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Environmental Efficiency Evaluation of Construction Waste Generation Based on Data Envelopment Analysis and Malmquist Index

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Abstract: The rapid development of urbanization in China in recent years has resulted in the production of large amounts of construction waste, which has placed certain constraints on the sustainable development of the construction industry. This study measures the environmental efficiency of construction waste generated in China from static and dynamic perspectives using the data envelopment analysis and the Malmquist index with data from 30 Chinese provinces during the period from 2011 to 2020. The results showed that, from a static perspective, the environmental efficiency of China's construction waste generation has been on a generally declining trend year by year, and the overall level is still not too high. At the regional level, there is a stepwise decline in the eastern, central, northeastern, and western regions. From a dynamic point of view, the overall Malmquist index in China has an average value of 1.016, indicating that the level of environmental efficiency of construction waste generation in China is in a state of improvement. From a regional perspective, the Malmquist index is highest in the east, indicating that the level of environmental efficiency of construction waste generation in the eastern region is developing well.

Keywords: construction waste; environmental efficiency; resilience; data envelopment analysis; Malmquist index

1. Introduction

China is in the era of large-scale urbanization, which consumes a lot of resources and produces a high volume of construction waste [1–4]. The enormous construction waste generation may cause environmental problems. To effectively manage the relationship between economic development and environmental protection, the promotion of economic development and the improvement of environmental quality should be closely integrated [5,6]. Currently, promoting green construction has become a top priority in China [7–11]. At the same time, it is also imperative to improve the environmental efficiency of construction waste [12]. However, the economic development and pollution control among different provinces in China are different in many aspects. In this context, investigating the issue of environmental protection in different provinces is of importance.

Environmental efficiency is a concept that takes into account the impact of economic development on the environment, and it is one of the indicators of sustainable development, reflecting the degree of economic and environmental coherence of a region [13]. This concept suggests achieving a harmonious integration of environmental protection and economic development. In the literature, scholars have applied the data envelopment analysis (DEA) method to study the issue of environmental efficiency [14,15]. However,

as the DEA method only evaluates efficiency from a static perspective, scholars further introduced the Malmquist index to dynamically analyze the efficiency. In this circumstance, some scholars have used both the DEA method and the Malmquist index in their respective studies [16–21]. The proposed methods have been proven to be effective, therefore, this study selects the Malmquist index based on the SBM model to analyze the dynamic trends of the environmental efficiency of construction waste generation in China. In addition, this study adds environmental factors to the production activity process of the construction industry and calculates the input–output ratio, where the environmental impact is expressed as the output of environmental pollutants.

The rest of the study is organized as follows: Section 2 presents the model construction, data sources, and indicator selection; Section 3 analyzes the environmental efficiency results of construction waste generation; and finally, Section 4 presents the main conclusions of the study.

2. Research Methodology

2.1. Model Construction

2.1.1. Data Envelopment Analysis

Data envelopment analysis (DEA) is often used in management, economics, and operations research on relative efficiency. DEA first originated when Farrell used a segment-by-segment convex function approximation method to calculate the efficiency of agricultural production in the UK, which led to the idea of input–output-based efficiency measures [22]. Then, Charnes, et al. [23] proposed the idea of DEA, which is based on the principle of accounting for efficiency scores, based on the deviation of the production frontier surface determined by mathematical planning from the projection of each decision making unit (DMU). The traditional DEA models usually evaluate efficiency issues in radial and angular terms, where radial means that efficiency is calculated according to a certain ratio of inputs and outputs, and angular means that efficiency is calculated through input orientation or output orientation. However, the traditional models ignored the impact of slack variables on DEA efficiency, where input redundancy or output shortfalls could occur in the production process, and inaccurate efficiency values can be obtained if these slack issues are not considered. Therefore, Tone [24] improved the classical DEA model and proposed a slacks-based measure (SBM) model that takes into account the input and output slack problems. Using the non-radial and non-angular SBM as a theoretical premise, the following models and assumptions were developed for this study:

Suppose there are "n" decision-making units, each DMU has "m" inputs and "s" expected outputs, "k" undesired outputs. Where $x \in R^m, y \in R^s, b \in R^k$, and define their matrices as follows:

$$
\begin{aligned}
X &= [x_1, \ldots\ldots, x_n] \in R^{m \times n} \\
Y &= [y_1, \ldots\ldots, y_n] \in R^{s \times n} \\
B &= [b_1, \ldots\ldots, b_n] \in R^{k \times n}
\end{aligned}
\tag{1}
$$

where in, $X > 0$; $Y > 0$; $B > 0$. The production possible value can be defined as:

$$
p = \{(x, y, b) | x \geq X\sigma, y \leq Y\sigma, b \geq B\sigma, \sigma \geq 0\}
\tag{2}
$$

