Energy Efficiency (2023) 16:23
https://doi.org/10.1007/s12053-023-10105-9

ORIGINAL ARTICLE

Check for updates

Eco-efficiency evaluation and productivity change of Yangtze River Economic Belt in China: a meta-frontier Malmquist-Luenberger index perspective

Yuhong Wang · Youyang Ren · Dongdong Wu · Wuyong Qian

Received: 7 March 2021 / Accepted: 11 March 2023

Abstract Using city-level panel data for 2008–2017, this paper uses the super-efficiency slack-based measure (SBM) model to measure the eco-efficiency in the Yangtze River Economic Belt (YREB). Based on the group-frontier Malmquist-Luenberger (GML) productivity index and meta-frontier Malmquist-Luenberger (MML) productivity index, the driving forces of the total factor ecological productivity are analyzed. The results show the following: (1) The overall eco-efficiency in the YREB was 0.599 and remained stable during the study period, showing only a fluctuating and slightly upward trend. (2) The annual average GML index was 1.091 in the YREB, and the main reason for the improvement in the GML index was technological progress. (3) The average annual growth of MML index in the YREB was 8.2%, and the change of the best practice gap ratio was the main reason for the MML index increase. (4) The technical gap ratio indicates that the gap between group-frontier and meta-frontier is narrowing slightly, which is conducive to the coordinated development of the ecology in the YREB.

Keywords Eco-efficiency · Total factor ecological productivity · Sustainable development · Meta-frontier Malmquist-Luenberger index · Yangtze River Economic Belt · Data envelopment analysis

Abbreviations

DEA	Data envelopment analysis
DMU	Decision-making unit
YREB	Yangtze River Economic Belt
YDUA	Yangtze River Delta Urban Agglomeration
YMUA	Urban Agglomeration in the Middle Reach of the Yangtze River
CYUA	Cheng-Yu Urban Agglomeration
TE	Technical efficiency
BPR	Best practice gap ratio
TGR	Technical gap ratio
TEC	Change of technical efficiency
BPC	Change of the best practice gap ratio
TGRC	Change of technical gap ratio
EC	Efficiency change
TC	Technical change
PEC	Pure efficiency change
PTC	Pure technology change

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12053-023-10105-9.

Y. Wang · Y. Ren · W. Qian
School of Business, Jiangnan University, Wuxi, Jiangsu Province 214122, People's Republic of China
e-mail: wyh2003@gmail.com

Y. Ren
e-mail: 7220912008@stu.jiangnan.edu.cn

W. Qian
e-mail: qianyijiaemail@163.com

D. Wu (✉)
College of Tourism and Service Management, Nankai University, Tianjin 300350, People's Republic of China
e-mail: dwu@mail.nankai.edu.cn

Published online: 25 March 2023

SEC	Scale efficiency change
STC	Scale technology change
PTCU	Pure technology catch-up index
FCU	Frontier catch-up index
MPI	Malmquist productivity index
ML	Malmquist-Luenberger productivity index
GML	Group-frontier Malmquist-Luenberger productivity index
MML	Meta-frontier Malmquist-Luenberger productivity index

Introduction

Since its reform and opening-up policy started in 1978, China has experienced a high rate of economic growth. However, this booming economy is heavily dependent on large-scale depletion of natural resources, and environmental pressures are becoming progressively conspicuous, which retards social and economic development (Yang & Yang, 2019). Sustainable growth and sustainable assessment have been of considerable concern to scholars and practitioners in recent decades (Caiado et al., 2017; Zhou et al., 2018). Therefore, maximizing economic gains while reducing resource use and causing the least environmental damage is an immediate and crucial task for sustainable development in China (Zhu et al., 2019). Moreover, it is essential to measure China's eco-efficiency to have a good view of the current condition of sustainable growth (Yang et al., 2020).

The Chinese government first proposed the strategy of ecological civilization in 2007 and emphasized on firmly pursuing it in the "13th Five-Year Plan (2016–2020)"[1] (Zhang et al., 2017). Meanwhile, developing the Yangtze River Economic Belt (YREB) has become one of China's three major regional development strategies; to do so, planners follow a fundamental discipline (i.e., higher requirements of ecological priority, green and low-carbon development) that was put forward in the "Yangtze River Economic Belt Development Planning Outline"[2] (Huang et al., 2018). The YREB is a vast economic zone with three main urban agglomerations that demonstrate wide differences in levels of growth, capital endowment, industrial structure, demographics, and other factors (Liu et al., 2020). Considering YREB cities are critical to pollution reduction, the green and sustainable development of the YREB is a microcosm of China (Hou et al., 2019). Therefore, it is increasingly necessary to protect the natural ecosystem and to achieve long-term sustainable growth in the YREB.

Charnes et al. (1978) initiated the data envelopment analysis (DEA), a non-parametric approach used to determine the relative performance of decision-making units (DMUs) with multiple inputs and multiple outputs (Wang et al., 2021). The DEA framework was commonly used to estimate the performance of DMUs, and eco-efficiency was evaluated using DEA models in several studies (Demiral & Sağlam, 2021; Zhou et al., 2018). DEA enables the environmental impacts to be integrated as undesirable outputs in the assessment (Wang et al., 2022). Numerous researches have incorporated environmental impacts as undesirable outputs in the eco-efficiency assessment of several types of production units. In addition, if the frontier is constructed using the traditional DEA method without considering variations among cities, the reference significance of the frontier is limited, as is the accuracy of the measurement results, such that the identification of critical influence factors is affected (Li et al., 2018).

Many researchers studied regional eco-efficiency and evaluated the growth rate in China but did not consider the heterogeneity of cities and assumed that all cities had the same production frontier (Wu et al., 2022). In this paper, we use the MML index to analyze and reveal the reasons for the changes in total factor ecological productivity through a comparison of region differences and historical evolution. We set three major urban agglomerations in the YREB as the groups, and the cities in each group are selected according to the Chinese government official definition to avoid the arbitrariness of artificial choices. Eco-efficiency evaluation could provide a theoretical framework and a certain reference value for long-term sustainable growth (Yang & Zhang, 2018). Furthermore, this paper can better provide guidelines for the formulation of regional policies.

To grasp the regional status on eco-efficiency and help facilitate sustainable growth, we estimate

[1] 13th Five-Year Plan (2016–2020) http://www.12371.cn/special/sswgh/.

[2] Development Plan of the YREB http://www.gov.cn/xinwen/2016-09/12/content_5107501.htm.

the eco-efficiency of cities in the YREB during 2008–2017 based on the super-efficiency slack-based measure (SBM) model considering the undesirable outputs. Meanwhile, the group-frontier Malmquist-Luenberger (GML) productivity index of each urban agglomeration is used to measure the total factor ecological productivity. Considering the heterogeneity among the three major urban agglomerations in the YREB, the meta-frontier Malmquist-Luenberger (MML) productivity index is used to analyze the technical ratio gap between the meta-frontier and each group-frontier.

The main research object is to measure the eco-efficiency and total factor ecological productivity of cities in the YREB. In addition, the technical gap ratio between the group-frontier of three major urban agglomerations and the meta-frontier of the YREB is analyzed to promote regional integration. The main contributions of this paper are as follows: (1) It analyzes the panel data of 71 cities in the YREB from 2008 to 2017, which is the latest decade after the strategy of ecological civilization proposed by the Chinese government. (2) We use the super-efficiency SBM model considering undesirable outputs to calculate the eco-efficiency from the perspective of city and urban agglomeration. (3) The GML index of each urban agglomeration is used to measure the total factor ecological productivity, and the decomposed indicators can provide each region's source of productivity change. (4) The MML index is used to analyze the technical ratio gap between the meta-frontier and each group-frontier, and the decomposed indicators can provide the source of productivity change from the perspective of regional integration.

This paper is structured as follows. The next section reviews the literature on eco-efficiency and the MML index, and then the methodology is laid out. After presenting the data description and research area, the results and discussion of the empirical study are provided subsequently. Finally, conclusions and practical implications are presented.

Literature review

Research on eco-efficiency evaluation using DEA

Eco-efficiency is a multidisciplinary concept and is thus complicated to evaluate since it involves a systematic approach that incorporates multiple performance measures into a single index (Fan et al., 2017). Eco-efficiency has been measured at a variety of different levels, such as national, provincial, industrial, and company levels (Arabi et al., 2016; Dirik et al., 2019; Lorenzo-Toja et al., 2016). Related evaluation methods were developed, such as the ratio approach, material flow analysis, stochastic frontier analysis, DEA, energy analysis, life cycle assessment, input–output analysis, and ecological footprint method. Because each of these research methods has its own benefits and disadvantages, we need to carefully select a research approach depending on the specific situation. Yang and Yang (2019) believed that DEA is the most commonly used methodology because it provides reliable and detailed metrics while dealing with multiple inputs and outputs. Several theoretical attempts have been made to develop the DEA models to achieve objective and accurate eco-efficiency results (Demiral & Sağlam, 2021; Liu et al., 2017; Wang et al., 2019a, b).

