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# Dynamic Estimation of Urban Land Use Efficiency and Sustainability Analysis in China

**Huifang Cheng [1], Ting Yu [1], Hao Zhang [2], Kaifeng Duan [3] and Jianing Zhu [4,*]**

1 School of Economics, Zhejiang University of Technology, Hangzhou 310023, China
2 Business School, University of Shanghai for Science and Technology, Shanghai 200093, China
3 School of Economics and Management, Fuzhou University, Fuzhou 350108, China
4 School of Economics and Management, Tongji University, Shanghai 200092, China
* Correspondence: 2030369@tongji.edu.cn

**Abstract:** With rapid urbanization in China, land use efficiency (LUE) and related sustainability should be reasonably evaluated and improved. Studies have rarely investigated urban LUE and lack an analysis from the sustainability perspective. Long-term analysis can help identify the weaknesses in LUE and obtain a more stable evaluation. Hence, in this paper we develop a dynamic data envelopment analysis (DEA) model to assess urban LUE considering the time dimension. Differing from studies on traditional static DEA models, this study connects the observed periods by creating a common objective function. In addition, a method for estimating the sustainability of urban LUE is proposed under the DEA framework. The proposed method was applied to 34 major Chinese cities over a 3-year period, from 2015 to 2017. The results reveal that urban LUE still has potential for improvement in most cities. There was a distinct difference in efficiency among eastern, central, and western cities during the observed period. The average efficiency was higher in eastern cities than in central and western cities. The potential to optimize the land area and GDP should be realized with more efforts by most cities to strengthen LUE. Additionally, most inefficient cities have weak performance regarding the sustainability of LUE. The proposed approach enriches the sustainable measurement of LUE. Some management implications are provided to improve urban LUE. The empirical findings provide important support for sustainable land use in practice, and the proposed model is an important empirical extension of the DEA method in the land management field.

**Keywords:** sustainability; land use efficiency; urbanization; data envelopment analysis; dynamic



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## 1. Introduction

Land is the carrier of the urban economy, society, and ecological environment, and plays an irreplaceable role in urban development [1,2]. Land utilization efficiency directly affects urban sustainable development [3–6]. Since the beginning of the 21st century, China has experienced rapid urbanization. The urban land area increased from 30,406.19 km$^2$ in 2004 to 60,721.32 km$^2$ in 2020, for an annual increase of 6.23%. China's National Bureau of Statistics reported that the urbanization rate experienced robust growth, increasing from 36.09% in 2000 to 63.89% in 2020. However, continuous urban sprawl and inefficient land use have caused a series of social and environmental problems [7], such as traffic jams, resource shortages, pollution, and noise [3,8,9]. In a constrained geographical space, improving urban land use efficiency (LUE) is the key to striking a balance between economic growth and sustainable development [10], which is a crucial issue in China's current urbanization [11]. Currently, LUE is usually defined as the conversion efficiency transferred from a system with multiple inputs, including land, to a system with multiple outputs, including economic and related products [3,12]. Measuring and comparing the LUE among cities and constantly pursuing dynamic growth are appropriate ways to achieve efficient land utilization. Therefore, urban LUE in major Chinese cities needs to be rationally estimated.

Urban LUE has been a topic of interest in recent years with regard to urban land use estimation (e.g., [11,13]), measurement methods (e.g., [14,15]), influencing factors (e.g., [16–18]), etc. In earlier studies, urban LUE was generally measured by a single indicator of economic output per unit of land area, such as gross domestic product (GDP) and output per square kilometer [19]. This single indicator measurement does not consider other inputs involved in land use. In practice, land use is a complex system composed of natural, economic, social, and other factors, which can be evaluated more reasonably with multiple indicators [3,11,12,20]. Moreover, with increasing awareness of environmental protection, undesirable outputs (e.g., pollutant emissions) derived from land use are considered in the measurement along with desirable outputs [21]. In multiple-indicator studies, researchers have used two primary approaches to assess urban LUE: non-parametric data envelopment analysis (DEA) and stochastic frontier analysis (SFA), an econometric or parametric method. Compared with the SFA, DEA can evaluate all aspects of a city's LUE using a single score without any predetermined formulas [12,22]. In practice, most studies apply DEA to analyze benchmarking efficiency in urban land use [21].