According to the SBM and the related processing methods of existing research, the following SBM method based on undesired output is constructed:

$$\min\rho = \frac{1-\dfrac{1}{m}\sum_{i=1}^{m}\dfrac{s_i^-}{x_{i0}}}{1+\dfrac{1}{s+k}\left(\sum_{r=1}^{s}\dfrac{s_r^+}{y_{r0}}+\sum_{r=1}^{k}\dfrac{b_t^-}{b_{t0}}\right)}$$

s.t.

$$x_{i0}= X\sigma + s_i^-$$
$$y_{r0}= Y\sigma - s_r^+$$
$$b_{t0}= B\sigma + b_t^-$$
$$\sum_{j=1}^{n}\sigma_j= 1$$
$$\sigma_j, s_i^-, s_r^+, b_t^- \geq 0$$

(3)

Among these, "ρ" represents the measured efficiency situation, s_i^- represents the input slack variable and s_r^+ represents the expected output slack, b_t^- represents the undesired output slack, and "σ" represents the weight of the variable in the model. When there is only "$\rho = 1$" in the model, the measured DMU is valid, and when "$\rho < 1$", the DMU is in an invalid state.

2.1.2. Malmquist Index

As the DEA method only measures the combined efficiency of a decision unit from a static perspective, the Malmquist index can be used to measure the dynamic productivity of a decision unit over a continuous period of time. Based on the Malmquist index computed by Fare in 1992, it is calculated as follows:

$$ML_t^{t+1} = \left[\frac{D_0^t(x_0^{t+1},y_0^{t+1})}{D_0^t(x_0^t,y_0^t)}\frac{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}{D_0^{t+1}(x_0^t,y_0^t)}\right]^{1/2}$$

(4)

The Malmquist Index can be further classified as the product between technical efficiency change (*EC*) and technological change (*TC*), expressed as follows:

$$ML_t^{t+1}= EC_t^{t+1}\times TC_t^{t+1}$$
$$EC_t^{t+1} = \frac{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}{D_0^t(x_0^t,y_0^t)}$$
$$TC_t^{t+1} = \left[\frac{D_0^t(x_0^{t+1},y_0^{t+1})}{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}\frac{D_0^t(x_0^t,y_0^t)}{D_0^{t+1}(x_0^t,y_0^t)}\right]^{1/2}$$

(5)

Among them, when the efficiency of DMU from t period to $t + 1$ period is improved, $ML > 1$; $ML < 1$ when the efficiency of DMU from t period to $t + 1$ period decreases. *EC* is technical efficiency change, where $EC > 1$ indicates an increase in technical efficiency change and $EC < 1$ indicates a decrease in technical efficiency change. *TC* is technological change, where $TC > 1$ indicates an increase in technological change and $TC < 1$ indicates a decrease in technological change.

2.2. Data sources and Indicator Selection

2.2.1. Data Sources

In view of the lag in the publication of statistical yearbooks, the data published in the current year are actually the data of the previous year. Given the availability and continuity of the data, the panel data of 30 provinces in China for a total of 10 years from 2011 to 2020 were selected as the data for this study. The relevant datasets were selected from the China

Statistical Yearbook (2012–2021) and the China Construction Industry Statistical Yearbook (2012–2021).

2.2.2. Indicator Selection

The key to using the DEA method is the selection of input and output indicators. The following principles are recommended for the selection of indicators: Firstly, objectivity is required; the selected indicators should be as free as possible from the subjective preferences of researchers and should try to construct an objective indicator system by selecting indicators that can objectively reflect the real situation of the decision-making unit. Secondly, comprehensiveness is considered; the selected indicators can fully reflect the overall situation of the decision-making unit. Lastly, feasibility is ensured; the selected indicators should be easy to collect and measurable for a reliable analysis.

This study used SBM to measure the environmental efficiency of construction waste generation in 30 Chinese provinces. The Cobb–Douglas production function is the form of production function used by most scholars in Chinese economics to analyze economic development [25–27]. In this production function, input labor and fixed capital are the key factors affecting economic growth. This study aims to examine the environmental efficiency of construction waste generation in each province, thus adding resource consumption as an input indicator to the traditional production function, coupled with the generation of construction waste that accompanies the construction process as a non-desired output. Therefore, based on the traditional economic growth theory, this study selected the total profit and tax as the desired output indicators and the amount of construction waste generated in each province as the non-desired output.

The input indicators were analyzed as follows:

(1) Labor input: The construction industry is a labor-intensive industry with a large demand for labor, and the level of development of the industry can be judged by the number of laborers engaged in the construction industry in each province. Therefore, this study chose the number of construction workers published in the China Statistical Yearbook in previous years as a measure of labor input.

(2) Capital input: The construction industry, as an industry of fixed asset investment, requires a large amount of investment in fixed and current assets during the construction process. The amount of total asset input invested each year affects the productivity of the industry to a certain extent, and has an impact on the environment. This paper selected the amount of total asset input provided by the China Construction Industry Statistical Yearbook in previous years as a measure of capital input.

