. When considering efficiency change (*EC*), NUA continues to lead with gains of 0.8 %, while both YRDA and PRDA lag with declines of −0.8 %. Notably, frontier shifts in NUA and YRDA are particularly prominent, with improvements of 3.8 % and 3.5 % respectively. The results indicate that YRDA and PRDA, as the most developed urban agglomerations, have improved their environmental productivity mainly through expanding the frontier (technological innovation). Conversely, NUA, as the least developed urban agglomeration, relies on catch-up effects. The positive *EC* in NUA suggests the existence of slight efficiency diffusion and spillover, but its further environmental productivity gains are constrained by high total pollution. By comparing productivity growth under the constraints of energy- and emission-related variables, this work has clustered the 45 cities into five groups and assigned source or end-of-pipe control policies for each group. Furthermore, it is important to note that the methodology introduced in the paper has certain limitations. The separate consideration of natural and managerial disposability for input-oriented variables, particularly for the labor force, may lead to an overestimation of the *GIE* scores and productivity gains. Similarly, managerial disposability could underestimate the *GIE* scores and productivity growth associated with industrial energy use and industrial capital inputs. These shortcomings will be the focus of our future research.

The findings presented in this study hold significant implications for industry, policymakers, and the advancement of UN SDGs related to sustainable cities and climate action (e.g., SDG 11 & 13). The highlighted need for technology transfer, particularly in renewable energy and capital investment, presents a clear path for industry regulation and policy interventions. Governments and regulatory bodies can incentivize such transfers through targeted subsidies, tax breaks, and collaborative programs between developed and developing regions within the TUAs. Furthermore, the study's quantification of the environmental productivity gains achievable through improved energy efficiency and emissions reductions (e.g., SO2) provides concrete targets for policymakers. By setting stringent yet achievable environmental standards and promoting their enforcement, policymakers can foster a more sustainable and efficient industrial sector across the TUAs, ultimately contributing to broader 'Carbon Peak' and 'Carbon Neutrality' goals while promoting responsible ESG practices."

6.2. Policy implications

Heterogeneous environmental performance has been observed among the 43 selected cities. To derive tailored policy implications, this work has categorized all regions into four urban agglomerations. The North China Urban Agglomeration is distinguished by the poorest environmental performance, which has been attributed to obsolete production capacities [71]. Prioritizing the resolution of dust (soot) pollution through an enhanced joint control system within these cities is imperative, given its relative underperformance. From the standpoint of individual variables, noteworthy inefficiencies have been identified in SO_2 emissions, largely owing to postponed enforcement of national regulations targeting this contaminant. Despite the introduction of the Rules on the Prevention and Control of Air Pollution within our sample, aiming to diminish coal consumption and regulate emissions, there remains a margin for advancement. The handling of NOx emissions also requires additional regulation, as their performance lags behind other factors. This research suggests that environmental performance shows improvement in later stages as opposed to early stages. Consequently, rigorous application of sustainability objectives is compulsory, especially in locales such as Taiyuan City, to elevate the general environmental standard. Moreover, collaborative inter-regional efforts are vital to the efficacy of policies intended to mitigate atmospheric pollution, recognizing that distinct pollution profiles exist within the four urban agglomerations. In the North China Urban Agglomeration, fostering the use of clean industrial energy and improving workforce quality are essential. For the Yangtze River Delta and Pearl River Delta Agglomerations, emphasis should be placed on cultivating a sustainable investment framework and fortifying labor quality during advanced stages. Consequently, our findings indicate that end-of-pipe measures surpass source control in bolstering environmental performance at the city level across these urban clusters.

Drawing on the analysis of *GE-TFP* performance in relation to inputs (energy consumption and industrial investment) and outputs (SO2 emissions and dust (soot)), this work has categorized all regions into five distinct regulatory trajectories (as shown in Table 3): Type I regions showcase growth in environmental performance across both inputs and outputs, with a notable lead in input metrics. Notable cities like Shanghai, Nanjing, and Qingdao exemplify this category and can act as benchmarks for enhancing input performance via proactive source control measures. Type II regions similarly exhibit an upsurge in productivity concerning both inputs and outputs—but with a pronounced edge in output metrics. For these regions, it is essential to highlight the importance of end-of-pipe regulations by taking a cue from exemplary models. A case in point is Beijing's adoption of the Regulations on the Prevention and Control of Air Pollution in 2013, which has focused on total emissions control and consequently led to commendable advances in environmental performance. Conversely, Types III, IV, and V depict various forms of waning environmental performance. Type III cities should align their environmental policymaking with Type II's successful strategies, whereas Type IV should look to replicate Type I's effective measures. Type V regions, which suffer from stagnated or regressive productivity in both inputs and outputs, demand a thoroughgoing policy overhaul that equally emphasizes cleaner energy adoption and emission curtailment, ensuring balanced attention to both end-of-pipe and source control tactics. The decomposition analysis yields actionable insights for cities to select the most efficacious route toward environmental enhancement. For regions recording positive technical evolution but a decline in environmental efficiency, this work advocates for the emulation of superior management practices and the adoption of technology transfer in clean production from more progressive areas. Such integration is anticipated to substantively boost environmental performance. Conversely, for regions encountering a regression in technical progression despite gains in environmental efficiency, emphasis should be placed on acquiring desulfurization and denitrification systems, along with cleaner production technologies. Implementing these initiatives is expected to stimulate further environmental performance improvement.

To broaden the implications of this work beyond local spheres, this article proposes the development of a universal analytical framework that can be adapted to varying geographic scenarios. Envisaging future research that encompasses a multitude of cities internationally, further analysis can perform a holistic evaluation of environmental efficiency and performance on a global stage. By calculating environmental inefficiency scores and monitoring changes in environmental productivity for each variable within an expansive range, this study has the potential to set a worldwide standard for gauging environmental efficiency. A meticulous decomposition analysis of productivity changes will streamline the identification of the most impactful regulatory approaches, primarily deciding between source control and end-of-pipe solutions, for a global constituency. Cities around the planet are grappling with distinct environmental challenges; hence, pinpointing the most effective regulations must be tailored to the intricate nuances of various urban ecosystems and governance structures. For such a universal exploration to be feasible, forging collaborations with international bodies and leveraging comprehensive global datasets will be indispensable. This concerted effort is anticipated to fortify our research outcomes with practical implications for environmental policymaking and performance metrics, casting influence not just within Targeted Urban Areas (TUAs) but also catalyzing eco-conscious urban development practices on a worldwide scale.

6.3. Limitations

Findings in this work appear to be intricately linked with various exogenous policy shocks, such as regional environmental regulations, mandatory environmental information disclosures, and international trade conflicts. To ascertain the robustness of these associations, future analyses should endeavor to construct an expansive framework that encapsulates these external uncertainties. With respect to data sampling, extending our analysis to encompass global manufacturing firms could yield additional valuable insights. Furthermore, considering the numerous enterprises that have adopted pollution mitigation measures, it is imperative to devise a model capable of integrating the treatment strategies employed by these firms, which should be a pivotal element of subsequent research efforts.

CRediT authorship contribution statement

Xiaodong Chen: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Zhuang Miao:** Data curation, Project administration. **Ge Wu:** Data curation, Project administration. **Pengyu Zhu:** Data curation, Project administration.

Declaration of Competing interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2024.114776.

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