While research is emerging on urban LUE, prior studies did not specifically investigate this issue in major Chinese cities from a sustainability perspective. Without a long-term view, major cities face more serious land use problems with rapid urbanization, including the explosive expansion of urban land scale, improper and inefficient land development, and unbalanced land use structure. With a mission of sustainable development, these cities should focus on long-term urban land use and emphasize effective land resource allocation rather than short-term outcomes. Hence, adding the time dimension to analyze the sustainability of urban LUE is vital. Omitting the time dimension can affect the fairness and objectivity of efficiency evaluation. The conventional DEA model cannot estimate long-term efficiency changes, since it does not consider the impact of two consecutive terms. In contrast, the dynamic DEA model can provide more precise estimation of multi-time dynamic efficiency [23]. In dynamic observation, the change trend and volatility of urban LUE can better reflect the state of sustainability. However, studies on dynamic efficiency evaluation in Chinese cities are scarce, and the sustainability of urban LUE is not fully investigated in the existing literature. There exists a research gap that needs to be filled. To this end, this paper develops a dynamic DEA model to investigate the urban LUE of major Chinese cities and proposes a measure to investigate sustainability.

This study aims to contribute to the literature in two aspects. First, we developed a dynamic DEA model to assess urban LUE and a measure to analyze its sustainability, which can enrich the theoretical framework. Second, we used the proposed approach to compute the LUE of 34 major Chinese cities. This empirical study offers some implications for improving efficiency and formulating sustainable land use policies.

The rest of the paper is organized as follows. Related important studies are reviewed in Section 2. The LUE measurement method is described in Section 3. Section 4 presents the method used on 34 Chinese major cities and analyzes the empirical results. Section 5 concludes the present study and describes the limitations for future research.

## 2. Literature Review

There are two parts in this section: an introduction to the DEA method and dynamic DEA model, and a review of the literature on LUE studies.

### 2.1. DEA and Dynamic DEA

The DEA method was developed by Charnes, Cooper, and Rhodes for calculating the relative efficiency of decision-making units (DMUs) based on multiple inputs and outputs. Because of the advantages of being nonparametric and not having a predetermined production function [24,25], DEA can compute the production efficiency of various production and service systems, and it has been widely applied in different sectors [26,27].

The time dimension is intrinsically important for almost all management decisions. However, traditional DEA models in the literature are always static [28,29]. One of the drawbacks of these models is that they ignore the influence of the time dimension and do not consider connecting activities between two consecutive terms [23]. To fill this gap, further important steps were taken in developing the dynamic DEA. The Malmquist productivity index was proposed to assess productivity change over time, which can be estimated by the DEA method [30]. Färe et al. [31] developed a DEA approach to evaluate the Malmquist productivity index, decomposing it into technical efficiency change and technological change. In addition, following basic DEA models, the window DEA was proposed to identify the efficiency trend over time considering the time dimension [32]. In the window DEA, each DMU in a different term is considered as a different DMU. In this way, the efficiency of a DMU in a given term can be compared with that of other DMUs as well as its own in other terms. Färe and Grosskopf [28] later developed a dynamic model that links periods through the production of intermediate outputs based on a network theory. Subsequently, Nemoto and Goto [29] created a dynamic DEA framework for evaluating the intertemporal behavior of a firm. Later, Tone and Tsutsui [23] developed a dynamic slack-based measure (SBM) model for estimating DMU efficiency for the whole term and specific terms. Additionally, Tone and Tsutsui [33] further established a dynamic network SBM model by combining dynamic DEA with network DEA. These studies made great contributions to the development of dynamic DEA and provide guidance for evaluation application in practice.