(3) Resource consumption: The main resources consumed during the construction phase of the building industry are steel, timber, cement, glass, and aluminum. In view of the availability of data, the consumption of steel, timber, cement, glass, and aluminum according to the China Construction Industry Statistical Yearbook in previous years was used as an approximate measure of resource consumption in this study.

Output indicators are divided into two categories: desired and undesired output.

(1) Desired output: Since total profits and taxes can directly reflect the economic benefits brought to society by the construction industry, this study chose the total profits and taxes in the China Construction Industry Statistical Yearbook of previous years as the expected output.

(2) Undesired output: As construction waste is often generated during the production process of engineering construction, the lower the amount of construction waste generated, the stronger the construction industry is in terms of environmental protection. In this study, the amount of construction waste generated was selected as the non-expected output, but China currently does not have statistics on the amount of construction waste generated in the construction industry. The relevant data was obtained by calculating the amount of construction waste generated during the engineering construction process provided in the Technical Standard for Construction

Waste Disposal (CJJ/T134-2019) promulgated by the Ministry of Housing and Urban-Rural Development, which is as follows:

$$M_g = R_g m_g \tag{6}$$

where M_g denotes the amount of construction waste generated by each province in t/a; R_g denotes the new construction area in 10^4 m^2/a; m_g denotes the base amount of construction waste generated per unit area in t/10^4 m^2, which can be chosen from 300 t/10^4 m^2 to 800 t/10^4 m^2. This study takes it to a value of 500 t/10^4 m^2. Amongst them, the statistical yearbook lacks data on new construction areas in each province, and considering that construction waste is generated in both the construction and completion stages, the construction area and completion area data counted in the China Construction Industry Statistical Yearbook (2012–2021) were used to sum up and obtain the value of new construction area in each region in each calendar year.

The specific input and output indicators selected are shown in Table 1.

Table 1. System of input and output indicators.

Indicator Category	Indicator Name	Specific Indicators
	Labor input	Number of construction workers (in1)
	Capital investment	Total asset investment (in2)
		Steel (in3)
Input indicator		Wood (in4)
	Resource consumption	Cement (in5)
		Grass (in6)
		Aluminum (in7)
Output indicator	Desired output	Total profit and tax (out)
	Undesired output	Construction waste generation (badout1)

2.3. Pearson Correlation Test for Input and Output Indicators

For scientific reasons, it is important to test whether the input and output indicators satisfy the principle of homogeneity. In this study, the Pearson correlation test was used to verify this. As shown in Table 2, at the 0.01 level of significance, there is a significant positive correlation between the seven input indicators and two output indicators, which in principle complies with the "homoscedasticity" requirement of the DEA model.

Table 2. Pearson correlation test for input and output indicators.

Variable	In1	In2	In3	In4	In5	In6	In7	Out1	Badout1
In1	1	0.582 **	0.846 **	0.800 **	0.643 **	0.823 **	0.519 **	0.879 **	0.959 **
In2	0.582 **	1	0.572 **	0.519 **	0.315 **	0.417 **	0.283 **	0.823 **	0.690 **
In3	0.846 **	0.572 **	1	0.813 **	0.689 **	0.800 **	0.567 **	0.790 **	0.826 **
In4	0.800 **	0.519 **	0.813 **	1	0.599 **	0.773 **	0.618 **	0.746 **	0.738 **
In5	0.643 **	0.315 **	0.689 **	0.599 **	1	0.616 **	0.453 **	0.532 **	0.608 **
In6	0.823 **	0.417 **	0.800 **	0.773 **	0.616 **	1	0.622 **	0.705 **	0.778 **
In7	0.519 **	0.283 **	0.567 **	0.618 **	0.453 **	0.622 **	1	0.451 **	0.446 **
Out1	0.879 **	0.823 **	0.790 **	0.746 **	0.532 **	0.705 **	0.451 **	1	0.927 **
Badout1	0.959 **	0.690 **	0.826 **	0.738 **	0.608 **	0.778 **	0.446 **	0.927 **	1

Note: ** indicates a significant correlation at the 0.01 level (two-tailed).

3. Results

3.1. Environmental Efficiency Measurement Based on the SBM Method

To measure the environmental efficiency of construction waste generation, this study uses MaxDEA software to measure the environmental efficiency of construction waste generation in 30 Chinese provinces from 2011 to 2020 based on a static perspective, using the formation of an SBM that considers undesired outputs. The results are shown in Table 3.

Table 3. Static results for environmental efficiency of construction waste generation.

