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Green productivity growth and competition analysis of road transportation at the provincial level employing Global Malmquist-Luenberger Index approach

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ABSTRACT

Road transportation has been playing an irreplaceable role in the process of pursuing sustainable development. This study employs a Global Malmquist-Luenberger Index approach to evaluate the green productivity growth of this industry at the provincial level based on the Data Envelopment Analysis and Directional Distance Function. Further, it decomposes green productivity growth into changes in various types of efficiency and technological progress. Finally, this study structures a novel quadrant matrix analysis framework based on the green productivity growth rate and stability, using the matrix to analyze the performance of provincial road transportation industries. This analysis results show that: (1) a fluctuating and slowly upward trend of green productivity over time exists; (2) at the regional level, the road transportation industries in Western and Central China achieved green productivity growth because of the catch-up effect and the economies of scale, respectively; (3) the green productivity in China's Eastern area (the most developed area) declined, giving opportunities for improvement in both technology and efficiency; and (4) the southeast coast and border provinces showed large fluctuations in terms of green productivity of road transportation because of the impact of foreign trade environment. Implications for transportation system planning are provided based on the results.

1. Introduction

Road transportation has been playing an irreplaceable role in the process of national economic development in China. The average passenger volume per year accounted for 85.63% of the whole transportation system total from 2010 to 2019, and the average freight volume per year accounted for 75.75% (NSBC, 2020). However, the air pollution, traffic accidents, and traffic noise produced by road transportation have excessively impacted the environment and economic development. Globally, because of the increasing energy consumption in the transportation industry, more and more exhaust gas, such as carbon dioxide (CO_2), is being discharged into the air (Wu et al., 2015). Worse than that, although exhaust gas emission is a crucial undesirable output, it is not the only negative byproduct of the transportation industry. The issues of both traffic noise and accidents also constitute significant undesirable outputs of the road transportation industry (Liu et al., 2020).

On average, 209,000 traffic accidents occurred per year during 2009–2018 in China, and the number of traffic accidents grew by an average of 1.76% per year. The direct economic losses caused by traffic accidents amount to 159 million USD per year on average (NSBC, 2020). Additionally, road traffic noise induces sleep disturbances such as insomnia in urban populations, even when the traffic noise is at a normal level (Sørensen et al., 2012). All of these environmental issues caused by road transport have been hindering the sustainable development of the transportation industry and even the economic growth in China (Zhu et al., 2020). In consequence, the sustainable development of the transportation industry should align with both the economic and ecological environment (Ghahari et al., 2019). To promote the development of road transportation while reducing each undesirable output, and to further accelerate the sustainability of economic development, it is essential to investigate the green development performance of this

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industry.

Generally, the green development performance of road transportation considering various undesirable harmful byproducts can be measured by green productivity (Sohrabi and Khreis, 2020; Nikolaou and Dimitriou, 2018), which takes into account both industrial development and social benefits. Green productivity is a key index to depict the performance in terms of sustainable development of an industry and is drawing increasing research interest (Shi and Li, 2019). It can be assessed in terms of environmental efficiency by the Data Envelopment Analysis (DEA) approach, which is a popular linear programming technique (Li et al., 2019). Focusing on employing DEA to evaluate environmental efficiency in the transportation industry, Zhang et al. (2015) analyzed the carbon emission efficiency change of this industry in China from 2002 to 2010. Analogously, Omrani et al. (2019) evaluated transportation environmental efficiency as a step toward reducing carbon emissions.

Like air pollution, traffic accidents are also an environmental issue, and their number is treated as an index to assess the safety and environmental performance of the road transportation industry. Traffic accidents should be minimized and treated as undesirable output because accidents comprise a harmful byproduct. As an undesirable output index, the number of accidents was used to assess the efficiency of this industry in India (Pal and Mitra, 2016), and it was also used to study the performance of road safety policies (Nikolaou and Dimitriou, 2018). Likewise, Wang (2019) evaluated the sustainability performance of the transportation industry by employing a slacks-based measure (SBM) DEA model.

Additionally, traffic noise was once ignored in green development of road transportation industry (Peng et al., 2019), but is now becoming garnering much attention as a research topic for scholars studying green development and social benefits. As defined in the national Environmental Quality Standard for Noise in China, road traffic noise value is expressed in decibels (Db(A)), which can be measured by the continual equivalent sound level. Accordingly, the noise is high-speed persistent streaming data. In terms of practical and theoretical contributions, considering noise is helpful to expand the study on environmental efficiency, and employing streaming data is of great significance to data processing in green productivity evaluation (Song et al., 2018; Zhou et al., 2020).

To promote green transportation development, many studies have investigated and improved environmental efficiency. However, it is not enough to improve just the environmental efficiency of a production unit; the impact of technological progress also has to be considered when promoting productivity (Qin et al., 2017). More research should be provided to promote green development from the perspectives of efficiency gains and technological progress (O'Donnell, 2012). Accordingly, the Global Malmquist-Luenberger Index (GMLI) approach is a popular technique to examine green productivity growth, efficiency changes, and technological progress when various undesirable outputs (e.g., CO_2, traffic noise) and desirable outputs are considered simultaneously (Oh et al., 2017). GMLI is free from the infeasibility problem that plagues the Malmquist index, and it is a helpful, environmentally sensitive, productivity growth index (Oh, 2010). Using the GMLI approach, Li et al. (2019) calculated the green total-factor productivity of water resources across 30 provinces in China from 2005 to 2015, and Wang et al. (2020) investigated the carbon emissions performance of 13 airlines from 2009 to 2013 in China, in terms of the static and dynamic efficiencies. Related to the transportation industry, Sun et al. (2019) examined the comprehensive impact of carbon emissions in this industry in China's Central area in the period of 2005–2016 employing the GMLI approach. However, in that study, only CO_2 emissions were considered as an undesirable output, and only the Central area was investigated.

In summary, to measure precisely and improve the efficiency gains and technological progress, the green productivity of road transportation must be investigated, which can provide insights into efficiency gains and technological progress (Baleentis et al., 2020; Song et al., 2020). Therefore, this study employed the Directional Distance Function (DDF), DEA, and GMLI to investigate the performance of road transportation industries at the provincial level from 2008 to 2017 in terms of green productivity growth while using traffic accidents, CO_2 emission, and traffic noise as the model's undesirable outputs. While our study has common ground with the previous papers, such as those considering CO_2 emission and focusing on industrial green productivity growth in China, the current study enriches the existing literature in four aspects.

First of all, unlike the studies of Nikolaou and Dimitriou (2018) and Liu et al. (2020), the current study decomposes the green productivity growth into changes in various efficiencies and technological progress. This technique elucidates an alternative research starting point for the study of green development performance of the road transportation industry. Secondly, unlike previous studies that considered only one or two undesirable outputs, the current study integrates three kinds of undesirable output—CO_2, traffic noise, and traffic accidents—to investigate the green productivity of road transportation, which enriches the content of green productivity evaluation. Thirdly, traffic noise is an example of streaming data, and we provide an approach to process streaming data to evaluate efficiency. By introducing streaming data into efficiency evaluation and processing it effectively, the selection scope of input and output indexes in environmental performance evaluation can be further expanded. Finally, we introduce a novel two-dimensional quadrant matrix based on green productivity growth rate and stability to analyze the performance of provincial road transportation industries. This analysis technique can be easily applied to other research topics to investigate comprehensive performance when results are reflected by two evaluation dimensions.