However, traditional DEA models, such as the CCR and BCC models, are radial projection constructs (Cook & Seiford, 2009), which means that the slack variable is not considered (Wu et al., 2020). Moreover, it is difficult to classify DMUs where more than one DMU is assumed to be efficient and the traditional assumption is not sufficient for the treatment of undesirable outputs. To avoid these problems, Tone (2001) suggested the SBM model to avoid the issue of radial projection. Tone (2002) further developed the super-efficiency SBM model to rank the efficient DMUs fully, which allows the efficiency score to be higher than 1. Cooper et al. (2006) developed the SBM model considering undesirable outputs. Following this research stream, super-efficiency SBM model and combined benchmark technology are widely used by scholars to investigate sustainability issues.

Recently, researchers have begun to concentrate on regional eco-efficiency because the status and improvements in eco-efficiency in urban agglomerations and economic zones are worth investigating. Zhu et al. (2019) investigated the temporal and spatial evolution characteristics, growth resources, and main driving factors of eco-efficiency in the Western Taiwan Straits Economic Zone. Huang et al. (2018) developed a new paradigm to study the eco-efficiency in the YREB using a dataset of 108 prefectural-level cities. Hou et al. (2019) focused on the impact of urbanization on the eco-efficiency of cultivated land utilization in the YREB. Liu et al. (2020) suggested a complex eco-efficiency system consisting of multi-dimensional components with entropy flows for the YREB. The regional scale is the most suitable scale for adopting policies to facilitate sustainable growth. It is also beneficial to consider eco-efficiency at a regional level due to the inter- and intra-regional disparity in China (Yu et al., 2018).

Study using the meta-frontier Malmquist-Luenberger index

Super-efficiency SBM models are based on cross-sectional data and are used to measure the eco-efficiency in a certain period. The Malmquist productivity index, proposed by Caves et al. (1982), can be used for inter-temporal comparisons based on panel data. Färe et al. (1994) and Chung et al. (1997) further formulated the Malmquist-Luenberger productivity (ML) index that considers undesirable outputs. However, the ML index has no transmissibility, and there is a defect that ML-related linear programs may have no feasible solution when measuring an inter-temporal comparative analysis of efficiency in a time series (Zhu et al., 2019). The global ML index, proposed by Oh (2010a), can overcome those deficiencies of the ML index.

Besides, it should be noted that the production technologies of these DMUs are distinct and the production efficiency of the various production sets cannot be directly compared (Oh, 2010b). Therefore, Oh and Lee (2010) introduced the novel meta-frontier Malmquist approach that can integrate the technology heterogeneity and demonstrate the productivity and technology gap. On this basis, Oh (2010b) proposed the MML index, which handles undesirable environmental factors. When there exists heterogeneity in the technology, the MML index is used to measure eco-efficiency and productivity change over a period. Recently, Tang et al. (2020) evaluated eco-efficiency and its decomposition indexes using the non-radial MML technique.

Due to spatial limitations, capital endowments, and policy direction, there are "congenital variations" between different regions (Shi & Li, 2019). Therefore, the MML index is adopted to study the heterogeneity of eco-efficiency between the YDUA, YMUA, and CYUA and the YREB. Utilizing the MML index has two advantages compared with the ML index: (1) it can consider undesirable output as a by-product of production; and (2) it can account for the heterogeneity of the producer group, such as production technology. However, there are few studies of eco-efficiency and total factor ecological productivity based on the MML index (Lin & Chen, 2019). Moreover, there is little research focused on the perspective of prefecture-level city and urban agglomeration to study the eco-efficiency changes in the YREB. Thus, it is interesting to explore the total factor ecological productivity from the perspective of meta-frontier based on the panel data of prefecture-level cities in the YREB.

Methodology

Super-efficiency SBM model

Assuming there are n observed DMUs, and each DMU consumes x inputs to obtain y^d desirable outputs and y^u undesirable outputs. The corresponding vectors set can be denoted by matrices as $X = \left[x_1, ..., x_n\right] \in R^{m\times n}$, $Y^d = \left[y_1^d, ..., y_n^d\right] \in R^{q_1\times n}$, and $Y^u = \left[y_1^u, ..., y_n^u\right] \in R^{q_2\times n}$ respectively. Among those vectors, m, q_1, and q_2 are the number of inputs, and desirable and undesirable output indicators, respectively. These data are all supposed to be positive and λ indicates the weighting vector. The production possibility set is represented as

$$P = \left\{(x, y^d, y^u)|\ x \geq \lambda X, y^d \geq \lambda Y^d, y^u \geq \lambda Y^u, \lambda \geq 0\right\} \tag{1}$$

The set P possesses the properties of null-jointness and either weak disposability or strong (free) disposability. It is often believed that P satisfies the standard axioms of the production theory, that is, being bounded, closed, and convex (Färe & Grosskopf, 2006).

1. Null-jointness (Shephard & Färe, 1974) indicates that ending the production process is the only way to eliminate all the undesirable outputs. If $(X, Y^d, Y^u) \in P$ and $Y^u = 0$, then $Y^d = 0$.
2. Weak disposability (Färe et al., 1989) means that the proportional reduction of both desirable and undesirable outputs is feasible. If $(X, Y^d, Y^u) \in P$ and $\theta \in [0, 1]$, then there must be $(X, \theta Y^d, \theta Y^u) \in P$.
3. Strong (or "free") disposability (Färe et al., 2005) excludes production processes that generate unde-

sirable outputs, which are costly to dispose of. If $(X, Y^d, Y^u) \in P$ and $(X, Y^{d*}, Y^u) \le (X, Y^d, Y^u)$, then $(X, Y^{d*}, Y^u) \in P$.

Inevitably, the production of desirable output is accompanied by undesirable outputs. Therefore, we adopt the super-efficiency SBM handling the undesirable outputs to calculating the efficiency of $DMU_k\left(x_k y_k^d y_k^u, k = 1, 2, ..., n\right)$. The super-efficiency SBM model that accounts for undesirable output is constructed as follows (Huang et al., 2014):

$$
\begin{gathered}
\rho^* = min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{d+}}{y_{rk}^d}+\sum_{t=1}^{q_2}\frac{s_t^{u-}}{y_{tk}^u}\right)} \\
s.t. \sum_{j=1,j\neq k}^{n}\lambda_j x_{ij} - s_i^- \le x_{ik}, i = 1, ..., m; \\
\sum_{j=1,j\neq k}^{n}\lambda_j y_{rj}^d + s_r^{d+} \ge y_{rk}^d, r = 1, ..., q_1; \\
\sum_{j=1,j\neq k}^{n}\lambda_j y_{tj}^u - s_t^{u-} \le y_{tk}^u, t = 1, ..., q_2; \\
1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{d+}}{y_{rk}^d} + \sum_{t=1}^{q_2}\frac{s_t^{u-}}{y_{tk}^u}\right) > 0; \\
\lambda_j, s_i^-, s_r^{d+}, s_t^{u-} \ge 0; j=1,...,n(j \neq k).
\end{gathered}
\tag{2}
$$

where ρ^* is the relative efficiency of DMU_k, s_i^- are the input slack variables, and $s_r^{d+}\left(s_t^{u-}\right)$ are the desirable (undesirable) output slack variables. For the evaluated DMU_k, x_{ik} is the i-th input variable, y_{rk}^d is the r-th desirable output variable, and y_{tk}^u is the t-th undesirable output variable. In model (2), the inefficiency of input and output is reflected in $(1/m)\sum_{i=1}^{m}s_i^-/x_{ik}$ and $\left[1/(q_1+q_2)\right]\left(\sum_{r=1}^{q_1}s_r^{d+}/y_{rk}^d + \sum_{t=1}^{q_2}s_t^{u-}/y_{tk}^u\right)$, respectively. The inequality $\rho^* \ge 1$ means that a DMU is efficient, whereas $\rho^* < 1$ shows that there is room for change in the performance of the DMU, which can be effectively improved by adjusting the slack variables.

Group-frontier Malmquist-Luenberger index

In this paper, a group-based measure of the ML index using the global technology set is denoted as the group-frontier Malmquist-Luenberger (GML) index. Based on the global ML index, the GML index from the t period to the $t+1$ period can be denoted as

$$
\begin{gathered}
GML_{t+1}^t(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \\
= \frac{1+D^t(x^t,y^t,b^t)}{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \left[\frac{1+D^G(x^t,y^t,b^t)}{1+D^t(x^t,y^t,b^t)} \times \frac{1+D^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+D^G(x^{t+1},y^{t+1},b^{t+1})}\right] \\
= EC_{t+1}^t \times TC_{t+1}^t
\end{gathered}
\tag{3}
$$

where $D^t(x, y, b)$ and $D^G(x, y, b)$ are the current and global directional distance functions, respectively. Here, x, y, and b denote the input, and desirable and undesirable output variables, respectively.