DMU	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Beijing	1	1	1	1	1	1	1	1	1	1	1
Tianjin	1	1	1	1	1	0.442	1	1	1	0.361	0.88
Hebei	0.424	0.409	0.433	0.388	0.388	0.414	0.346	0.504	0.328	0.253	0.389
Shanghai	1	1	1	0.703	1	0.524	0.463	1	0.429	0.327	0.745
Jiangsu	1	1	1	1	1	1	1	1	1	1	1
Zhejiang	1	1	0.521	0.598	0.547	0.522	0.489	0.357	0.333	0.314	0.568
Fujian	0.755	0.761	0.551	0.562	1	1	1	1	1	1	0.863
Shandong	1	0.505	0.805	0.843	0.607	0.539	0.595	0.703	0.481	0.365	0.644
Guangdong	1	1	1	1	1	0.629	0.729	1	0.560	0.295	0.821
Hainan	1	1	1	1	1	1	1	1	1	1	1
Eastern mean	0.918	0.868	0.831	0.809	0.854	0.707	0.762	0.856	0.713	0.592	0.791
Shanxi	0.635	1	0.621	0.657	0.578	0.404	0.388	0.666	0.529	0.341	0.582
Anhui	0.540	0.660	1	0.452	0.635	0.538	0.485	0.663	0.367	0.402	0.574
Jiangxi	0.366	1	1	1	1	0.622	0.534	0.583	0.498	0.544	0.715
Henan	1	1	1	1	0.796	1	1	1	1	1	0.98
Hubei	1	1	1	1	1	0.559	0.599	1	1	1	0.916
Hunan	1	1	1	1	1	0.551	0.502	1	0.502	0.668	0.822
Middle mean	0.757	0.943	0.937	0.852	0.835	0.612	0.585	0.819	0.649	0.659	0.765
Inner Mongolia	1	1	1	1	0.484	0.411	0.535	0.636	0.653	0.481	0.720
Guangxi	0.305	0.34	0.308	0.286	0.401	0.36	0.326	0.415	0.41	0.299	0.345
Chongqing	0.685	1	0.835	1	1	1	1	1	0.855	1	0.938
Sichuan	0.466	0.474	0.445	0.351	0.368	0.273	0.302	0.627	0.403	0.476	0.419
Guizhou	0.279	0.261	0.239	0.246	0.2	0.153	0.298	0.478	0.309	0.256	0.272
Yunnan	0.636	1	1	0.536	0.736	0.592	1	1	1	1	0.850
Shanxi	1	1	0.762	0.652	0.498	0.461	0.442	0.660	0.409	0.335	0.622
Gansu	0.414	0.518	0.489	0.499	1	0.603	0.746	0.858	0.802	0.303	0.623
Qinghai	1	1	1	1	1	1	1	1	1	1	1
Ningxia	1	0.684	0.429	1	0.56	1	1	1	1	1	0.867
Xinjiang	0.308	0.551	1	1	1	1	1	1	1	0.373	0.823
Western mean	0.645	0.712	0.682	0.688	0.659	0.623	0.695	0.789	0.713	0.593	0.680
Liaoning	1	1	1	0.49	0.514	0.258	0.345	1	0.358	0.263	0.623
Jilin	1	0.382	0.416	1	0.728	0.652	1	1	1	0.640	0.782
Heilongjiang	0.452	1	0.566	1	1	1	0.575	1	1	0.586	0.818
Northeast mean	0.817	0.794	0.661	0.83	0.747	0.637	0.640	1	0.786	0.496	0.741
National mean	0.776	0.818	0.781	0.775	0.768	0.650	0.690	0.838	0.708	0.596	0.740

The level of economic development is uneven across China's provinces, and as a result, there may also be some degree of regional variation in the environmental efficiency of construction waste generation. Table 3 shows the environmental efficiency of construction waste generation by each province from 2011 to 2020. From the above table, there are significant differences in the environmental efficiency of construction waste generation across China's provinces. It is possible to classify them into three scenarios as follows:

(1) There are four provinces where the average environmental efficiency of construction waste generation is equal to 1, namely Beijing, Jiangsu, Hainan, and Qinghai, accounting for 13.33% of the provinces studied. Beijing and Jiangsu, which have been on the environmental frontier during the 10-year studied period, are among the eastern economic prosperous provinces. It can be seen that these regions, even though they generate a lot of construction waste during the construction and production process, also attach great importance to the related environmental pollution remediation cost investment, and their economic development status and the environmental efficiency of construction waste generation are positively influenced by the relationship. The environmental efficiency of Hainan and Qinghai is also 1, which may be related to the direction of their industrial structure, as the leading industry in these regions is not the secondary industry of construction. For example, Hainan's leading industry is the tertiary industry of tourism, and Qinghai's mainstay industry is the primary industry

of agriculture. Thus, to improve the environmental efficiency of construction waste generation in each province, the industrial structure could be adjusted appropriately, and the level of economic development could be improved, while at the same time focusing on the investment in environmental management costs in the construction industry.