Sections 2 to 4 of the current study are constructed as follows. The research framework, which incorporates DDF, DEA, and GMLI, is proposed in Section 2. In Section 3, three harmful byproduct outputs, including traffic accidents, CO_2 emissions, and traffic noise, are analyzed as undesirable output indexes to examine green productivity growth and the performance of components of road transportation. Finally, Section 4 discusses implications and contributions.

2. Research framework

In this study, the GMLI model is proposed to calculate the green productivity of the road transportation industry based on DDF and DEA. Therefore, both DDF and DEA are necessary steps to achieve GMLI assessment. In order to highlight the connection between DDF, DEA, and GMLI, a graphical framework is depicted in Fig. 1.

As illustrated in Fig. 1, we propose using the DDF, DEA, and GMLI approaches in sequence, and further illustrate how to obtain each index's value.

2.1. Directional distance function approach

Suppose there are n observed sample points in our study, each called a Decision Making Unit (DMU). For a given DMU_j, let x_{ij}^{t} be the observed input resources, y_{rj}^{ht} be the observed desirable output products, and y_{kj}^{ut} be the undesirable output byproducts in period t. Here, $i = 1, 2, \ldots, m$; $r = 1, 2, \ldots, s$; $k = 1, 2, \ldots, b$; $t = 1, 2, \ldots, T$; and $j = 1, 2, \ldots, n$. Superscript h and u only represent the desirable

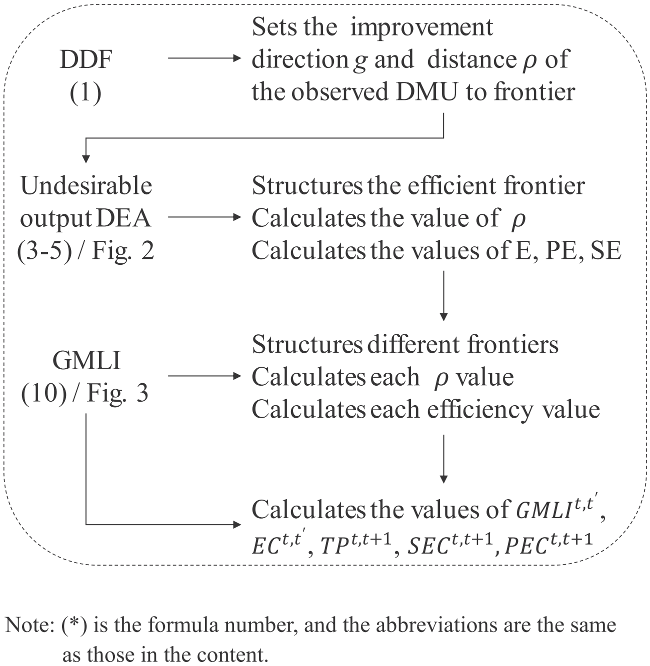


Fig. 1. Connections among DDF, DEA, and GMLI
Note: (*) is the formula number, and the abbreviations are the same as those in the content.

output and the undesirable output, respectively.

Accordingly, let $X = (x_1, x_2, \ldots, x_m)$ be the aggregate input, $Y^h = (y_1^h, y_2^h, \ldots, y_s^h)$ be the aggregate desirable output, and $Y^u = (y_1^u, y_2^u, \ldots, y_b^u)$ be the aggregate undesirable output. Symbols *s, m, b,* are the number of desirable output indexes, number of input indexes, and number of undesirable output indexes, respectively. Accordingly, the production possibility set (PPS) is expressed as formula (1):

$$P(X) = \left\{ \left(Y^h, Y^u\right) \middle| X \text{ produces } \left(Y^h, Y^u\right) \right\} \tag{1}$$

Let $g = (g_x, g_h, g_u)$ be the direction vector of each index, indicating the improvement directions of input, desirable output, and undesirable output. Then the DDF can be defined as formula (2):

$$D^t\left(X^t, Y^{ht}, Y^{ut}; g_x^t, g_h^t, g_u^t\right) = \max\left\{\rho \middle| \times \left(X^t - \rho X^t, Y^{ht} + \rho Y^{ht}, Y^{ut} - \rho Y^{ut}\right) \in P^t\left(X^t\right)\right\} \tag{2}$$

where P is the PPS, and ρ is the directional distance of the observed DMU to its potential optimal state in the tth period (Zhou et al., 2012), indicating the optimal improvement ratio of input, desirable output, and undesirable output. The goal of formula (2) is to maximize the desirable outputs while simultaneously minimizing both the inputs and undesirable outputs. Because of the flexibility and clear interpretation it provides in choosing the projection direction to the efficient production frontier, DDF is often used in DEA and GMLI to evaluate relative efficiency or productivity growth (Oh, 2010).

2.2. DEA efficiency based on DDF

DEA is a data-oriented and nonparametric frontier technique to measure the relative efficiency of observed DMUs (Emrouznejad and Yang, 2018). The technique performs well when there are multiple inputs, multiple desirable outputs, and multiple undesirable outputs in each DMU (e.g., m inputs, s desirable outputs, and b undesirable outputs). In the evaluation process, the best practice DMUs construe the efficient frontier, and the distance of DMU_0 (denoting the DMU being evaluated) to the frontier is its relative efficiency. Based on the DDF approach, the DEA model for the efficiency of DMU_0 is expressed as formula (3):

$$\begin{aligned}
&\max \rho \\
&s.t. \quad \sum_{j=1}^{n} x_{ij}^t \lambda_j \le (1-\rho) x_{io}^t, \quad i = 1,2,\ldots,m; \\
&\qquad \sum_{j=1}^{n} y_{rj}^{ht} \lambda_j \ge (1+\rho) y_{ro}^{ht}, \quad r = 1,2,\ldots,s; \\
&\qquad \sum_{j=1}^{n} y_{kj}^{ut} \lambda_j \le (1-\rho) y_{ko}^{ut}, \quad k = 1,2,\ldots,b; \\
&\qquad \lambda_j \ge 0, \quad x_{ij}^t \ge 0, \quad y_{rj}^{ht} \ge 0, \quad y_{kj}^{ut} \ge 0; \\
&\qquad j = 1,2,3,\ldots,n.
\end{aligned} \tag{3}$$

where ρ is the distance of DMU_0 to the frontier in the tth period. The efficiency obtained from formula (3) is $(1-\rho)/(1+\rho)$, which is called technical efficiency (E), and we calculate it with the constant returns to scale assumption. The value of E is between 0 and 1. If the value of ρ_0^t equals zero, then the efficiency value is one and DMU_0 is defined as efficient, indicating that DMU_0 is the best practice one; otherwise, it is inefficient (Wu et al., 2016). According to Oggioni et al. (2011) and Riccardi et al. (2012), if we add the additional convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$, $j = 1, 2\ldots, n$ to formula (3), we get formula (4). This formula can be used to obtain the pure technical efficiency.

$$\begin{aligned}
&\max \rho' \\
&s.t. \quad \sum_{j=1}^{n} x_{ij}^t \lambda_j \le (1-\rho') x_{io}^t, \quad i = 1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}^{ht} \lambda_j \ge (1+\rho') y_{ro}^{ht}, \quad r = 1,2,\ldots,s; \\
&\sum_{j=1}^{n} y_{kj}^{ut} \lambda_j \le (1-\rho') y_{ko}^{ut}, \quad k = 1,2,\ldots,b; \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0, \quad x_{ij}^t \ge 0, \quad y_{rj}^{ht} \ge 0, \quad y_{kj}^{ut} \ge 0; \\
&j = 1,2,3,\ldots,n.
\end{aligned} \tag{4}$$

where ρ' is the distance of DMU_0 to the frontier in the tth period. The pure technical efficiency (PE) can be obtained using formula (4); PE is defined as $(1-\rho')/(1+\rho')$ and represents the comprehensive managerial ability of DMU_0 (Yang and Lu, 2006). As before, DMU_0 is defined to be efficient when the efficiency value is one; otherwise, DMU_0 is inefficient.