According to the study of Färe et al. (1992), the GML index can be decomposed into efficiency change (EC) and technical change (TC) as shown in Eq. (3). Färe et al. (1994) and Zofio (2007) decomposed the GML index into pure efficiency change (PEC), scale efficiency change (SEC), pure technical change (PTC), and scale technical change (STC):

$$
GML = EC \times TC = PEC \times PTC \times SEC \times STC \tag{4}
$$

Therefore, the GML index can be decomposed into PEC, PTC, SEC, and STC as shown in Eq. (4). If $GML > 1$, then the efficiency shows an upward trend; otherwise, it presents a downward trend. The relations $PEC > 1$, $PTC > 1$, $SEC > 1$, and $STC > 1$ respectively indicate that the change of pure efficiency, the change of pure technical scale, and the change of scale efficiency show rising trends, and the change of technical scale deviates from the constant returns to scale (CRS). In this paper, the GML index can be used to better understand the sources of eco-efficiency growth in the YDUA, UAMA, and CYUA.

Meta-frontier Malmquist-Luenberger index

The MML index is introduced to investigate the heterogeneity of the total factor ecological productivity. All DMUs are classified into K groups, and the feasible input–output combinations of DMUs in each group G_k belong to the same technology set.

1. The contemporaneous benchmark technology set of group G_k in period t is defined as $P_{G_k}^{C^t} = \{(x^t, y^t, b^t)|x^t canproduce(y^t, b^t)\}, t = 1, ..., T$ This set contains all the observations of group G_k but only in period t.
2. The inter-temporal benchmark technology set of group G_k is defined as $P_{G_k}^I = P_{G_k}^{c^1} \cup P_{G_k}^{c^2} ... \cup P_{G_k}^{c^T}$. This set includes all observations of group G_k in all the periods.
3. The global benchmark technology set is defined as $P^G = P_{G_1}^I \cup P_{G_2}^I ... \cup P_{G_k}^I$. This set includes all observations of all groups in all the periods.

Similar to Oh (2010b), the MML index can be decomposed into the TEC index, the best practice gap change (*BPC*) index, and the technical gap ratio change (*TGRC*) index with the following equation:

$$\begin{aligned} MML_{t+1}^{t}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \\ &= \frac{1+D^{C^t}(x^t,y^t,b^t)}{1+D^{C^{t+1}}(x^{t+1},y^{t+1},b^{t+1})} \times \frac{(1+D^I(x^t,y^t,b^t))/(1+D^{C^t}(x^t,y^t,b^t))}{(1+D^I(x^{t+1},y^{t+1},b^{t+1}))/(1+D^{C^{t+1}}(x^t,y^t,b^t))} \\ &\times \frac{(1+D^G(x^t,y^t,b^t))/(1+D^I(x^t,y^t,b^t))}{(1+D^G(x^{t+1},y^{t+1},b^{t+1}))/(1+D^I(x^t,y^t,b^t))} \\ &= \frac{TE^{t+1}}{TE^t} \times \frac{BPR^{t+1}}{BPR^t} \times \frac{TGR^{t+1}}{TGR^t} = TEC_{t+1}^t \times BPC_{t+1}^t \times TGRC_{t+1}^t \end{aligned} \tag{5}$$

In Eq. (5), represents technical efficiency in period t. BPR^t represents best practice gap ratio between best practice frontier and inter-temporal best practice frontier. The technical gap ratio in period t is denoted by TGR^t, which represents the gap between inter-temporal technology and global technology. $TGR^t = 1$ indicates that the DMU is on the meta-frontier with innovation technology in period t. The explanations of *TEC*, *BPC*, and *TGRC* are detailed as follows:

1. *TEC* represents the technical efficiency change between two periods, reflecting relative change rate when DMUs move to the contemporaneous benchmark technology frontier during period t to $t+1$. If $TEC > 1$, then technical efficiency improves.
2. *BPC* represents the change of the best practice gap ratio between two periods, reflecting technical change. If $BPC > 1$, then the technology progresses.
3. *TGRC* is the change of technical gap ratio between the inter-temporal and global benchmark technology frontiers between two periods. If $TGRC > 1$, then a narrowing trend exists between a specific group and the global frontier technology. *TGRC* reflects the technical catch-up effect of DMUs. In fact, *TGRC* can be represented as $TGRC_{t+1}^t = MML_{t+1}^t / GML_{t+1}^t$.

Following the study of Chen and Yang (2011), we can extend the MML index and decompose *TGRC* into the pure technical catch-up (*PTCU*) index and the frontier catch-up (*FCU*) index.

$$\begin{aligned} TGRC_{t+1}^t &= \left[\frac{TGR^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{TGR^t(x^t,y^t,b^t)} \times \frac{TGR^t(x^{t+1},y^{t+1},b^{t+1})}{TGR^{t+1}(x^t,y^t,b^t)}\right]^{\frac{1}{2}} \\ &= \frac{TGR^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{TGR^t(x^t,y^t,b^t)} \times \left[\frac{TGR^t(x^{t+1},y^{t+1},b^{t+1})}{TGR^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \frac{TGR^t(x^t,y^t,b^t)}{TGR^{t+1}(x^t,y^t,b^t)}\right]^{\frac{1}{2}} \\ &= PTCU_{t+1}^t \times FCU_{t+1}^t \end{aligned} \tag{6}$$

Then, the MML index and its components can be represented as the following Eq. (7), which is followed by explanations of *PTCU*, *FCU*, and MML in detail.

$$MML = TEC \times BPC \times PTCU \times FCU \tag{7}$$

1. *PTCU* is the pure technical catch-up, capturing the change in *TGR* from period t to period $t+1$. The relation $PTCU > 1$ indicates a convergence of the gap lying between the existing and the potential technical level, that is, the meta-frontier.
2. *FCU* is the frontier catch-up and is a geometric mean composed of two inverse changes in *TGR* from period t to period $t+1$. If $FCU > 1$, then there is an increase in room to improve the technical level.
3. $MML > 1$ means an improvement in productivity; $MML < 1$ means worsening of the productivity; and MML=1 means that the productivity has not changed across years.

Data description and research area

Data description

We use panel data from 71 cities for the years 2008 to 2017 to evaluate the eco-efficiency of the YREB. The data comes from the *China City Statistical Yearbook*,[3] *China Statistical Yearbook*,[4] *China Energy Statistical Yearbook*,[5] and Statistical Yearbook of each province[6] for 2009–2018. Some missing data were obtained from statistical communiques on the national economy and the social development of each city. Table 1 shows the literature summary for eco-efficiency indicators selection.

Capital investment is an indispensable economic input in the production process. Energy, water, and land are important natural resources in the production system of any city. Labor integrates and transforms

[3] China City Statistical Yearbook http://data.cnki.net/yearbook/Single/N2019070173.
[4] China Statistical Yearbook http://data.cnki.net/yearbook/Single/N2019110002.
[5] China Energy Statistical Yearbook http://data.cnki.net/yearbook/Single/N2019080025.
[6] Statistical Yearbook of each province http://data.stats.gov.cn.

Table 1 Literature summary for eco-efficiency indicators selection

Reference	Input	Desirable output	Undesirable output
Fan et al. (2017)	Land, energy, water	Industrial value added	Solid waste, chemical oxygen demand, SO_2
Yu et al. (2018)	Capital, labor, land, water, energy	Gross value of industrial output	Environmental pollution index
Yang and Zhang (2018)	Capital, labor, land, water, energy	GDP	Solid waste, soot and dust, waste water, SO_2, household refuse
Huang et al. (2018)	Capital, labor, land, energy	GDP	Soot and dust, waste water, SO_2, CO_2
Zhu et al. (2019)	Capital, labor, land, water, energy	GDP	Waste water, waste gas, solid waste
Zhou et al. (2019)	Capital, labor, land, water, electricity	GDP	Industrial SO_2, waste water, smoke dust, CO_2
Wang and Yang (2019)	Capital, labor, water, energy	Industrial value added	Soot and dust, solid waste, waste water, waste gas
Yang et al. (2020)	Capital, labor, water, energy	GDP	Soot and dust, waste water, SO_2, CO_2

Table 2 Indicator system for eco-efficiency evaluation

Dimension	Criteria	Variable	Unit
Input	Capital investment	Capital stock	100 million yuan
	Resources input	Energy consumption	Million TCE
		Water consumption	100 million m^3
		Urban built-up area	Square kilometers
	Labor input	Employment population	10 thousand people
Output	Desirable output	GRP	100 million yuan
	Undesirable outputs	Industrial sulfur dioxide	Tons
		Industrial wastewater	10 thousand tons
		Industrial smoke dust	Tons
		Carbon dioxide emission	10 thousand tons