(2) The provinces with the lowest average environmental efficiency of construction waste generation are Hebei, Guangxi, and Guizhou, all of which are below 0.4, with Guizhou having the lowest environmental efficiency of construction waste generation at 0.272. These provinces are far from the environmental frontier surface, and assuming that the reference object is a province with effective environmental efficiency of construction waste generation, then with constant inputs and outputs, Hebei, Guangxi, and Guizhou's construction waste generation could be reduced by more than 60%. This shows that there is a large difference in the environmental efficiency of construction waste generation between provinces, with lower values of environmental efficiency of construction waste generation indicating that there is much room for development in reducing construction waste generation in the construction sector in that province.

(3) The average value of the overall engineering environmental efficiency in China from 2011 to 2020 is 0.740, which is not too high overall. At the same time, the average environmental efficiency of construction waste generation from 2011 to 2020 shows a general downward trend, which indicates that the environmental pollution caused by the construction process needs to be improved, and the overall level still needs to be improved. To analyze the differences in the environmental efficiency of construction waste generated in the four major regions of China, this study divides the 30 provinces to be studied into four regions: eastern, northeastern, central, and western, according to the division of China's economic situation by relevant Chinese departments. Amongst them, the eastern regions are composed of 10 provinces including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the northeastern region is composed of the three provinces of Liaoning, Jilin, and Heilongjiang; the central region is composed of the six provinces of Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; the provinces in the western region consist of the 11 provinces of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang. It can be seen that the environmental efficiency of construction waste generation in the eastern region is the highest, with a mean value of 0.791; the environmental efficiency of construction waste generation in the central region follows with a mean value of 0.765; the environmental efficiency of construction waste generation in the northeastern region ranks third, with a mean value of 0.741; and the environmental efficiency of construction waste generation in the western region is the lowest, with a mean value of 0.680. The average environmental efficiency of construction waste generation in the eastern, central and northeastern regions is greater than the Chinese average, while the average environmental efficiency in the western region is lower than the Chinese average. The above ranking shows that there is a gradient difference in the environmental efficiency of construction waste generation between the eastern, central, northeastern and western regions, probably because the regional economic development status has some influence on the level of development of the construction industry. The eastern region is more advanced in the development of the construction industry, and the technology level is more mature. Therefore, the amount of construction waste generated is less, the resource utilization rate is higher; thus, the environmental efficiency of construction waste generation is higher.

3.2. Dynamic Analysis Based on the Malmquist Index

Using panel data from 30 provinces in China over a 10-year period from 2011 to 2020, the Malmquist (ML) Index for each province was measured using MaxDEA to reveal the dynamic changes in the environmental efficiency of construction waste generation

in China. The technical efficiency change (EC) and technological change (TC) are the two decomposition indices of the change in the Malmquist Index, which is equal to EC multiplied by TC.

3.2.1. Analysis of the Overall Changes in the Malmquist Index in China

The dynamics of the ML, EC, and TC for the 30 Chinese provinces over the period from 2011 to 2020 are shown in Table 4. Overall, in terms of the average value of the overall Malmquist Index, the average Malmquist Index for the 30 Chinese provinces between 2011 and 2020 was 1.016, an increase of 1.6%, indicating a relatively steady growth in the level of environmental efficiency generated by construction waste in China. The average EC increased by 7.6% and the average technological level increased by 1.4%, indicating that both EC and TC contributed to the development of environmental efficiency in construction waste generation, but that EC was the main driving factor. Moreover, whenever EC grows, it always meets the constraint of a decline in technological change, and it is rare for both to grow at the same time. The change in the Malmquist Index by stage shows that the growth in the level of environmental efficiency generated by construction waste was dynamic from 2011 to 2013, with a maximum value (1.388) in 2013, followed by a significant decline, and a small upward trend in the level of environmental efficiency generated by construction waste since 2014, with fluctuations after 2018. This suggests that 2013 was an important turning point, and that, since 2011, Chinese policy has called for an emphasis on technological research, allowing environmental science and technology to play a full leading role in environmental protection. Upgrading construction waste management technology will help to maintain a stable level of environmental efficiency generated by construction waste.

Table 4. Dynamics of environmental efficiency of construction waste generation in China.