### 2.2. Land Use Efficiency Evaluation

Recently, LUE estimation is emerging in academia. In the literature, researchers frequently use DEA and SFA to investigate LUE in cities (e.g., [21,34]), regions (e.g., [2,35]), or urban agglomerations (e.g., [18,36]). Liu et al. [2] adopted SFA to compute regional LUE in China and explore the effect of pollutant emissions on efficiency. Chen et al. [3] employed DEA to assess built-up land efficiency in 336 Chinese cities during 2005–2012. Huang and Xue [37] adopted the super-efficiency DEA model to calculate the LUE of Xi'an city in China and analyze spatiotemporal changes. Depending on the estimation methods used, there can be significant disparities in the results of urban LUE. DEA, with its advantages of being non-parametric and not having pre-determined formulas, is widely applied in the evaluation of land use efficiency [34,37].

In the existing literature, a considerable number of studies focus on LUE using the DEA method based on different land types. With regard to urban construction land, Jingxin et al. [34] proposed a two-stage DEA model to measure the LUE of the urban agglomeration in China's Yangtze River area, suggesting that the LUE is higher in the construction stage than in the production stage. Zhou et al. [22] used a slacks-based measure DEA model to compute the construction LUE of 41 Chinese cities and analyzed the temporal and spatial differentiation characteristics. The findings indicated that efficiency was at a low level during the study period. Yao and Zhang [4] used a super super-efficiency SBM model to measure the construction LUE of 32 cities in China's Sichuan Province. Although the results showed a gap across cities, it was found that the gap in LUE is gradually narrowing. Lin and Ling [38] calculated the green construction LUE of 41 Chinese cities from 2006 to 2018 considering industrial pollution. The findings demonstrated that efficiency had a fluctuating upward trend during the observed time. Zhu et al. [21] applied a super-efficiency SBM model to assess urban construction LUE of 35 major Chinese cities between 2008 and 2015, and showed that LUE was relatively low, and pure technical efficiency strongly affected comprehensive efficiency. With regard to cultivated land, Xie et al. [39] adopted the non-radial direction distance function to measure the green efficiency of China's arable land use between 1995 and 2013. The results showed that efficiency first decreased and then increased and that there were regional differences during the study period. Kuang et al. [40] used an SBM approach to assess the efficiency of cultivated land use in 31 Chinese provinces during 2000–2017. The results showed that efficiency in most provinces was at a lower level, with significant spatial disparities. Regarding industrial land, Chen et al. [41] used DEA to assess the LUE of 109 resource-based cities in China during

2006–2015. The results confirmed that the distribution of efficiency varied depending on region, resource type, and development stage, and industrial land in most cities was redundant. Xie et al. [36] employed the sequential generalized directional distance function and meta-frontier non-radial Malmquist index to analyze the industrial LUE of urban areas around the mid-Yangtze River region between 2003 and 2012. They asserted that there was significant potential to improve efficiency and reduce industrial land wastage. As for built-up areas, Zhu et al. [42] applied a super-efficiency SBM model to compute the urban LUE of 35 Chinese cities. Urban LUE showed a fluctuating increase trend during 2007–2015, and efficiency showed strong spatial heterogeneity, with significant differences between different areas. Lu et al. [43] took environmental pollution into account and applied an SBM model to evaluate urban LUE in 31 Chinese provinces during 2001–2014. The findings showed an overall upward trend nationwide (from 0.7585 to 0.7989 on average).

The studies on LUE mentioned above mostly used traditional static DEA models. However, static DEA models are not suitable for assessing long-term efficiency changes, as they do not consider the impact of the time dimension. To estimate the long-term land use of a city, some scholars apply dynamic DEA models to estimate LUE. For instance, Fu et al. [44] employed SBM window analysis to investigate the efficiency of urban land use in China's Jiangsu Province from 2006 to 2017. They found that LUE was high, and the potential for land use improvement was small. Han and Zhang [45] used the minimum distance to strong efficient frontier and Malmquist productivity index to statically and dynamically measure the cultivated LUE in 30 provinces in China from 1997 to 2017. They observed significant differences in efficiency among four areas and an uncoordinated phenomenon of carbon emission reduction and economic growth in the process of cultivated land utilization. Tan et al. [46] combined the SBM model with variation and kernel density to dynamically assess the urban land green use efficiency of 25 Chinese cities between 2004 and 2015, showing a highly skewed distribution and different degrees of polarization with time.