TCE indicates metric tons of standard coal equivalent; *GRP* represents gross regional product

capital and energy into economic outputs, while pollution emissions represent negative environmental impacts. In this paper, the following input–output variables are chosen (see also Table 2):

1. *Capital stock*. The perpetual inventory method is typically used to measure the capital stock. The calculation formula is as follows:$K_{i,t} = I_{i,t} + (1 - \delta_{i,t})K_{i,t-1}$. Here, i and t represent the cities and years, respectively; $I_{i,t}$ represents the investment in fixed assets; $\delta_{i,t}$ represents the depreciation rate with the default being 9.6%; and $K_{i,t}$ and $K_{i,t-1}$ represent the current and previous capital stock, respectively. According to the study of Young (2003), the capital stock of the base year is calculated at 10 times the investment in fixed assets of the year. Meanwhile, we use the fixed assets price index to deflate the amount of investment in fixed assets (the base year is 2008). Due to the lack of a fixed assets price index in prefecture-level cities, the provincial fixed assets price index is adopted.
2. *Energy consumption*. Economic growth relies on a great deal of energy usage (Du et al., 2023), so we choose the total energy consumption, which is converted into standard coal equivalent. Due to the availability of prefecture-level cities data, electricity, coal, natural gas, and liquefied petroleum gas consumptions are converted to standard coal by the reference coefficient.
3. *Water consumption*. Fresh water has a huge influence on sustainability, and water shortage and pollution have become a significant issue

in China. In this paper, the total water supply is used to represent water resource consumption.

4. *Urban built-up area*. The actual space used and its pattern of utilization differ considerably from year to year. Therefore, land becomes a key input that must not be neglected. Since data on the space used is difficult to collect, this paper adopts the urban built-up area as a proxy for land use.
5. *Employment population*. Depending on the extent of data availability, the total number of employees at the end of the year was adopted as the labor.
6. *Desirable output*. In this paper, we use GRP deflator to convert the nominal GRP of each city year by year to obtain actual GRP based on the nominal GRP in the year 2008. To be consistent with the fixed assets price index, the GRP index from each province is adopted even though the GRP index of each city could have been obtained.
7. *Undesirable outputs*. Considering the data availability, industrial sulfur dioxide, waste water, smoke dust, and carbon dioxide emission are treated as undesirable outputs.

Research area

The Yangtze River Economic Belt (YREB) includes three major (state-level) urban agglomerations: the Yangtze River Delta Urban Agglomeration (YDUA), Urban Agglomeration in the Middle Reach of the Yangtze River (YMUA), and Cheng-Yu Urban Agglomeration (CYUA). At present, the development of the YREB is facing many difficulties and problems urgently needing solutions, including severe problems in the ecological environment. Descriptive statistics of each indicator mentioned above in the YREB and three major urban agglomerations are listed in Supplementary Information Table S1. Due to the significant difference of indicators among the three urban agglomerations, regional heterogeneity should be considered when evaluating the eco-efficiency and total factor ecological productivity in the YREB.

The "National New Urbanization Plan (2014–2020)"[7] was implemented in 2014, including urban agglomeration taking a prominent role in promoting the development of new urbanizations. After that, the "Development plan for Urban Agglomeration in the Middle Reach of the Yangtze River"[8] and the "Development plan for Cheng-Yu Urban Agglomeration"[9] were proposed by the Chinese government in 2015 and 2016, respectively. Recently, the Chinese government issued the "Outline of the plan for the integrated development of the Yangtze River Delta"[10] and the integrated development of the YDUA has become a national strategy. In this paper, we select 71 cities in the YREB as the research sample according to the division of urban agglomeration by the Chinese government. Supplementary Information Table S2 provides more details about the division of cities into regions. It should be noted that cities of Yunnan and Guizhou province, which do not belong to the three major urban agglomerations, are excluded to study regional heterogeneity in this paper.

Results and discussion

Eco-efficiency analysis and dynamic evolution

According to the calculation results, Shanghai, Wuxi, Suzhou, Wenzhou, Jinhua, Taizhou, Huanggang, Changsha, and Changde were eco-efficient in each year of the study period. The average number of efficient cities of eco-efficiency during the study period is 19, representing 26.8% of the 71 cities. In other words, the eco-efficiency of approximately three-quarters of the cities in the YREB has not achieved an efficient state and there is still an opportunity to save energy and reduce emissions. Wuhu, Tongling, Chizhou, Jingdezhen, Ezhou, and Chongqing are extremely eco-inefficient cities, scoring below 0.4 in each year of the study period. The average number of cities below the average eco-efficiency during the study period is 46, which is 64.8% of the 71 cities. This statistic means that the eco-efficiencies of more than half of the cities in the YREB had not reached the average score, and significant disparities in cities'

[7] National New Urbanization Plan (2014–2020) http://www.gov.cn/zhengce/2014-03/16/content_2640075.htm.

[8] Development Plan of the YMUA area http://www.gov.cn/xinwen/2015-04/16/content_2848120.htm.

[9] Development Plan of the CYUA area http://www.gov.cn/zhengce/content/2016-04/15/content_5064431.htm.

[10] Development Plan of the YDUA area http://www.gov.cn/zhengce/2019-12/01/content_5457442.htm.

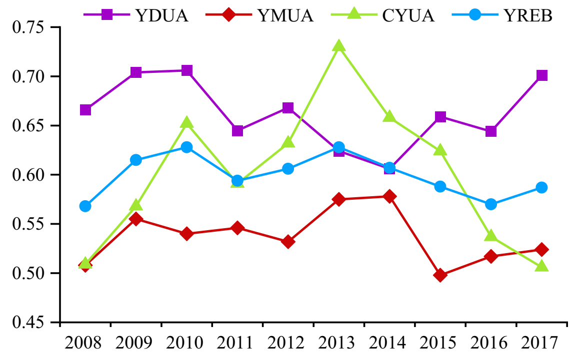


Fig. 1 Dynamic evolution of average eco-efficiency in the YREB

development patterns can be seen. Zhenjiang, Yueyang, Zigong, and Ziyang attained a more than 2% increase in eco-efficiency scores during the study period, which is an obvious improvement in their eco-efficiency.

Supplementary Information Table S3 shows the average eco-efficiency of various YREB cities during 2008–2012, 2013–2017, and the whole study period. There are nine eco-efficient cities according to the average eco-efficiency scores during the whole study period in the YREB, which were consistent with the efficient cities in each year. During 2008–2012 and 2013–2017, there are three more cities (Shaoxing, Loudi, Dazhou), and two more cities (Zigong, Ziyang) were deemed as eco-efficient. The average eco-efficiency during the whole study period is 0.599. The average eco-efficiency during 2008–2012 (0.602) is higher than that during 2013–2017 (0.596), which results in the average eco-efficiency during the whole period (0.599). These averages show an obvious decrease in the eco-efficiency of 71 cities in the YREB during 2013–2017.

Figure 1 shows the dynamic evolution trend of eco-efficiency in the YDUA, YMUA, and CYUA, and the entire YREB. The overall eco-efficiency stayed steady during 2008–2017, as can be observed, although it showed a fluctuating and slightly upward trend.

1. The YDUA has the highest average eco-efficiency (0.662), followed by the CYUA (0.601) and the YMUA (0.537). The eco-efficiency in the YDUA decreased marginally after peaking in 2010 and then increased after its minimum in 2014. The decline during 2010–2014 resulted from the rapid population growth, overconsumption of natural resources, and environmental degradation during the rapid economic development of the region. Since the implementation of the "13th Five-Year Plan (2006–2020)" and the development plan of urban agglomeration in the YDUA, the eco-efficiency increased rapidly.
2. The eco-efficiency in the CYUA had the greatest fluctuation, peaking in 2013 (0.730) and bottoming out in 2017 (0.506), a gap of approximately 44.3%. The rapid drop of eco-efficiency in the CYUA since 2013 indicates an imbalance between resource consumption, environmental protection, and economic development.
3. The eco-efficiency in the YMUA shows a slow fluctuation and an upward trend. Since the average eco-efficiency in the YMUA is the lowest among the three regions, the priority should be given on fostering the creation of an ecological civilization and improving its potential for sustainable growth.