Year	Malmquist (ML)	Technical Efficiency Change (EC)	Technological Change (TC)
2011–2012	0.978	1.436	0.726
2012–2013	1.388	1.042	1.34
2013–2014	0.885	0.921	0.991
2014–2015	0.949	1.236	0.807
2015–2016	1.013	0.849	1.215
2016–2017	1.029	1.097	0.942
2017–2018	1.122	1.478	0.824
2018–2019	0.868	0.812	1.092
2019–2020	0.912	0.815	1.192
Mean	1.016	1.076	1.014

Based on Figure 1, for a more visual understanding of the dynamics of the environmental efficiency of construction waste generation, it can be observed that the ML Index shows a clear volatility with an overall upward trend. 2012–2014 and 2017–2019 both show a significant decrease, and even 2011–2012, 2013–2014, 2014–2015, 2018–2019, and 2019–2020 showed negative growth, which was mainly caused by a decline in EC. The reason behind the continued improvement in the environmental efficiency of construction waste generation from 2015–2018 is the continued improvement in the EC. EC includes pure technical efficiency and scale efficiency; pure technical efficiency refers to the efficiency changes caused by management systems, staff technical familiarity, etc., and scale efficiency refers to the impact of production efficiency due to the size of the enterprise.
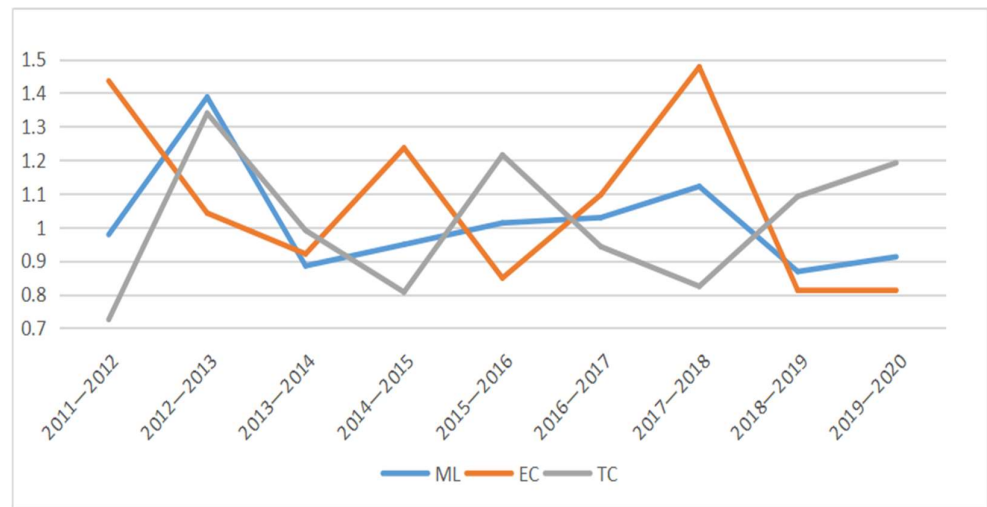
Figure 1. Time trend of the mean and decomposition of the Malmquist Index.

3.2.2. Analysis of Regional Variations in the Malmquist Index for China

Again, using MaxDEA software, the dynamic changes in the environmental efficiency of construction waste generation from 2011 to 2020 were obtained for each province in China using the input generation indicator system collected and collated and constructed. This is shown in Table 5.

Table 5. Dynamics of environmental efficiency of construction waste generation.

DMU	Malmquist (ML)	Technical Efficiency Change (EC)	Technological Change (TC)
Beijing	1.111	1	1.111
Tianjin	0.929	1.056	1.042
Hebei	0.967	0.986	1.022
Shanghai	0.987	1.006	1.198
Jiangsu	1.13	1.229	0.979
Zhejiang	0.934	1.019	0.972
Fujian	0.942	1.278	0.898
Shandong	1.051	1.006	1.013
Guangdong	1.058	1.043	1.014
Hainan	1.131	1.254	0.981
Eastern mean	1.024	1.088	1.023
Shanxi	0.945	1.021	1.091
Anhui	1.013	1.045	0.982
Jiangxi	0.977	1.138	0.938
Henan	1.044	1.122	0.945
Hubei	1.057	1.041	1.001
Hunan	0.965	1.144	0.899
Middle mean	1	1.085	0.976
Inner Mongolia	0.927	0.907	1.066
Guangxi	1.005	1.023	1.004
Chongqing	1.08	1.103	1.007
Sichuan	1.05	1.07	1.004
Guizhou	1.043	1.077	1.033
Yunnan	1.08	1.119	1.003
Shanxi	0.935	0.946	1.032
Gansu	0.936	1.008	1.013
Qinghai	0.979	1	0.979
Ningxia	1.073	1.038	1.049
Xinjiang	1.074	1.126	1.141
Western mean	1.017	1.038	1.03
Liaoning	0.976	1.217	1.026
Jilin	1.052	1.079	1.028
Heilongjiang	1.029	1.186	0.956
Northeast mean	1.019	1.161	1.003
National mean	1.016	1.076	1.014