The above-mentioned studies applied dynamic DEA to investigate LUE considering the continuity of carryovers from period to period, while they did not further discuss the sustainability of LUE. An appropriate method should be developed for evaluating the sustainability of LUE in long-term observations to achieve more accurate measurement. Multi-period dynamic assessment can reflect the sustainability of LUE and provide long-term decision support for resource allocation in urban land administration and utilization. This may lead to new management insights for the sustainable development of the cities.

## 3. Methodology

This section introduces the evaluation model for urban LUE. First, the selected variables are introduced to describe the land use process. Second, the efficiency evaluation model is constructed based on the dynamic DEA. Third, a method for estimating the sustainability of LUE is proposed. Finally, the measures for improvement potentials are presented.

### *3.1. Input and Output Variables*

Before using the DEA method to evaluate efficiency, appropriate input and output variables must be selected. Generally, the resources utilized in the production and service process should be considered as inputs and the results should be taken as outputs. In reality, the process of urban land use mainly includes investing in land and engaging in various production activities on the land to obtain outputs.

Based on prior literature (e.g., [1,11,21,22,36,39,41,43,46]), in this paper we selected three inputs and two outputs to compute urban LUE. Specifically, population, fixed asset investment, and built-up area are considered as inputs. GDP is treated as a desirable output, while $SO_2$ emission is taken as an undesirable output. Figure 1 shows the process of urban land use, where population, fixed asset investment, and land area are utilized to generate GDP and $SO_2$ emission.

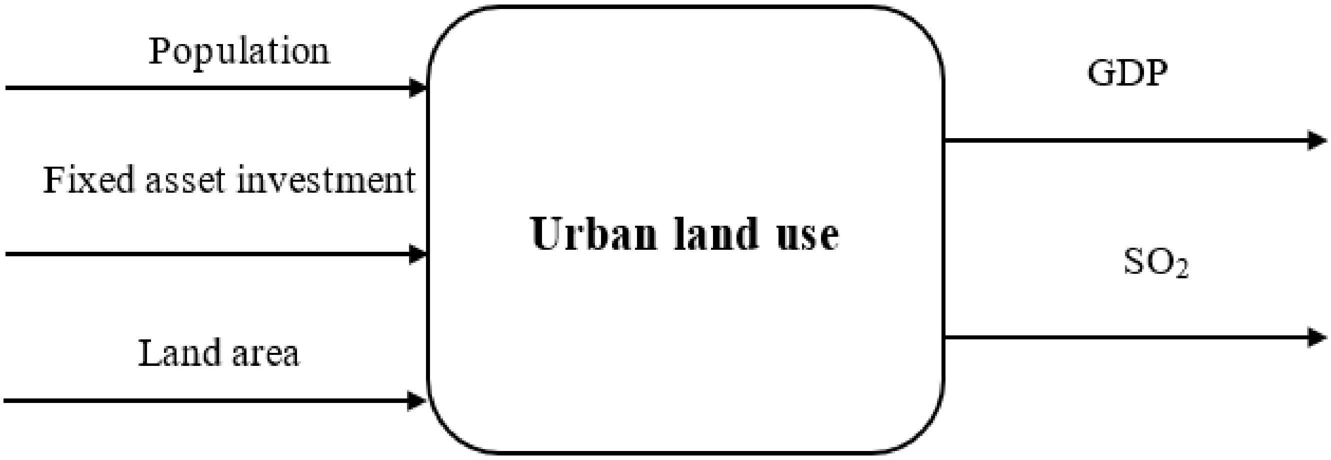


**Figure 1.** Production process of urban land use system.

### 3.2. Traditional DEA Model for Estimating Land Use Efficiency

As shown in Figure 1, population ($XP$), fixed asset investment ($XK$), and land area ($XL$) are the three inputs. GDP ($YG$) and $SO_2$ emission ($YB$) are desirable and undesirable outputs, respectively. Each city utilizes $XP$, $XK$, and $XL$, and then produces $YG$ and $YB$. To evaluate LUE, each city is considered as one DMU, expressed as $DMU_j$ ($j = 1, 2, \ldots, n$).