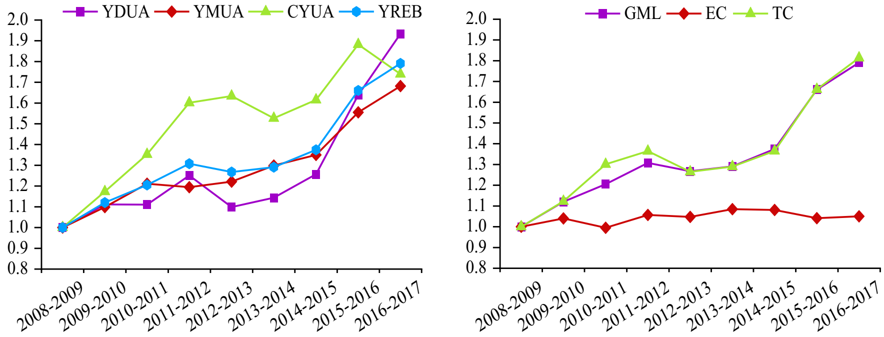
Group-frontier ML index and its decomposition

For the cities in the YDUA, YMUA, and CYUA, respectively, we take each group as the frontier, and the decomposition index can explain the growth of eco-efficiency in each group. Based on Eq. (3), we

Table 3 GML index in different regions from 2008 to 2017

Region	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017
YREB	1.127	1.120	1.088	1.098	0.984	1.034	1.072	1.206	1.088
YDUA	1.074	1.112	1.011	1.123	0.908	1.051	1.100	1.303	1.189
YMUA	1.165	1.099	1.109	1.015	1.031	1.059	1.056	1.141	1.063
CYUA	1.150	1.173	1.182	1.198	1.031	0.960	1.054	1.155	0.959

Fig. 2 Description of accumulated GML index



(a) Accumulated GML index in different regions from 2008-2017

(b) Accumulated GML index and its decomposed factors

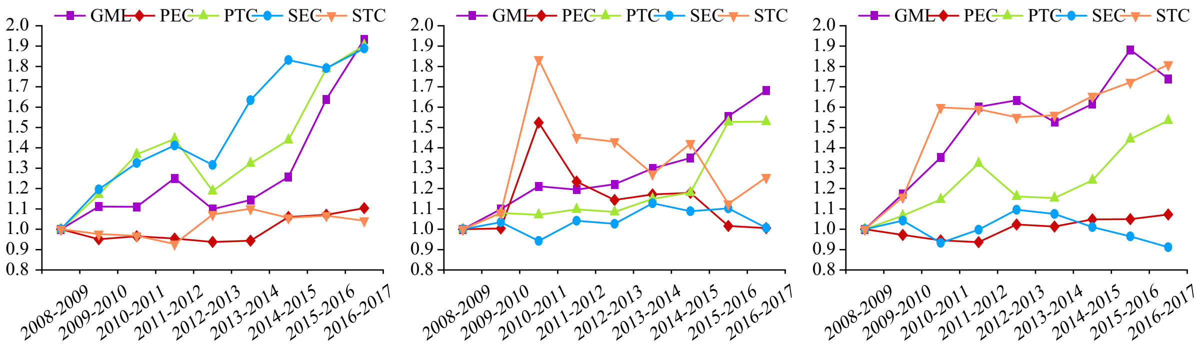
obtain the GML index of cities in the YREB during 2008–2017. Table 3 shows the GML index in different regions for 2008–2017, while Fig. 2a shows the accumulated GML index during the study period. According to the results of Table 3, the annual average GML index in the YREB is 1.091, which indicates an improvement in the eco-efficiency. From the overall trend, the GML index in the YREB increased during the study period at both the aggregate and regional levels. According to Fig. 2a, the YDUA has the largest improvement in the GML index, followed by the CYUA and YMUA. The improvement in the YREB is higher than the CYUA and YMUA, which indicates these two areas have potential to improve eco-efficiency.

As shown in Table 4 and Fig. 2b, all the changes in technological progress from 2008–2017 are greater than 1, and the accumulated value of TC has an obvious upward trend. Therefore, the main explanation for the increase in the GML index is technological progress. The average value of TC during the study period is 1.105, with an accumulated value of 1.814, while the average EC over the period 2008–2017 is 1.033, with an accumulated value of 1.050. Although not as important as technological progress, the improvement of the management level is vitally important in the YREB.

As in Eq. (4), we decompose the GML index into four indexes: pure efficiency change (PEC), scale efficiency change (SEC), pure technical change (PTC), and scale technical change (STC), which reflect the level of changes of institutional management, technical change, economies of scale, and preference for technical scale, respectively. The annual average change of each index by their arithmetic mean over the years is shown in Supplementary Information Table S4. The GML index values for the YDUA, YMUA, and CYUA were 1.097, 1.082, and 1.096, which indicate that the eco-efficiency improved by 9.7%, 8.2%, and 9.6%, respectively. Among the three areas, the GML growth rate of the YDUA ranked first (9.7%), and its growths in PTC (11.0%) and SEC (8.7%) were the fastest, which implies that the YDUA benefited significantly from technological progress and scale economy. The YMUA had the slowest GML growth in eco-efficiency (8.2%), and its growths in SEC and PEC were 3.7% and 6.7%, which implies that the YMUA had a marked potential for improving its scale economy and management. Similarly, the CYUA also should pay attention to the scale economy since its SEC is only 0.7%. These results indicate that the development of different elements is unbalanced, which is not conducive to sustainable development in the YREB. In addition, compared to technological

Table 4 GML index decomposition results

Year	GML	EC	TC
2008–2009	1.127	1.057	1.123
2009–2010	1.120	1.040	1.123
2010–2011	1.088	0.975	1.180
2011–2012	1.098	1.088	1.049
2012–2013	0.984	1.053	1.001
2013–2014	1.034	1.052	1.032
2014–2015	1.072	1.022	1.082
2015–2016	1.206	1.000	1.251
2016–2017	1.088	1.013	1.105
Average	1.091	1.033	1.105



(a) Accumulated GML index and its decomposition in the YDUA area

(b) Accumulated GML index and its decomposition in the YMUA area

(c) Accumulated GML index and its decomposition in the CYUA area

Fig. 3 Accumulated GML index and its decomposition in different areas

progress, the improvement of the management level is more vital.

As shown in Supplementary Information Table S5 and Fig. 3a, the major factors contributing to the improvements in the GML index of the YDUA are scale efficiency change (SEC) and pure technical change (PTC), which means that the scale economy and the technological progress are the main driving force behind the improvement of the GML index. The accumulated PEC, PTC, SEC, and STC are 1.104, 1.904, 1.889, and 1.042, respectively. The PEC and STC do not obviously impact the GML index, which indicates that the management level and the preference for variable technical scale should be an improvement direction in the YDUA.

At the individual city level of the YDUA, the GML indexes were greater than 1 in all cities, among which Zhoushan (1.194), Anqing (1.187), and Shanghai (1.169) had the highest GML index growth scores. Zhoushan, which had the highest GML index growth, was helped by an improvement of management (PEC: 1.249) and a preference for variable technical scale (STC: 1.266), but at the same time restricted by a decrease in technological progress (PTC: 0.907) and scale economy (SEC: 0.882). Similarly, the SEC (1.192) contributed most of Anqing's GML index, indicating the growth of eco-efficiency is driven primarily by scale economy. The PTC (1.156) contributed the most to Shanghai's GML index, indicating the growth of its eco-efficiency is driven mainly by technological progress. The preference for constant technical scale ($STC < 1$) restricted the growth of eco-efficiency in both Anqing and Shanghai.

As shown in Supplementary Information Table S6 and Fig. 3b, the major factors contributing to the improvements in the GML index of the YMUA are scale technical change (STC) and pure technical change (PTC). The accumulated PEC, PTC, SEC, and STC are 1.006, 1.529, 1.007, and 1.255, respectively, which means that technological progress is the main driving force. The average value of PTC during the study period is 1.111, and the PTC has the largest increase in the YMUA. The impact of STC on the GML index is second only to that of PTC. In addition, the average values of PEC and SEC are 1.067 and 1.037, respectively, which indicate that the scale economy and management level have considerable room for improvement.

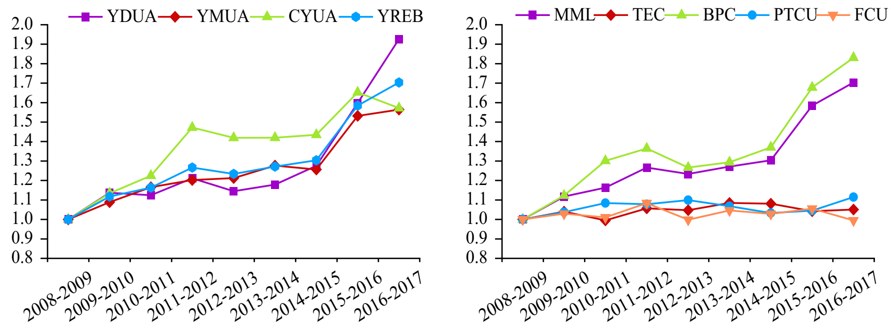
At the individual city level of the YMUA, the GML indexes of Yichun (0.971) and Loudi (0.965) were lower than 1, showing a declining trend in eco-efficiency. The PEC (0.913) was the main driving force behind the drop of Yichun's GML index, indicating a decline in management. Xinyu had the highest GML index growth, which contributed to the increase of all four decomposed indexes, among which PEC (1.160) and STC (1.132) contributed the most, indicating the growth of eco-efficiency was driven mainly by management and preference for variable technical scale.