Finally, the scale efficiency (SE) also can be obtained by SE = E/PE (formula (5)), according to Banker et al. (1984). SE represents the economies of scale of DMU_0 (Giokas, 1991). When the value of SE is equal to one, the production of DMU_0 is in the stage of optimal economies of scale; otherwise, it is not.

2.3. GMLI model and its decomposition

The value obtained by formulas (3) and (4) measures the efficiency performance of every DMU in a given year, but cannot depict the dynamic trend of productivity growth. The Malmquist index approach is the most common way to measure efficiency changes and productivity growth (Pastor et al., 2020). The classical Malmquist index is obtained based on the contemporaneous benchmark (Zhang et al., 2015), a technique that constructs the benchmark production frontier only at the given time. Moreover, the undesirable output index cannot be involved in the PPS, as shown in formula (6).

$$M^z\left(X^t, Y^{ht}, X^{t'}, Y^{ht'}\right) = \frac{E^z\left(X^{t'}, Y^{ht'}\right)}{E^z\left(X^t, Y^{ht}\right)} \tag{6}$$

where superscript z=t, t+1, indicate the benchmark technology frontier. In order to consider the undesirable output index, Chung et al. (1997) developed a Malmquist-Luenberger (ML) index model to deal with both undesirable outputs and desirable outputs simultaneously. Additionally, to get more precise results, the ML index is usually calculated as the geometric mean of the indices of two consecutive periods, year t and year $t+1$, which is shown in formula (7):

$$\begin{aligned}
&ML^{t,t'}\left(X^t, Y^{ht}, Y^{ut}, X^{t'}, Y^{ht'}, Y^{ut'}\right) \\
&= \left[\frac{E^t\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \times \frac{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^{t'}\left(X^t, Y^{ht}, Y^{ut}\right)}\right]^{1/2} = \left[\frac{E^t\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \times \frac{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^{t'}\left(X^t, Y^{ht}, Y^{ut}\right)} \times \frac{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \times \frac{E^t\left(X^t, Y^{ht}, Y^{ut}\right)}{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}\right]^{1/2} \\
&= \frac{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \times \left[\frac{E^t\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)} \times \frac{E^t\left(X^t, Y^{ht}, Y^{ut}\right)}{E^{t'}\left(X^t, Y^{ht}, Y^{ut}\right)}\right]^{1/2} = EC^{t,t'} \times TC^{t,t'}
\end{aligned} \tag{7}$$

where t'=t+1,t=1,2, ...,T-1. The ML index can be further decomposed into different components of productivity growth, which are efficiency change (EC) and technological change (TC). TC measures how much the technology frontier in year t shifts towards the technology frontier in year $t+1$ in the direction of less X and Y^u but more Y^h. Technology progresses, regresses, and remains when the value of TC is greater than 1, less than 1, and equal to 1, respectively.

While formula (7) is a general ML index model, through which the ML index is calculated by comparing two consecutive periods, there may be no feasible solutions when the convexity constraint $\sum_{j=1}^{n}\lambda_j = 1,\ j = 1, 2 \ldots, n$ is added (Pastor and Lovell, 2005). Therefore, Oh (2010) proposed the GMLI model based on Chung et al. (1997): the PPS in GMLI is the union of the production technologies in all periods. Then the DDF can be defined as formula (8):

$$\begin{aligned}
D^G\left(X, Y^h, Y^u; g_x, g_y, g_u\right) = max\Big\{\rho \Big| \\
\times \left(X - \rho X, Y^h + \rho Y^h, Y^u - \rho Y^u\right) \in P^G(X)\Big\}
\end{aligned} \tag{8}$$

where $P^G(X) = \cup_{t=1}^{T} P^t(X)$. Also, the GMLI model can be expressed and decomposed as formula (9):

$$\begin{aligned}
&GMLI^{t,t'}\left(X^t, Y^{ht}, Y^{ut}, X^{t'}, Y^{ht'}, Y^{ut'}\right) \\
&= \frac{E^G\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^G\left(X^t, Y^{ht}, Y^{ut}\right)} \\
&= \frac{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \times \frac{E^t\left(X^t, Y^{ht}, Y^{ut}\right) / E^G\left(X^t, Y^{ht}, Y^{ut}\right)}{E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right) / E^G\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)} \\
&= EC^{t,t'} \times \frac{E^G\left(X^{t'}, Y^{ht'}, Y^{ut'}\right) / E^{t'}\left(X^{t'}, Y^{ht'}, Y^{ut'}\right)}{E^G\left(X^t, Y^{ht}, Y^{ut}\right) / E^t\left(X^t, Y^{ht}, Y^{ut}\right)} \\
&= EC^{t,t'} \times TP^{t,t'}
\end{aligned} \tag{9}$$

where the superscript indicates benchmark technology frontier. The parameters t, t', and $EC^{t,t'}$ are the same as in formula (7). The expression $E^G(X^t, Y^{ht}, Y^{ut})/E^t(X^t, Y^{ht}, Y^{ut})$is the gap from the technology frontier in year t to the global technology frontier, and $E^G(X^{t'}, Y^{ht'}, Y^{ut'})/E^{t'}(X^{t'}, Y^{ht'}, Y^{ut'})$ is the gap from the technology frontier in year t+1 to the global technology frontier. The ratio of the gap in numerator to the gap in the denominator is the gap change for years t and t+1. Since the benchmark frontier in each gap is the same global technology frontier, the gap change measures the technological progress (regress) as measured by TC in formula (7). In the same way, technology progresses, regresses, and remains when the value of TP is greater than 1, less than 1, and equal to 1, respectively. Oh et al. (2017) proved that transport production service activity enables more desirable output, such as freight volume, and less undesirable outputs and inputs when $GMLI^{t,t'} > 1$, which indicates that productivity increased. Otherwise, productivity declined when $GMLI^{t,t'} < 1$ or remained unchanged when $GMLI^{t,t'} = 1$.