CCR-DEA and BCC-DEA are two classical and important radial models in DEA theory. The difference is that the former assumes that return to scale (RTS) is constant, while the latter assumes that RTS is variable. Following previous studies (e.g., [4,19]), in this paper we adopted the CCR model to assess urban LUE. On the basis of the input and output variables described above, an efficiency evaluation model is constructed as follows:

$$\begin{aligned} & \min \theta_i \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j XP_j \leq \theta_i XP_i, \sum_{j=1}^{n} \lambda_j XK_j \leq \theta_i XK_i, \sum_{j=1}^{n} \lambda_j XL_j \leq \theta_i XL_i, \\ & \sum_{j=1}^{n} \lambda_j YG_j \geq YG_i, \sum_{j=1}^{n} \lambda_j YB_j = YB_i, \\ & \lambda_j \geq 0, \quad j = 1, 2, \ldots, n. \end{aligned} \tag{1}$$

Model (1) is an input-oriented DEA method. In Model (1), $\theta_i$ represents the LUE score, and $\lambda_j$ is the intensity variable expressing the participation degree of each DMU in forming the production frontier. The range of $\theta_i$ is (0, 1]. If $\theta_i^* = 1$, the land use of a city would be estimated as efficient; otherwise, it is inefficient. If one city has a larger score, it indicates that this city exhibits better land utilization than the others.

### 3.3. Dynamic DEA Model for Estimating Land Use Efficiency

In reality, urban land use has continuity. If the characteristic of time continuity is not considered in the evaluation, accurate efficiency scores may not be obtained. Therefore, a dynamic DEA evaluation model is developed in this section. In this model, the urban land use process is regarded as a system with multiple inputs and outputs composed of three time periods considering the continuity characteristic of operation activities. LUE can be measured by Model (2) as follows:

$$
\begin{aligned}
&\min\ (\theta_i^t + \theta_i^{t+1} + \theta_i^{t+2}) \\
\text{s.t.}\quad &\left.\begin{aligned}
&\sum_{j=1}^{n} \lambda_{1j} XP_j^t \le \theta_i^t XP_i^t,\ \sum_{j=1}^{n} \lambda_{1j} XK_j^t \le \theta_i^t XK_i^t,\ \sum_{j=1}^{n} \lambda_{1j} XL_j^t \le \theta_i^t XL_i^t, \\
&\sum_{j=1}^{n} \lambda_{1j} YG_j^t \ge YG_i^t,\ \sum_{j=1}^{n} \lambda_{1j} YB_j^t = YB_i^t,
\end{aligned}\right\} period\ \ t \\
&\left.\begin{aligned}
&\sum_{j=1}^{n} \lambda_{2j} XP_j^{t+1} \le \theta_i^{t+1} XP_i^{t+1},\ \sum_{j=1}^{n} \lambda_{2j} XK_j^{t+1} \le \theta_i^{t+1} XK_i^{t+1},\ \sum_{j=1}^{n} \lambda_{2j} XL_j^{t+1} \le \theta_i^{t+1} XL_i^{t+1}, \\
&\sum_{j=1}^{n} \lambda_{2j} YG_j^{t+1} \ge YG_i^{t+1},\ \sum_{j=1}^{n} \lambda_{2j} YB_j^{t+1} = YB_i^{t+1},
\end{aligned}\right\} period\ \ t+1 \\
&\left.\begin{aligned}
&\sum_{j=1}^{n} \lambda_{3j} XP_j^{t+2} \le \theta_i^{t+2} XP_i^{t+2},\ \sum_{j=1}^{n} \lambda_{3j} XK_j^{t+2} \le \theta_i^{t+2} XK_i^{t+2},\ \sum_{j=1}^{n} \lambda_{3j} XL_j^{t+2} \le \theta_i^{t+2} XL_i^{t+2}, \\
&\sum_{j=1}^{n} \lambda_{3j} YG_j^{t+2} \ge YG_i^{t+2},\ \sum_{j=1}^{n} \lambda_{3j} YB_j^{t+2} = YB_i^{t+2},
\end{aligned}\right\} period\ \ t+2 \\
&\sum_{j=1}^{n} \lambda_{1j} XK_j^{t+1} \le \sum_{j=1}^{n} \lambda_{2j} XK_j^{t+1},\ \sum_{j=1}^{n} \lambda_{2j} XK_j^{t+2} \le \sum_{j=1}^{n} \lambda_{3j} XK_j^{t+2}, \\
&0 \le \theta_i^t \le 1,\ 0 \le \theta_i^{t+1} \le 1, 0 \le \theta_i^{t+2} \le 1, \lambda_{1j} \ge 0,\quad \lambda_{2j} \ge 0,\quad \lambda_{3j} \ge 0,\ t = 1, 2, \ldots, T.
\end{aligned}
\tag{2}
$$