As shown in Supplementary Information Table S7 and Fig. 3c, the major factors contributing to the improvements in the GML index of the CYUA are STC and PTC. The accumulated PEC, PTC, SEC, and STC are 1.073, 1.534, 0.912, and 1.809, respectively, which means

Table 5 MML index in different regions from 2008 to 2017

Region	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017
YREB	1.138	1.117	1.050	1.091	0.984	1.034	1.033	1.207	1.083
YDUA	1.073	1.137	1.004	1.080	0.953	1.032	1.081	1.251	1.196
YMUA	1.215	1.089	1.074	1.037	1.010	1.050	0.996	1.205	1.045
CYUA	1.112	1.134	1.087	1.204	0.993	1.007	1.018	1.135	0.957

Fig. 4 Description of accumulated MML index



(a) Accumulated MML index in different regions from 2008-2017

(b) Accumulated MML index and its decomposed factors

that technological progress is the main driving force. The STC has the largest increase in the YMUA, which indicates that the preference for variable technical scale is the main driving force. The impact of PTC on the GML index is second only to that of STC. Similar to the results for the YMUA, the scale economy and management level in the CYUA also have considerable room for improvement.

At the individual city level of the CYUA, the GML indexes were greater than 1 in all cities, among which Chengdu (1.231), Zigong (1.220), and Suining (1.140) had the highest GML index growth. The PTC (1.113) and SEC (1.098) were the main contributors to Chengdu's GML index, suggesting that the rise of eco-efficiency was driven primarily by technological progress and the scale economy. Zigong's GML index was raised by an improvement in management (PEC: 1.118) and a preference for variable technical scale (STC: 1.265) while being restricted by a decrease in technological progress (PTC: 0.955) and scale economy (SEC: 0.942). Similarly, a preference for variable technical scale (STC: 1.246) was the main contribution to Suining's GML index.

Meta-frontier ML index and its decomposition

Based on Eq. (5), we obtain the MML index of cities in the YREB for 2008–2017. Table 5 shows the MML index in the regions from 2008 to 2017, while Fig. 4a shows the accumulated MML index during the study period. According to the results shown in Table 5, the value of the MML index is greater than 1 in most years, which indicates there was an improvement in the total factor ecological productivity. From the overall trend, the MML index in the YREB increased during the study period at both the aggregate and regional levels. According to Fig. 4a, the YDUA had the largest improvement in the MML index, while the YMUA and CYUA had smaller improvements with similar values. The YDUA has a growth trend similar to that of the YREB, but the gap has been widening in recent years.

As indicated in Eq. (7), we decompose the MML index into four indexes: technical efficiency change (TEC), technological progress (BPC), pure technical catch-up (PTCU), and frontier catch-up (FCU). Through decomposing the MML index, we will obtain a better understanding of the factors that are

Table 6 MML index decomposition results

Year	MML	TEC	BPC	PTCU	FCU
2008–2009	1.138	1.057	1.123	1.121	0.989
2009–2010	1.117	1.040	1.123	1.037	1.030
2010–2011	1.050	0.975	1.180	1.056	1.004
2011–2012	1.091	1.088	1.049	0.999	1.068
2012–2013	0.984	1.053	1.002	1.096	1.034
2013–2014	1.034	1.052	1.033	0.983	1.079
2014–2015	1.033	1.022	1.082	0.988	1.003
2015–2016	1.207	1.000	1.269	1.031	1.034
2016–2017	1.083	1.012	1.106	1.094	0.976
Average	1.082	1.033	1.107	1.045	1.024

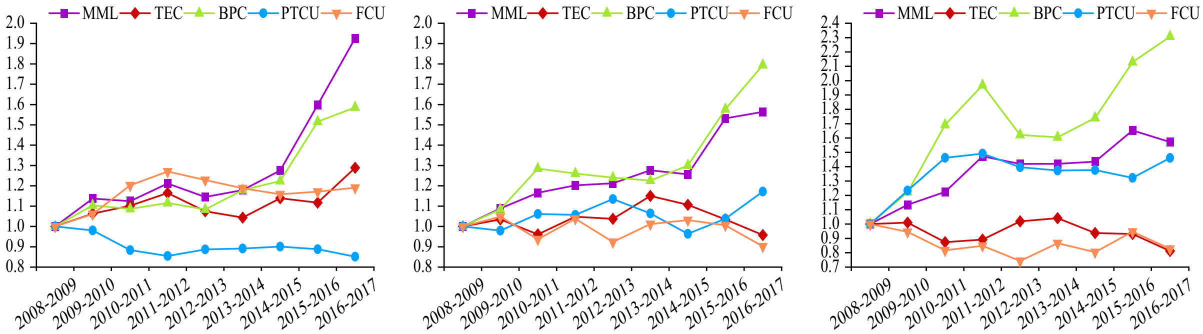
responsible for dynamic changes in eco-efficiency. The four indexes influence eco-efficiency via different mechanisms. As shown in Table 6 and Fig. 4b, all the annual MML indexes are greater than 1, and the accumulated MML index kept increasing except in 2013, which indicates the eco-efficiency improved. All the changes in technological progress from 2008 to 2017 are greater than 1, and the accumulated value of BPC has a more evident upward trend. We can conclude that the changes in technological progress are the main explanation for the improvement of eco-efficiency.

Supplementary Information Table S8 lists the average MML index and its decomposition in the YREB. The average MML index for all cities from 2008 to 2017 was 1.082, and an upward trend was seen in the YREB. The MML index of 70 cities is greater than 1, with only 1 city having index less than 1. Xiaogan (1.193) has the highest MML index, and Yichun (0.977) has the lowest MML index. From the decomposition index of the MML index, we see that all indicators are greater than 1. The average TEC of all 71 cities in the YREB during 2008–2017 was 1.033, indicating that technical efficiency increased by 3.3%. BPC describes the degree to which the contemporaneous benchmark technology frontier advances into the inter-temporal benchmark frontier and characterizes technological progress (Shi & Li, 2019). As shown in Supplementary Information Table S8, the average BPC for all cities from 2008 to 2017 was 1.107, indicating the technological progress increased by 10.7%. In contrast to TEC and TGRC, BPC is the main reason for the increase of the MML index in the YREB. In this paper, TGRC describes the distance change between the group and the global benchmark technology frontier, and it represents the degree of leading innovation (Shi & Li, 2019). The average TGRC for all cities is 1.011, which indicates that there exists a narrowing of the gap between group-frontier and meta-frontier technologies and that there exists a technical catch-up effect.

The TGRC can be divided into PTCU and FCU. PTCU captures the catching-up in technology without the elements of technical inefficiency from the view of a group-frontier. FCU captures the velocity of change of the meta-frontier relative to that of the group frontier (Shi & Li, 2019). When the upward shift of the group-frontier is faster than that of the meta-frontier, the FCU index will exhibit a value less than 1. According to Supplementary Information Table S8, the average PTCU and FCU of all 71 cities in the YREB during 2008–2017 was 1.045 and 1.024, indicating that technical efficiency increased by 4.5% and 2.4%, respectively. The PTCU in 56 of the YREB cities was greater than 1, which indicates a convergence of the gap lying between the existing and the potential technical level. The FCU in 51 cities was greater than 1, which indicates an increase in the room to improve the technical level.

As shown in Supplementary Information Table S9 and Fig. 5a, the major factors contributing to the improvements in the MML index of the YDUA are technological progress, technical efficiency change, and the frontier catch-up effect. The accumulated TEC, BPC, PTCU, and FCU are 1.289, 1.586, 0.851, and 1.191, respectively. The YDUA has the highest increase in BPC, reflecting the shift of DMUs to the technological frontier, which means a boost in performance at the same technical level. The increase in technological progress is greater than technical efficiency changes and the frontier catch-up effect. The YDUA has the most sophisticated technologies to get it closer to the meta-frontier. Thus, the effect of pure technical catch-up is not obvious in that area.