When the E in $(t+1)^{th}$ period is compared to itself in the tth period, the efficiency change can be obtained, as well as PE and SE, where t = 1, 2 … T-1. According to Färe et al. (1994) and Zofio (2007), $EC^{t,t'}$ can be decomposed into scale efficiency change (SEC) and pure technical efficiency change (PEC). Accordingly, the $GMLI^{t,t'}$ can be decomposed, as shown in formula (10):

$$GMLI^{t,t'} = EC^{t,t'} \times TP^{t,t'} = PEC^{t,t'} \times SEC^{t,t'} \times TP^{t,t'} \tag{10}$$

2.4. Calculation illustration

Fig. 2 illustrates how to calculate E, PE, and SE. In Fig. 2, the straight blue line and curved blue line are the efficient frontiers under constant return to scale (CRS) and variable return to scale (VRS), respectively. Also, P^{CRS} and P^{VRS} are the different production possibility sets, and b' and b'' are the efficient projections of DMU b onto the frontiers under VRS and CRS, along the direction of g.

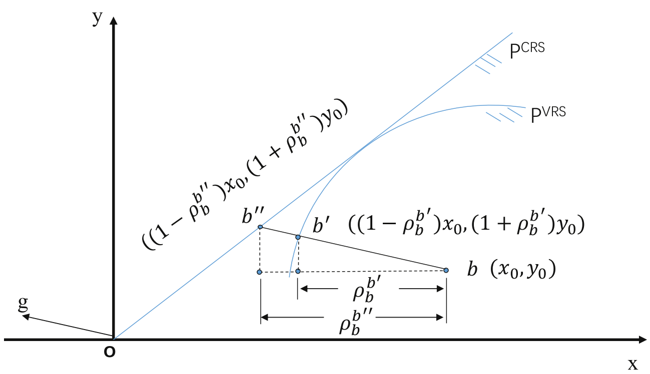


Fig. 2. Illustration of efficiency calculation in DEA.

According to Färe et al. (2015), the efficiency of DMU b under CRS means that the ratio of output to input of b is compared to that of other DMUs on the efficient frontier and can be calculated as $E = \frac{y_0/x_0}{(1+\rho_b^{b''})y_0/(1-\rho_b^{b''})x_0} = \frac{1-\rho_b^{b''}}{1+\rho_b^{b''}}$. Analogously, the efficiency under VRS is $PE = \frac{y_0/x_0}{(1+\rho_b^{b'})y_0/(1-\rho_b^{b'})x_0} = \frac{1-\rho_b^{b'}}{1+\rho_b^{b'}}$. Accordingly, SE can be obtained by formula (5). Here, both $\rho_b^{b''}$ and $\rho_b^{b'}$ are improvement ratios of input and output, and can be calculated by formulas (3) and (4).

Based on Figs. 2 and 3 illustrates how to calculate the GMLI. In Fig. 3, P^t, P^{t+1}, and P^G are the production possibility sets with the tth, *(t+1)*th, and global production technology respectively, as defined before. Points a and a' are the same DMU to be evaluated in the tth and *(t+1)*th years, respectively. Like point b' in Fig. 2, the other points in Fig. 3 are the efficient projections of a and a' onto the different frontiers, along the direction of g.

According to formula (8), $GMLI^{t,\,t+1}$ can be obtained as:$GMLI^{t,t+1} = E^G(X^{t+1}, Y^{h(t+1)}, Y^{u(t+1)})/E^G(X^t, Y^{ht}, Y^{ut}) = \frac{(1-\rho_{a'}^{a'G})/(1+\rho_{a'}^{a'G})}{(1-\rho_a^{aG})/(1+\rho_a^{aG})}$. Likewise, $EC^{t,t+1} = E^{t+1}/E^t = \frac{(1-\rho_{a'}^{a't+1})/(1+\rho_{a'}^{a't+1})}{(1-\rho_a^{at})/(1+\rho_a^{at})}$, and $TP^{t,t+1} = \frac{E^G(X^{t+1},Y^{h(t+1)},Y^{u(t+1)})/E^{t+1}}{E^G(X^t,Y^{ht},Y^{ut})/E^t} = \frac{[(1-\rho_{a'}^{a'G})/(1+\rho_{a'}^{a'G})]\big/[(1-\rho_{a'}^{a't+1})/(1+\rho_{a'}^{a't+1})]}{[(1-\rho_a^{aG})/(1+\rho_a^{aG})]\big/[(1-\rho_a^{at})/(1+\rho_a^{at})]}$.

Finally, according to formula (5), $EC^{t,t+1} = E^{t+1}/E^t = (PE^{t+1} \times SE^{t+1})/(PE^t \times SE^t) = \frac{PE^{t+1}}{PE^t} \times \frac{SE^{t+1}}{SE^t} = PEC^{t,t+1} \times SEC^{t,t+1}$. Here, the value of each ρ can be obtained by formulas (3) and (4).

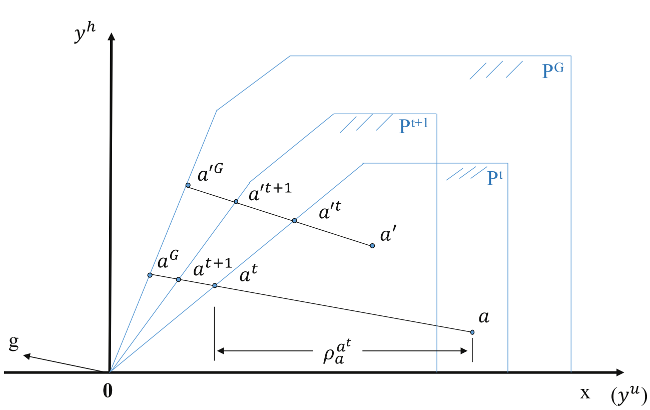


Fig. 3. Illustration of GMLI calculation.

3. Performance evaluation of road transportation in terms of green productivity

3.1. Indexes and data

A thorough investigation of the green productivity growth of a road transportation industry requires consideration of various resources that keep transportation systems operating. Typically, the infrastructure and the number of operating vehicles are treated as inputs to reflect the service ability (Zhang and Wei, 2015; Wu et al., 2016). In addition to service resources, labor and energy are necessary inputs to maintain transportation operation. According to Chai et al. (2016) and Liu et al. (2020), highway mileage and the number of employees always represent road transportation infrastructure and labor in this industry. Since various types of energy are used in road transportation, the standard coal consumed is used to represent energy consumption. Therefore, we select highway mileage, number of employees in this industry, number of operating vehicles, and standard coal consumption as our model's input variables.

Moreover, the significant function and the most prominent socioeconomic value of road transportation is the provision of passenger and freight services (Kishimoto et al., 2017). Accordingly, both the freight and passage turnover volumes are always selected as desirable output indexes to investigate the transportation industry performance (Baležentis et al., 2016). These two indexes represent road transportation production capacity. Along with these desirable outputs, various undesirable outputs are byproducts of road transportation operation. Since green development involves not only natural environmental pollution but also the safety environment, we select traffic accidents, traffic noise, and CO_2 emissions as the undesirable output indexes in our study (Sánchez et al., 2018; Egbetokun et al., 2020).

In conclusion, our model uses the indexes highway mileage, number of employees, number of operating vehicles, freight turnover volume, standard coal consumption, and passenger turnover volume. These, as well as the selected undesirable output indexes, are shown in Table 1.

In this study, the data related to the indexes of highway mileage, number of operating vehicles, number of employees, traffic accidents, freight turnover volume, and passenger turnover volume are available in the China Statistical Yearbook 2009–2018. The data related to the index of standard coal consumption is obtained from the China Energy Statistical Yearbook 2009–2018.