Table 5 shows the mean values of the Malmquist Index and its decomposition term for 30 provinces in China for the period 2011–2020. The Malmquist Index varies considerably between regions in China, with the average Malmquist Index for China being 1.016. The highest Malmquist Index province in China is Hainan, with a growth rate of 1.1%, while Inner Mongolia ranks at the bottom with a Malmquist Index growth rate of −7.3%. Based on the distribution of provinces, Hainan, Jiangsu, Beijing, Chongqing, Yunnan, Xinjiang, Ningxia, Guangdong, Hubei, Jilin, Shandong, Sichuan, Henan, Guizhou, and Heilongjiang are all above the average Malmquist Index for China as a whole, while the remaining provinces are significantly below the average Malmquist Index. Based on the overall Malmquist Index decomposition of the specific distribution of each province, the EC and TC of Shanghai, Tianjin, Liaoning, Chongqing, Yunnan, Xinjiang, Ningxia, Guangdong, Hubei, Jilin, Shandong, Sichuan, Guizhou, Guangxi, Shanxi, and Gansu are all greater than 1, indicating that the environmental efficiency generated by construction waste in these provinces can be better developed as a result of the combined effect of efficiency and TC. For the EC, only the EC of Inner Mongolia, Shanxi, and Hebei are less than 1, indicating that the environmental efficiency generated by construction waste is declining; the EC of Beijing and Qingdao are equal to 1, indicating that the level of environmental efficiency generated by construction waste remains stable; the EC of the remaining provinces are all greater than 1, indicating that the environmental efficiency generated by construction waste is in an improving state.

In terms of the eastern, central, western, and northeast regions, the Malmquist Index was greater than 1 during the study period, with the eastern region showing the greatest increase, with a growth rate of 2.4%, and the northeast region the next largest, with a growth rate of 1.9%. The Malmquist Index for the central and western regions is lower than that of the eastern region, which is largely due to the higher level of economic development and more mature technology in the eastern coastal region, as well as the increased innovation in advanced technology, which has given full play to the advantages of technological efficiency, leading to progress in production efficiency, and thus the fastest development in the level of environmental efficiency generated by construction waste.

4. Conclusions

This study mainly explores the environmental efficiency of construction waste generation in 30 Chinese provinces from 2011 to 2020, based on both static and dynamic perspectives. From a static perspective, the overall environmental efficiency of construction waste generation in China was not too high and showed a general downward trend, indicating that the environmental pollution caused by construction projects needs to be improved. From a dynamic perspective, the average Malmquist Index value indicated that the level of environmental efficiency of construction waste generation in China is in a state of improvement. The contribution of this study is to further expand the research field of sustainable development in the construction industry. At the same time, the characteristics and patterns of environmental efficiency generated by construction waste in different provinces and regions can be fully understood, providing a basis for justifying the formulation of economic and construction waste policies.

Based on the derived findings, several recommendations could be made. Firstly, it is suggested that construction waste policies should be made considering the different levels of development. Secondly, it is recommended that the industrial structure could be optimized to increase the proportion of tertiary industries in the economic development of each region, thereby achieving environmentally friendly growth. Finally, the government should strengthen publicity and education to raise people's awareness of environmental protection concerning construction waste generation. Potential research directions may include considering the variable of time to investigate the future trends and relating indices with more social or engineering variables that could compensate for the decrease in the efficiency of waste generation. In addition, as the volumes of other waste streams (e.g.,

municipal solid waste) are also huge, future research may further integrate other waste to reach environmental efficiency.