As shown in Supplementary Information Table S10 and Fig. 5b, the major factors contributing to the improvement in the YMUA are technological progress and the pure technical catch-up effect. The accumulated TEC, BPC, PTCU, and FCU are 0.958, 1.794, 1.172, and 0.902, respectively. Due to the transition of technologies from the YDUA and the development of



(a) Accumulated MML index and its decomposition in the YDUA area

(b) Accumulated MML index and its decomposition in the YMUA area

(c) Accumulated MML index and its decomposition in the CYUA area

Fig. 5 Accumulated MML index and its decomposition in different areas

its technical level, the production frontier in the YMUA has obviously improved. The increase in technological progress is greater than the pure technical catch-up effect. However, the actual production of undesirable output increased at the same technology level, resulting in a decline in TEC. In addition, the average value of the frontier catch-up effect is 1.011, and its accumulated value is 0.902. This indicates that the FCU would not make a substantial contribution to the improvement of the eco-efficiency in the YMUA.

As shown in Supplementary Information Table S11 and Fig. 5c, the main influencing factor in the CYUA is technological progress. The technology level in the CYUA is lower than that of the other areas. Technological progress and the pure technical catch-up effect improved the eco-efficiency of the CYUA. The annual value of the technological progress change over the period 2008–2017 was greater than 1 except for 2013, with an average value of 1.152 and an accumulated value of 2.307. The average pure technical catch-up effect over the study period is 1.091, with an accumulated value of 1.462; its impact on the MML index is second only to that of BPC. The accumulated changes of TEC and FCU are 0.812 and 0.827, respectively, showing a downward trend. These changes indicate that the technical efficiency change and frontier catch-up effect reduce the MML index of the CYUA.

Comparison between group-frontier and meta-frontier

In Table 7 and Fig. 6, we compare the change between group-frontier and meta-frontier using the TGRC

Table 7 Comparison between group-frontier and meta-frontier

Year	MML	GML	TGRC
2008–2009	1.138	1.127	1.023
2009–2010	1.117	1.120	1.010
2010–2011	1.050	1.088	0.993
2011–2012	1.091	1.098	1.013
2012–2013	0.984	0.984	1.023
2013–2014	1.034	1.034	1.015
2014–2015	1.033	1.072	0.973
2015–2016	1.207	1.206	1.013
2016–2017	1.083	1.088	1.038
Average	1.082	1.091	1.011

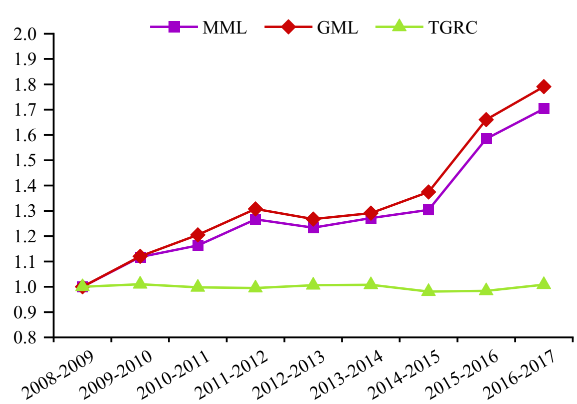


Fig. 6 Accumulated growth factors of group-frontier and meta-frontier

index. The annual value of MML in the YREB during 2008–2017 is 1.082, with an accumulated value of 1.704. The annual value of GML is 1.091, with an accumulated value of 1.791. These figures mean the MML and GML indexes both improved in the YREB, which measures the improvement of the eco-efficiency. Moreover, the annual value of TGRC is 1.011, with an accumulated value of 1.008, which indicate that the gap between group-frontier and meta-frontier is narrowing slightly. This is conducive to the coordinated development of ecological improvement in the YREB.

Conclusions and practical implications

This paper evaluated the eco-efficiency and total factor ecological productivity of 71 cities during 2008–2017 in the YREB. We applied the super-efficiency SBM model considering undesirable output to measure the eco-efficiency of both cities and regions. Moreover, we calculated the GML index scores and decomposed the scores into four parts, namely PEC, PTC, SEC, and STC, to measure the total factor ecological productivity of each area. Also, we considered the MML index and decomposed the index into four parts, namely, TEC, BPC, PTCU, and FCU, to combine the group-frontier and meta-frontier analysis approaches. Also, the technical gap ratio was analyzed based on the GML index and MML index. This paper provides a comprehensive analytical framework for eco-efficiency evaluation and productivity change of cities in the agglomeration. Besides, the changes of GML and MML indexes with detailed decomposition indexes could provide practical implications for managers and practitioners to better understand and promote sustainable development.

Conclusions

This paper enriches the empirical studies regarding regional eco-efficiency in China. From its research results, the main conclusions of this paper are as follows.

1. In terms of eco-efficiency and its dynamic evolution, the YREB overall eco-efficiency remained stable during 2008–2017, showing a fluctuating and slightly upward trend. The average eco-efficiency during the whole study period was 0.599, and an obvious decrease in the eco-efficiency of 71 cities in the YREB was apparent during 2013–2017. Meanwhile, the eco-efficiency of nearly three-quarters of the cities in the YREB did not reach an efficient state, so these cities have the ability to save energy and reduce emissions.
2. Analysis of the GML index and its decomposition showed that the annual average GML index in the YREB was 1.091. During the study period, the GML index in the YREB improved at both the aggregate and regional levels, and technological progress was the key reason for the change in the GML index. The major factors contributing to improvements in the GML index of the YDUA were SEC and PTC; the major factor contributing to the improvements in the GML index of the YMUA was PTC; and the major factor contributing to the improvements in the GML index of the CYUA was STC.
3. From the MML index and its decomposition, the average annual growth of MML index in the YREB was 8.2%. In contrast to TEC and TGRC, BPC was the main reason for the increase of MML index in the YREB. The major factors contributing to the improvements in the MML index of the YDUA were TEC, BPC, and FCU; and the main influencing factor in both the YMUA and CYUA was BPC.
4. Consistent with the research result of Yang and Zhang (2018), analysis of the decomposition of productivity growth indicates that technological progress was the decisive factor in promoting the eco-efficiency of the YREB, while decreasing management level, especially in the CYUA, was the main obstacle to improvement in eco-efficiency. In addition, the technical gap ratio indicated that the gap between group-frontier and meta-frontier narrowed slightly.

Practical implications

Although eco-efficiency can be used to measure sustainability, there is still an issue about how to improve eco-efficiency. The following policy implications are justified based on the findings of this study.

1. The YDUA should continue to maintain its current technical increasing trend. Technological

progress has greatly promoted the growth of eco-efficiency in the YDUA. Therefore, enterprises in the YDUA should be converted from producing high energy-intensive primary goods to doing low energy-intensive deep processing to ensure international competitiveness.

2. The technical catch-up effect did not play any significant role in improving eco-efficiency in the YMUA, so improvement efforts should focus on resource utilization and technology level. This region is rich in natural resources, which can be used to increase its use rate while improving its technology and industrial machinery. Therefore, the YMUA should concentrate on improving its management capabilities, in addition to driving technical development, rather than relying on blind investment and low-level growth.
3. Improvements in both the level of technology and the efficiency of technology usage are required to ensure the improvement in eco-efficiency. The government should play a leading role in the construction of ecological civilization and strengthen environmental governance. Enterprises in the CYUA should take advantage of the advanced production technology and management experience from the YDUA and YMUA. With the background of supply-side structural reform, local governments should help the enterprises to adjust without undermining economic development and ecological protection.
4. The realization of sustainable development goals in a particular region or urban agglomeration should be based on the coordination of all the systems within it. Hence, the regional government should also take effective measures to encourage scientific and technological cooperation from the perspective of regional integrity. For example, the development of the Yangtze River Delta is proceeding in the context of a commitment to regional integration, which can be extended to other regions or urban agglomerations.

Acknowledgements The authors would like to thank editors and anonymous reviewers for their helpful comments and suggestions.

Author contribution All the authors contributed to the study conception and design. Yuhong Wang: methodology, writing-original draft, writing-reviewing and editing, supervision, funding acquisition; Youyang Ren: conceptualization, software, writing-reviewing and editing; Dongdong Wu: conceptualization, data curation, formal analysis, writing-original draft; Wuyong Qian: data curation, software, writing-reviewing and editing. All the authors read and approved the final manuscript.

Funding The research reported in this paper was partially supported by the National Natural Science Foundation of China (No. 71871106) and the Fundamental Research Funds for the Central Universities (Nos. JUSRP1809ZD; 2019JDZD06; JUSRP321016). The work was also sponsored by the Major Projects of Educational Science Fund of Jiangsu Province in 13th Five-Year Plan (No. A/2016/01); the Key Projects of Philosophy and Social Science Research in Universities of Jiangsu Province (No. 2018SJZDI051); the Major Projects of Philosophy and Social Science Research of Guizhou Province (No. 21GZZB32); the Projects of Chinese Academic Degrees and Graduate Education (No. 2020ZDB2); and the Major Projects of the 14th Five-Year Plan for Higher Education Scientific Research of Jiangsu Higher Education Association (No. ZDGG02).

Data availability All data generated or analyzed during this study are included in this article.