Unfortunately, official statistics about CO_2 emissions at the transportation industry level do not exist. Accordingly, various models are used to estimate CO_2 emissions, such as the fuel-based carbon footprint model (Chang et al., 2013) and the CO_2 emission model based on standard coal (Tu and Liu, 2014). Since the energy input is standard coal consumption in the road transportation industry, we employ the approach of Tu and Liu (2014) to estimate

Table 1
Output and input indexes.

	Variables	Units
Inputs	Highway mileage	10^4 km
	Operating vehicles	10^4 vehicles
	Employees	Persons
	Standard coal consumption	10^4 tons
Desirable Outputs	Passenger turnover volume	10^8 passenger-km
	Freight turnover volume	10^8 ton-km
Undesirable Outputs	CO_2 emissions	Tons
	Traffic accidents	Number of accidents
	Noise	Db(A)

the CO_2 emissions of road transportation, thereby obtaining a result almost the same as the reference values of the Japanese Institute of Energy Economics and Energy Information Administration.

Accordingly, CO_2 emissions in the road transportation industry are estimated through the formula $CO_2^E = SSC \times 2.53$, where CO_2^E is the estimated CO_2 emissions, SSC is the standard coal consumption, and 2.54 is the conversion coefficient from standard coal to CO_2. Thus, the CO_2 emissions in this study can be obtained.

Finally, the road transportation noise level can be calculated through continuous point-to-point monitoring. According to the technical specification for noise monitoring issued by the Ministry of Environmental Protection of China in 2012, the extent of road traffic noise can be calculated as formula (11):

$$\overline{V} = \frac{1}{l} \sum_{i=1}^{n} (l_i \times V_i) \tag{11}$$

Here, $\overline{V}$ is the average value of equivalent continual sound levels of road traffic noise,l_i is the ith monitored road length, $l = \sum_{i=1}^{n} l_i$ (all lengths in meters), and V_i is the sound level of the ith monitored road.

In the next section, we use the specified model to examine the green productivity growth of 30 provincial-level regional road transportation industries in China from 2008 to 2017. Furthermore, the productivity growth is decomposed into different efficiency changes and technological progress.

3.2. Provincial green productivity growth analysis

In line with the current research framework, this study evaluates the road transportation green productivity growth in China in 30 provincial-level regions, taking into account undesirable outputs. Moreover, the green productivity growth of road transportation is further decomposed into TP, PEC, and SEC in the period 2008–2017, as shown in Table 2.

Table 2 shows that the annual average value of GMLI was 1.0090, which indicates that green productivity grew slightly during 2008–2017. Efficiency change is one of the driving forces of productivity growth in the road transportation industry. The annual average value of efficiency change is 1.0178, but the annual average value of technological progress is less than one, at only 0.9961. This difference indicates that the green productivity growth mainly results from efficiency change rather than technological progress. In detail, both scale efficiency and pure technical efficiency boosted green productivity growth. Table 2 exhibits data showing that the road transportation industry achieved green productivity growth (GMLI > 1) considering various undesirable outputs in four out of nine years while reductions (GMLI < 1) were seen in the other five years.

In order to clarify understanding of the green productivity of road transportation industries in different regions, the technological progress and efficiency changes are illustrated precisely according to their provincial characteristics. This research aims to promote green productivity growth, sustainable technology, and various efficiencies on a larger scale, so the thirty administrative regions are divided into three areas based on the geography and their economic level: the Eastern area, Western area, and Central area (Wu et al., 2016). The areas are depicted in Fig. 4.

The regional green productivities of road transportation industries were diverse because of their different economic development levels. While the regions in the Eastern area are close to China's southeast coast and belong to economically developed areas, the Western regions are all inland provinces with relatively backward economic development. The economic level of the Central area is between the Eastern and Western area levels. In general, China's economic development level is low in the west and high in the east. Using the information in Fig. 4, the performance of the road transportation industry in terms of green productivity growth and the decomposition are listed in Table 3.

Table 3 shows that the annual average values of GMLI in the Eastern, Central, and Western areas were 0.9968, 1.0094, and 1.0219, respectively, which reveals that in terms of green productivity growth, the Western area outperformed the Central and Eastern areas. While green productivity increased in the Western and Central areas, with an annual average growth rate of 2.19% and 0.94%, respectively, it declined slightly in the Eastern area. To be more specific, the green productivity growth in the Western area resulted from increases in PEC, SEC, and TP. The values of TP, PEC, and SEC were 1.0027, 1.0018, and 1.0213, respectively, indicating that the technology and pure technical efficiency level of the road transportation industry in the Western area improved during the study period, and the economies of scale in road transportation were further exploited.

On the contrary, the regional green productivity growth in the Central area was only driven by scale efficiency change, with an annual average growth rate of 2.59% (SEC = 1.0259). However, both the pure technical efficiency and the technology of the transportation industry in the Central area fell by an average of 0.7 and 1.17 percentage points a year (PEC = 0.9993, TP = 0.9883), respectively. It is gratifying that the negative effects of pure technical efficiency and technology degradation are covered due to the larger growth effect of scale efficiency. Accordingly, the green productivity rose in the Central area, though not as much as in the Western area.