References

1. You, Z.J.; Wu, C.; Zheng, L.Q.; Feng, L.J. An Informatization Scheme for Construction and Demolition Waste Supervision and Management in China. *Sustainability* **2020**, *12*, 1672. [CrossRef]
2. Wu, Z.; Yang, K.; Xue, H.; Zuo, J.; Li, S. Major barriers to information sharing in reverse logistics of construction and demolition waste. *J. Clean. Prod.* **2022**, *350*, 131331. [CrossRef]
3. Pittau, F.; Giacomel, D.; Iannaccone, G.; Malighetti, L. Environmental consequences of refurbishment versus demolition and reconstruction: A comparative life cycle assessment of an Italian case study. *J. Green Build.* **2020**, *15*, 155–172. [CrossRef]
4. Bao, Z.K.; Laovisutthichai, V.; Tan, T.; Wang, Q.; Lu, W.S. Design for manufacture and assembly (DfMA) enablers for offsite interior design and construction. *Build. Res. Inf.* **2022**, *50*, 325–338. [CrossRef]
5. Phillips, H.; Handy, R.; Sleeth, D.; Thiese, M.S.; Schaefer, C.; Stubbs, J. Taking the "LEED" in indoor air quality: Does certification result in healthier buildings? *J. Green Build.* **2020**, *15*, 55–66. [CrossRef]
6. Wu, Z.; He, Q.; Yang, K.; Zhang, J.; Xu, K. Investigating the Dynamics of China's Green Building Policy Development from 1986 to 2019. *Int. J. Environ. Res. Public Health* **2021**, *18*, 196. [CrossRef] [PubMed]
7. Barth, K.B.; Formoso, C.T. Requirements in performance measurement systems of construction projects from the lean production perspective. *Front. Eng. Manag.* **2021**, *8*, 442–455. [CrossRef]
8. Zeng, N.; Liu, Y.; Gong, P.; Hertogh, M.; König, M. Do right PLS and do PLS right: A critical review of the application of PLS-SEM in construction management research. *Front. Eng. Manag.* **2021**, *8*, 356–369. [CrossRef]
9. Wei, Y.; Li, Y.; Liu, X.; Wu, M. Sustainable development and green gross domestic product assessments in megacities based on the emergy analysis method—A case study of Wuhan. *Sustain. Dev.* **2019**, *28*, 294–307. [CrossRef]
10. Yang, L.C.; Ao, Y.B.; Ke, J.T.; Lu, Y.; Liang, Y. To walk or not to walk? Examining non-linear effects of streetscape greenery on walking propensity of older adults. *J. Transp. Geogr.* **2021**, *94*, 103099. [CrossRef]
11. Fu, H.; Niu, J.; Wu, Z.; Xue, P.; Sun, M.; Zhu, H.; Cheng, B. Influencing Factors of Stereotypes on Wastewater Treatment Plants-Case Study of 9 Wastewater Treatment Plants in Xi'an, China. *Environ. Manag.* **2022**, 1–10. [CrossRef] [PubMed]
12. Liu, J.; Gong, E.; Wang, D.; Lai, X.; Zhu, J. Attitudes and behaviour towards construction waste minimisation: A comparative analysis between China and the USA. *Environ. Sci. Pollut. Res.* **2019**, *26*, 13681–13690. [CrossRef] [PubMed]
13. Song, M.L.; Zhang, L.L.; An, Q.X.; Wang, Z.; Li, Z. Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002–2010–2012. *J. Clean. Prod.* **2013**, *42*, 42–51. [CrossRef]
14. Halkos, G.; Petrou, K.N. Assessing 28 EU member states' environmental efficiency in national waste generation with DEA. *J. Clean. Prod.* **2019**, *208*, 509–521. [CrossRef]
15. Kim, H.; Son, J. Analyzing the Environmental Efficiency of Global Airlines by Continent for Sustainability. *Sustainability* **2021**, *13*, 1571. [CrossRef]
16. Guo, X.J.; Wang, X.; Wu, X.L.; Chen, X.P.; Li, Y. Carbon Emission Efficiency and Low-Carbon Optimization in Shanxi Province under "Dual Carbon" Background. *Energies* **2022**, *15*, 2369. [CrossRef]
17. Li, J.K.; Ma, J.J.; Wei, W. Analysis and Evaluation of the Regional Characteristics of Carbon Emission Efficiency for China. *Sustainability* **2020**, *12*, 3138. [CrossRef]
18. Li, Y.J.; Hou, W.H.; Zhu, W.W.; Li, F.; Liang, L. Provincial carbon emission performance analysis in China based on a Malmquist data envelopment analysis approach with fixed-sum undesirable outputs. *Ann. Oper. Res.* **2021**, *304*, 233–261. [CrossRef]

19. Wang, R.; Feng, Y. Research on China's agricultural carbon emission efficiency evaluation and regional differentiation based on DEA and Theil models. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1453–1464. [CrossRef]

20. Xu, J.; Jiang, Y.C.; Guo, X.; Jiang, L. Environmental Efficiency Assessment of Heavy Pollution Industry by Data Envelopment Analysis and Malmquist Index Analysis: Empirical Evidence from China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5761. [CrossRef] [PubMed]

21. Guo, S.D.; Li, H.; Zhao, R.; Zhou, X. Industrial environmental efficiency assessment for China's western regions by using a SBM-based DEA. *Environ. Sci. Pollut. Res.* **2019**, *26*, 27542–27550. [CrossRef]

22. Farrell, M.J. The Measurement of Productive Efficiency. *J. R. Stat. Soc.* **1957**, *120*, 253–290. [CrossRef]

23. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision-making units. *Eur. J. Oper. Res.* **1979**, *3*, 429–444. [CrossRef]

24. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]

25. Abbas, A.; Zhao, C.; Waseem, M.; Ahmad, R. Analysis of energy input–output of farms and assessment of greenhouse gas emissions: A case study of Cotton Growers. *Front. Environ. Sci.* **2022**, *9*, 725. [CrossRef]

26. Singh, G.; Singh, P.; Sodhi, G.P.S.; Tiwari, D. Energy auditing and data envelopment analysis (DEA) based optimization for increased energy use efficiency in wheat cultivation (*Triticum aestium* L.) in north-western India. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101453. [CrossRef]

27. Wan, B.H.; Zhou, E.D. Research of Total Factor Productivity and Agricultural Management Based on Malmquist-DEA Modeling. *Math. Probl. Eng.* **2021**, *2021*, 1–8. [CrossRef]