Declarations

Ethics approval Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

References

Arabi, B., Munisamy, S., Emrouznejad, A., Toloo, M., & Ghazizadeh, M. S. (2016). Eco-efficiency considering the issue of heterogeneity among power plants. *Energy, 111*, 722–735.

Caiado, R. G. G., de Freitas Dias, R., Mattos, L. V., Quelhas, O. L. G., & Leal Filho, W. (2017). Towards sustainable development through the perspective of eco-efficiency - a systematic literature review. *Journal of Cleaner Production, 165*, 890–904.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *The Economic Journal, 92*(365), 73–86.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chen, K.-H., & Yang, H.-Y. (2011). A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: With application to banking industries in Taiwan and China. *Journal of Productivity Analysis, 35*(3), 197–212.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management, 51*(3), 229–240.

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)-thirty years on. *European Journal of Operational Research, 192*(1), 1–17.

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to data envelopment analysis and its uses: with DEA-solver software and references*. Springer Science & Business Media.

Demiral, E. E., & Sağlam, Ü. (2021). Eco-efficiency and eco-productivity assessments of the states in the United States: A two-stage non-parametric analysis. *Applied Energy, 303*, 117649.

Dirik, C., Şahin, S., & Engin, P. (2019). Environmental efficiency evaluation of Turkish cement industry: An application of data envelopment analysis. *Energy Efficiency, 12*(8), 2079–2098.

Du, X., Wu, D., & Yan, Y. (2023). Prediction of electricity consumption based on GM(1, Nr) model in Jiangsu Province. *China. Energy, 262*, 125439.

Fan, Y., Bai, B., Qiao, Q., Kang, P., Zhang, Y., & Guo, J. (2017). Study on eco-efficiency of industrial parks in China based on data envelopment analysis. *Journal of Environmental Management, 192*, 107–115.

Färe, R., & Grosskopf, S. (2006). *New directions: efficiency and productivity*. Springer Science & Business Media.

Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis, 3*(1–2), 85–101.

Färe, R., Grosskopf, S., Lovell, C. K., & Pasurka, C. (1989). Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *The Review of Economics and Statistics, 71*(1), 90–98.

Färe, R., Grosskopf, S., Noh, D.-W., & Weber, W. (2005). Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics, 126*(2), 469–492.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review, 84*(1), 66–83.

Hou, X., Liu, J., Zhang, D., Zhao, M., & Xia, C. (2019). Impact of urbanization on the eco-efficiency of cultivated land utilization: A case study on the Yangtze River Economic Belt, China. *Journal of Cleaner Production, 238*, 117916.

Huang, J., Yang, X., Cheng, G., & Wang, S. (2014). A comprehensive eco-efficiency model and dynamics of regional eco-efficiency in China. *Journal of Cleaner Production, 67*, 228–238.

Huang, Y., Li, L., & Yu, Y. (2018). Do urban agglomerations outperform non-agglomerations? A new perspective on exploring the eco-efficiency of Yangtze River Economic Belt in China. *Journal of Cleaner Production, 202*, 1056–1067.

Li, W., Wang, W., Wang, Y., & Ali, M. (2018). Historical growth in total factor carbon productivity of the Chinese industry - a comprehensive analysis. *Journal of Cleaner Production, 170*, 471–485.

Lin, B., & Chen, X. (2019). Evaluating the CO_2 performance of China's non-ferrous metals industry: A total factor meta-frontier Malmquist index perspective. *Journal of Cleaner Production, 209*, 1061–1077.

Liu, X., Chu, J., Yin, P., & Sun, J. (2017). DEA cross-efficiency evaluation considering undesirable output and ranking priority: A case study of eco-efficiency analysis of coal-fired power plants. *Journal of Cleaner Production, 142*, 877–885.

Liu, Y., Zhu, J., Li, E. Y., Meng, Z., & Song, Y. (2020). Environmental regulation, green technological innovation, and eco-efficiency: The case of Yangtze River Economic Belt in China. *Technological Forecasting and Social Change, 155*, 119993.

Lorenzo-Toja, Y., Vázquez-Rowe, I., Amores, M. J., Termes-Rifé, M., Marín-Navarro, D., Moreira, M. T., & Feijoo, G. (2016). Benchmarking wastewater treatment plants under an eco-efficiency perspective. *Science of the Total Environment, 566*, 468–479.

Oh, D.-H. (2010a). A global Malmquist-Luenberger productivity index. *Journal of Productivity Analysis, 34*(3), 183–197.

Oh, D.-H. (2010b). A metafrontier approach for measuring an environmentally sensitive productivity growth index. *Energy Economics, 32*(1), 146–157.

Oh, D.-H., & Lee, J.-D. (2010). A metafrontier approach for measuring Malmquist productivity index. *Empirical Economics, 38*(1), 47–64.

Shephard, R. W., & Färe, R. (1974). *The law of diminishing returns, production theory* (pp. 287–318). Springer.

Shi, X., & Li, L. (2019). Green total factor productivity and its decomposition of Chinese manufacturing based on the MML index: 2003–2015. *Journal of Cleaner Production, 222*, 998–1008.

Tang, J., Tang, L., Li, Y., & Hu, Z. (2020). Measuring eco-efficiency and its convergence: Empirical analysis from China. *Energy Efficiency, 13*, 1075–1087.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498–509.

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research, 143*(1), 32–41.

Wang, D., Wan, K., & Yang, J. (2019a). Measurement and evolution of eco-efficiency of coal industry ecosystem in China. *Journal of Cleaner Production, 209*, 803–818.

Wang, H., & Yang, J. (2019). Total-factor industrial eco-efficiency and its influencing factors in China: A spatial panel data approach. *Journal of Cleaner Production, 227*, 263–271.

Wang, X., Ding, H., & Liu, L. (2019b). Eco-efficiency measurement of industrial sectors in China: A hybrid super-efficiency DEA analysis. *Journal of Cleaner Production, 229*, 53–64.

Wang, Y., Wu, D., Qian, W., & Li, H. (2021). Cross-efficiency intervals integrated ranking approach based on the generalized Fermat-Torricelli point. *Computers & Industrial Engineering, 162*, 107786.

Wang, Y., Wu, D., & Li, H. (2022). Efficiency measurement and productivity progress of regional green technology innovation in China: A comprehensive analytical framework. *Technology Analysis & Strategic Management, 34*(12), 1432–1448.

Wu, D., Li, H., & Wang, Y. (2022). Measuring sustainability and competitiveness of tourism destinations with data

envelopment analysis. *Journal of Sustainable Tourism*. https://doi.org/10.1080/09669582.2022.2042699
Wu, D., Wang, Y., & Qian, W. (2020). Efficiency evaluation and dynamic evolution of China's regional green economy: A method based on the Super-PEBM model and DEA window analysis. *Journal of Cleaner Production, 264*, 121630.
Yang, L., Ma, C., Yang, Y., Zhang, E., & Lv, H. (2020). Estimating the regional eco-efficiency in China based on bootstrapping by-production technologies. *Journal of Cleaner Production, 243*, 118550.
Yang, L., & Yang, Y. (2019). Evaluation of eco-efficiency in China from 1978 to 2016: Based on a modified ecological footprint model. *Science of the Total Environment, 662*, 581–590.
Yang, L., & Zhang, X. (2018). Assessing regional eco-efficiency from the perspective of resource, environmental and economic performance in China: A bootstrapping approach in global data envelopment analysis. *Journal of Cleaner Production, 173*, 100–111.
Young, A. (2003). Gold into base metals: Productivity growth in the People's Republic of China during the reform period. *Journal of Political Economy, 111*(6), 1220–1261.
Yu, Y., Huang, J., & Zhang, N. (2018). Industrial eco-efficiency, regional disparity, and spatial convergence of China's regions. *Journal of Cleaner Production, 204*, 872–887.
Zhang, J., Liu, Y., Chang, Y., & Zhang, L. (2017). Industrial eco-efficiency in China: A provincial quantification using three-stage data envelopment analysis. *Journal of Cleaner Production, 143*, 238–249.
Zhou, H., Yang, Y., Chen, Y., & Zhu, J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions. *European Journal of Operational Research, 264*(1), 1–16.
Zhou, Y., Kong, Y., Sha, J., & Wang, H. (2019). The role of industrial structure upgrades in eco-efficiency evolution: Spatial correlation and spillover effects. *Science of the Total Environment, 687*, 1327–1336.
Zhu, W., Xu, L., Tang, L., & Xiang, X. (2019). Eco-efficiency of the Western Taiwan Straits Economic Zone: An evaluation based on a novel eco-efficiency model and empirical analysis of influencing factors. *Journal of Cleaner Production, 234*, 638–652.
Zofio, J. L. (2007). Malmquist productivity index decompositions: A unifying framework. *Applied Economics, 39*(18), 2371–2387.