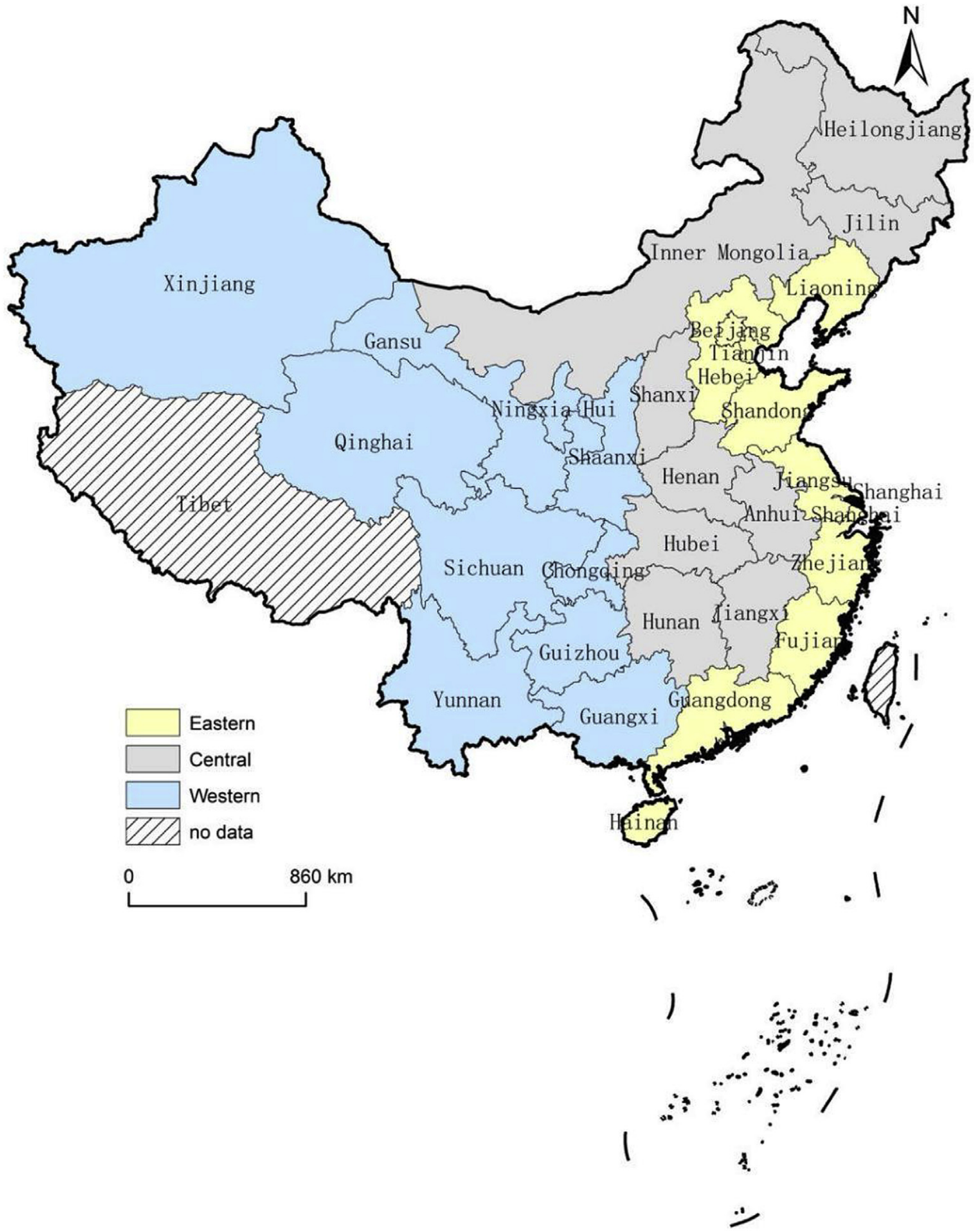
The Eastern area, which includes first-tier administrative regions such as Beijing, Shanghai, and Guangdong, is the most economically developed area. Surprisingly, the green productivity of the transportation industry in the Eastern area actually fell by an annual average rate of 0.32%. It is not difficult to see that green productivity was affected by technological degradation. More precisely, the annual average values of TP, PTC, and SEC are 0.9964, 1.0001, and 1.0053, which means that the transportation technology regressed while pure technical efficiency and scale efficiency increased. We infer that while the management ability and economies of scale of the road transportation industry in the Eastern area improved, it is still difficult to eliminate the impact of the decline in transportation production technology. What is more, it should be noted that the growth of pure technical efficiency in the Eastern area is slight; the change in scale efficiency is the main force driving the growth of the green productivity of road transportation in the Eastern area.

3.3. Cumulative green productivity analysis

Generally, it is a long-term task to improve green productivity

Table 2
Green productivity growth and the components.

Year\Index	GMLI	EC	TP	PEC	SEC
2008–2009	0.9725	0.9860	0.9885	0.9958	0.9898
2009–2010	0.9875	0.9812	1.0087	1.0078	0.9738
2010–2011	0.9902	1.0710	0.9355	1.0024	1.0677
2011–2012	1.0132	1.0006	1.0150	0.9981	1.0024
2012–2013	1.0795	1.0748	1.0025	0.9964	1.0776
2013–2014	0.9888	0.9439	1.0528	0.9864	0.9569
2014–2015	1.0572	1.1189	0.9502	1.0185	1.0977
2015–2016	1.0048	1.0106	0.9972	0.9985	1.0122
2016–2017	0.9869	0.9733	1.0144	1.0001	0.9734
Average	1.0090	1.0178	0.9961	1.0004	1.0168



Note: We consider only administrative regions in Mainland China.

Fig. 4. Different areas and the provincial regions in each area Note
: We consider only administrative regions in Mainland China.

(Adamopoulos, 2011), and the time required signifies that temporal trend analysis in the road transportation industry is essential. According to Oh (2010), GMLI has the property that it is multiplicative. That is:

$$GMLI^{t-1,t} \times GMLI^{t,t+1} = GMLI^{t-1,t+1} \quad (12)$$

Therefore, the cumulative GMLI is calculated as the sequential product of the productivity growth. Cumulative measures of the components of GMLI are calculated analogously. The temporal trend of cumulative green productivity growth in each area and its decomposition components are shown in Figs. 5–8.

Fig. 5 illustrates the temporal trend of cumulative green productivity growth in different areas. In Fig. 5, the green productivity of the road transportation industry shows a trend of falling before rising in every area. The differences lie in when the green productivity in each area begins to rise and how high it eventually reaches. In detail, the green productivity in the Western area rose first and rose the most, followed by that of the Central area. The green productivities in both the Western and Central areas were higher at the end of the study period than at the beginning. It is disappointing that, as the most developed area, the green productivity in the Eastern area was consistently lower than at the beginning of the study period, failing to grow. It is worth noting that the green productivity in three areas dropped from 2013 to 2014, which is most likely because of the economic structural adjustment economic transformation (Liu, 2016) requiring that

Table 3
Green productivity growth and its decomposition in three areas.

	Periods	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	Average value
Eastern	GMLI	0.9769	0.9963	0.9579	0.9754	1.0601	0.9749	1.0181	1.0122	0.9995	0.9968
	EC	1.0074	0.9991	0.9776	0.9818	1.1158	0.8885	1.1358	0.9828	0.9672	1.0062
	TP	0.9705	0.9971	0.9824	0.9969	0.9484	1.1050	0.9032	1.0300	1.0344	0.9964
	PEC	0.9985	1.0012	0.9993	0.9991	0.9992	0.9810	1.0253	1.0000	0.9969	1.0001
	SEC	1.0089	0.9980	0.9780	0.9830	1.1153	0.9059	1.1062	0.9827	0.9700	1.0053
Central	GMLI	0.9921	0.9830	0.9953	1.0284	1.0663	1.0163	1.0251	0.9759	1.0022	1.0094
	EC	1.0085	0.9770	1.1388	0.9969	1.0582	1.0004	1.0719	0.9901	0.9911	1.0259
	TP	0.9881	1.0112	0.8916	1.0345	0.9984	1.0150	0.9582	0.9864	1.0114	0.9883
	PEC	0.9951	1.0082	1.0053	0.9981	0.9934	0.9840	1.0120	1.0036	0.9941	0.9993
	SEC	1.0123	0.9689	1.1319	0.9988	1.0630	1.0165	1.0576	0.9868	0.9974	1.0259
Western	GMLL	0.9500	0.9819	1.0210	1.0411	1.1127	0.9794	1.1290	1.0227	0.9594	1.0219
	EC	0.9422	0.9651	1.1128	1.0246	1.0448	0.9539	1.1426	1.0598	0.9640	1.0233
	TP	1.0086	1.0192	0.9235	1.0175	1.0658	1.0293	0.9947	0.9709	0.9949	1.0027
	PEC	0.9935	1.0146	1.0031	0.9972	0.9959	0.9944	1.0169	0.9922	1.0088	1.0018
	SEC	0.9485	0.9514	1.1087	1.0271	1.0493	0.9593	1.1243	1.0674	0.9556	1.0213

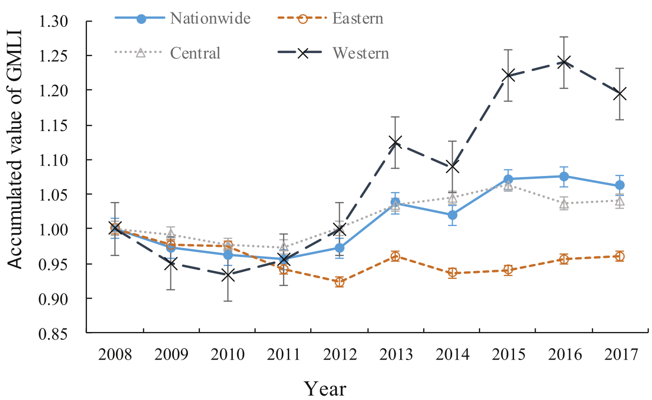


Fig. 5. Trend analysis of cumulative green productivity growth. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

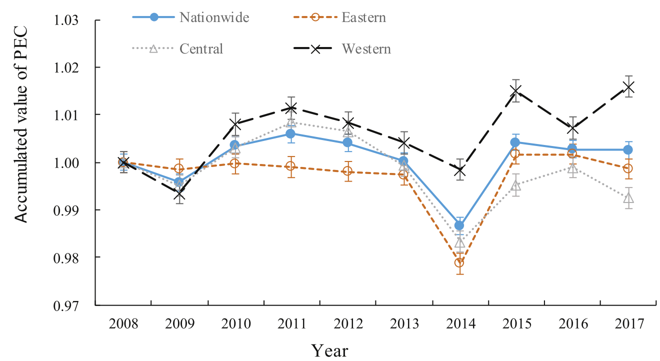


Fig. 7. Temporal trend of cumulative pure technical efficiency change.

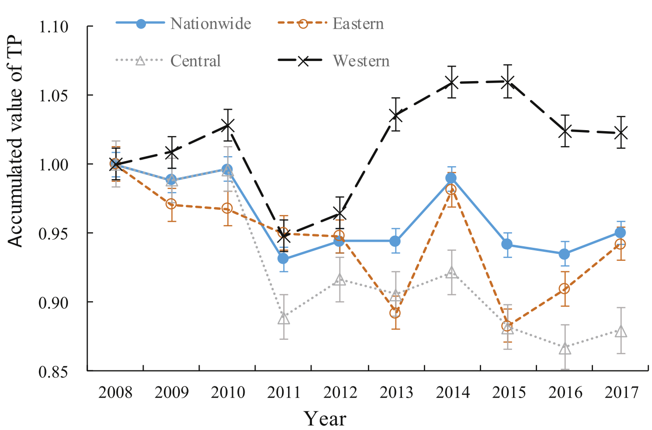


Fig. 6. Temporal trend of cumulative technological progress.

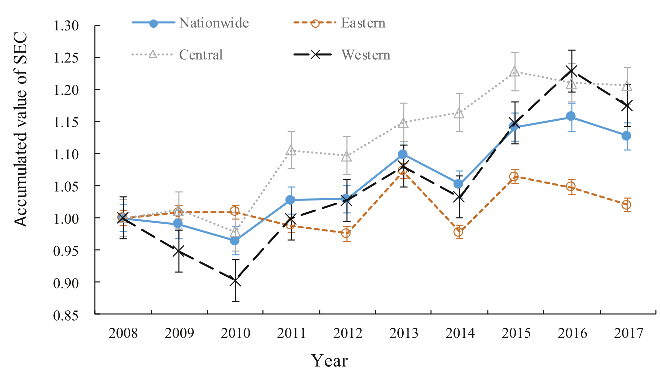


Fig. 8. Temporal trend of cumulative scale efficiency change.

extensive operation should be replaced by intensive operation in the road transportation industry.

Fig. 6 reports the temporal trend of cumulative technological change in the road transportation industry, from which we can see that only the road transport industry of the Western area achieved technological growth, while technological decline emerged in the other areas. These findings are partially consistent with Liu et al. (2019), whose study revealed that the road transportation industries in both the Western and Central areas achieved technological growth. Considering the great Western development strategy of China (Chen et al., 2010), it can be inferred that the green productivity in the Western area was boosted by technological catch-up in the study period, and the operation technology progress played an important role.

As one of the driving factors, pure technical efficiency change reflects changes in the transportation management level. Fig. 7 shows that the PTE increased only in the Western area by the end of the study period, although there were large fluctuations. The PTEs in all the areas underperformed in 2014, especially in the Eastern area, meaning that the management level declined. We believe this happened because the demand in the road transportation industry decreased as a result of industrial overcapacity and because of external shocks due to international trade.

Different from the performance of PTEC, SEC showed an increasing tendency while fluctuating during the study period, as shown in Fig. 8. What the change of scale efficiency exhibits is the recalibration of the road transportation scale. The increase in SEC indicates that the scale of the road transportation industry is getting closer and closer to its optimal scale. In Fig. 8, the performance of road transportation in the Central area is remarkable, much better than in the other areas.

Combined with the above analysis, it is interesting that the green productivity in the Western area performed best, and that of the Eastern area performed worst, which is the opposite of the regional economic development levels. We infer that the gaps between green productivities of road transportation industries in the areas were narrowing during the study period.

3.4. Competition analysis

To better exhibit the underlying relationship between the green productivity growth rate and its fluctuations, all the administrative regions were plotted onto a two-dimensional matrix with the X-axis denoting the stability of the green productivity growth rate and the y-axis denoting the green productivity growth rate of the provincial road transportation industries. The matrix is shown in Table 4.

In Table 4, all administrative regions are classified into four quadrants according to: (1) whether the annual average green productivity growth rate of a provincial road transportation industry is greater or less than one; and (2) whether the standard deviation of a region's annual average green productivity is greater or less than the mean standard deviation of all regions.

Quadrant GH − green productivity growth and high stability: Provincial road transportation industries in this quadrant should continue by maintaining their operational advantages, leading to stable growth. Note that the provincial green productivities in the Western area are not only growing fast but are also stable. Although the Western area is the least economically developed of the three areas, its growth rate appears to be high when undesirable byproducts such as CO_2 are included in the productivity analysis (Oh, 2010), which implies that the stable green productivity growth is due to the lower energy consumption and pollution emissions in the Western area.

Quadrant DH − green productivity decline but high stability: Provincial road transportation industries in this quadrant operated consistently at a relatively slow level of green productivity decline. This quadrant accounts for much of the underperformance of the provincial road transportation industries over time. Five out of eight regions in this quadrant are economically developed regions. Rapid economic development leads to environmental problems in the process of road transportation (Carlan et al., 2019); thus, green productivity declines when harmful byproducts are considered in the analysis. It should be noted that in order to make the green productivity consistent with the economic development level, the undesirable outputs of these road transportation industries should be reduced while developing the regions' economies.

Quadrant GL − green productivity growth and low stability: Provincial road transportation industries in this quadrant operated with relatively unstable green productivity growth over time. Five regions in this quadrant (Shanghai (E), Fujian (E), Guangdong (E), Neimenggu (C), and Guizhou (W)) are located along the southeast coast or the border of China. Generally, the low stability of economic development for this quadrant is due to the impact of foreign trade environment (Chen et al., 2019), which can further lead to the fluctuation of green productivity growth.

Quadrant DL − green productivity decline and low stability: Only Ningxia (W) and Xinjiang (W) are in this quadrant, both of which are Western regions. The green productivities of these regions declined while fluctuating significantly. Combined with quadrant GH, it can be seen that both the best and worst performers are in the Western area in terms of green productivity of the road transportation industry. This geographical phenomenon indicates not only that differences of green productivity growth exist in the road transportation industries among the Eastern, Central and Western areas, but also that the gaps among regions in the Western area are conspicuous. These features deserve more attention from departments concerned with road transportation.

4. Implications and conclusions

4.1. Findings

China's economy has entered a stage of high-quality development, which requires both economic development and social benefits, including environmental benefits. The green productivity of the road transportation industry involves not only the industrial production service ability but also environmental improvement, which is an important way to achieve green sustainable development. Therefore, in the current study, the GMLI approach based on DDF is employed to investigate green productivity and its driving elements in the context of road transportation industries at the provincial level in China from 2008 to 2017. Furthermore, the GMLI is decomposed into TP, PTC, and SEC to analyze the performance of provincial road transportation industries considering three types of undesirable outputs. The main findings from different perspectives are summarized below.

From the national perspective, green productivity grew slightly during the study period, and the efficiency improvement was the only factor driving the productivity growth of the road transportation industry. By area, the industry performance in the Western area exceeded that in the Central and Eastern areas, in terms of green productivity growth. The annual average growth rate was 2.19%, 0.94%, and −0.32% in Western, Central, and Eastern areas, respectively. Technology progress, improvement in pure technical efficiency, and economies of scale drove the productivity growth in the Western area, and improvement in economies of

Table 4
Green productivity growth and stability matrix.

	High stability	Low stability
Productivity growth	***Quadrant GH:*** Hebei (E), Liaoning (E), Jiangsu (E), Jilin (C), Heilongjiang (C), Henan (C), Hubei (C), Chongqing (W), Sichuan (W), Yunnan (W), Shaanxi (W), Gansu (W), Qinghai (W)	***Quadrant GL:*** Shanghai (E), Fujian (E), Guangdong (E), Shanxi (C), Hunan (C), Neimenggu (C), Guizhou (W)
Productivity decline	***Quadrant DH:*** Beijing (E), Tianjin (E), Zhejiang (E), Shandong (E), Hainan (E), Anhui (C), Jiangxi (C), Guangxi (W)	***Quadrant DL:*** Ningxia (W), Xinjiang (W)

Notes: 1. Growth means the growth rate >1, and decline means growth rate <1.2. Stability is high when the standard deviation is less than the mean value; otherwise, it is low. 3. G, D, H, and L are the abbreviations of growth, decline, high, and low, respectively. 4. E, C, and W are abbreviations of Eastern, Central, and Western.

scale drove the productivity growth in the Central area. Moreover, technology regress was the only factor hindering productivity growth in the Eastern area.

From the perspective of growth rate and stability, provincial green productivities in the Western area are both growing fast and stable (Quadrant GH in Table 4). Surprisingly, five out of eight regions in Quadrant DH are economically developed regions, yet their provincial road transportation industries operated consistently at a relatively slow level of green productivity decline. Meanwhile, the road transportation industries in five regions located along the southeast coast or the border of China operated with relatively unstable green productivity growth over time (Quadrant GL in Table 4). The productivity declined and is unstable in only two of the western regions.

To summarize, this study shows both the temporal trend analysis in terms of cumulative performance and competition analysis in terms of growth rate and stability. From these analyses, implications are obtained.

4.2. Practical and theoretical implications

From the perspective of practical contributions, the empirical results can provide helpful implications to improve the green productivity of road transportation industries in China, considering various undesirable outputs. Important implications at the national level can be distilled from these research findings. The results exhibit a fluctuating but slowly upward trend of green productivity over time, calling for more attention to be paid to measures to further strengthen green productivity growth. What calls for special attention is that better industry performance in terms of green productivity could be achieved by enhancing the pure technical efficiency and technological progress of the road transportation industry, as has been advocated by Liu et al. (2019). Backward production techniques hinder both the efficient use of existing resources and the reduction of pollutant emissions. Accordingly, vigorously developing road transportation while ignoring the application of advanced technology related to green productivity will likely lead to a waste of resources and environmental and safety problems. Therefore, to improve productivity while reducing carbon emissions, traffic noise, and accident rates, top priority should be given to introducing advanced transportation technology and equipment, and continuously expanding their application scope.

At the regional level, while road transportation industries in both the Western and Central areas achieved green productivity growth, these two areas differ in terms of the driving forces of green productivity growth. The main driving force in the Western area is the catch-up effect of technology, indicating its progress rate of transportation technology from backward to advanced is the fastest. The main driving force of green productivity growth in the Central area, however, is that the economies of scale of transportation are becoming more and more prominent. On the basis of these conclusions, the best measures in the Western and Central areas are to maintain the economies of scale and to promote the application of advanced technology, respectively. Both of the measures recommended for the Western and Central areas should be the main focus to improve the green productivity of road transportation industries in the Eastern area. Fortunately, the green productivity in most regions was steady, although some border provinces and southeast coastal provinces showed large fluctuations in green productivity. Therefore, the management departments of road transportation industries should focus on eliminating the fluctuation caused by the change of foreign trade environment to reduce the corresponding effects on the road transportation industry.

In terms of theoretical contributions, firstly, previous studies on the green development of the road transportation industry always focus on environmental efficiency improvement, as exemplified by Wu et al. (2016), Nikolaou and Dimitriou (2018), and Liu et al. (2020). In contrast to these, the current study not only examined green productivity growth but also decomposed the green productivity growth into technological progress and changes in pure technical efficiency and scale efficiency. This decomposition provides a new research perspective for studying the green development of the road transportation industry. Secondly, the undesirable outputs involved in previous studies of the road transportation industry were mainly either CO_2 emissions (Park et al., 2018) or traffic accidents (Pal and Mitra, 2016), with little attention paid to traffic noise (Liu et al., 2020). The current study integrates all three undesirable outputs in the model to investigate the green productivity of road transportation. The integration contributes by enriching the techniques for green productivity evaluation. Thirdly, while traffic noise has been studied previously as an undesirable, harmful byproduct (Sánchez et al., 2018), this study is the first to consider it as a kind of streaming data to evaluate the green productivity of road transportation. This study shows a novel application of streaming data to a real-world problem. Finally, the current study introduces a two-dimensional quadrant matrix based on green productivity growth rate and stability to summarize the performance of the provincial road transportation industries in 30 administrative regions in China.

Although this study gives suggestions based on its analysis, it has limitations that inspire further research. First, a list of specific driving forces related to the green productivity growth of the road transportation industry was considered, but this list is not exhaustive. Other driving forces, such as clean energy input or driver training, could be added to the model in future studies to explain green productivity growth. More importantly, the applicability of the findings in this study is limited by the data collected and the study period. Accordingly, the results and measures should be interpreted for the road transportation industry during the study period only.

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CRediT authorship contribution statement

Hongwei Liu: Conceptualization, Methodology, Writing - original draft. **Ronglu Yang:** Visualization, Investigation. **Dongdong Wu:** Data curation. **Zhixiang Zhou:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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