In Model (2), $t$ ($t = 1, 2, \ldots, T$) expresses the time period; $\lambda_j^t$, $\lambda_j^{t+1}$, and $\lambda_j^{t+2}$ are the intensity variables of each DMU in periods $t$, $t$ + 1, and $t$ + 2, respectively; and $\theta_i^t$, $\theta_i^{t+1}$, and $\theta_i^{t+2}$ represent LUE scores in periods $t$, $t$ + 1, and $t$ + 2, respectively. The objective function represents the LUE score in the three periods. Similarly, if $\theta_i^{t*} = 1$ ($\theta_i^{t+1*} = 1$ or $\theta_i^{t+2*} = 1$), the land use of a city could be regarded as efficient in period $t$ ($t$ + 1 or $t$ + 2). In addition, if the land use is efficient in all three periods ($t$, $t$ + 1, and $t$ + 2), the sustainability of LUE can be considered perfect by default.

### 3.4. Method for Sustainability of Land Use Efficiency

Generally, the greater the increase and the smaller the fluctuation in LUE over certain periods, the better the sustainability. Hence, in this paper we propose a new method to estimate the sustainability of inefficient cities' land use. First, an indicator of the changing intensity of LUE, denoted as $C_i$, is proposed to reflect sustainability, as follows:

$$C_i = \frac{\theta_i^{t+2} - \theta_i^t}{\theta_i^t s_i^2}\ (t = 1, 2, \ldots, T) \tag{3}$$

where $\frac{\theta_i^{t+2} - \theta_i^t}{\theta_i^t}$ represents the efficiency change rate, and $s_i^2$ expresses the variance of LUE over certain periods, from period $t$ to $t$ + 2.

Furthermore, identifying the return to scale (RTS) status of DMUs can contribute to understanding the sustainability of LUE and improving efficiency. In economics, if the increase proportion of outputs and inputs is equal, it is called constant return to scale (CRS). If the increase proportion is greater for outputs than production inputs, it is called increasing return to scale (IRS), otherwise, it is called decreasing return to scale (DRS). The specific conditions for identifying RTS are as follows. We always assume IRS and CRS conditions with larger outputs will have greater potential for sustainability.

(i) If $\sum \lambda_j^* < 1$ for all alternate optima, the DMU is in the IRS stage.
(ii) If $\sum \lambda_j^* = 1$ in any alternate optimum, the DMU is in the CRS stage.
(iii) If $\sum \lambda_j^* > 1$ for all alternate optima, the DMU is in the DRS stage.

Taken together, indicator $C_i$ and RTS are considered to reasonably estimate and analyze the sustainability of LUE. To further make sense of the findings, a four-quadrant classification is developed, as shown in Figure 2. In this classification, inefficient cities are divided into two proportionally equal groups according to the ranking of indicator $C_i$;

further, the cities can be classified into two groups according to RTS stages. Note that cities in the IRS and CRS stages are in one group, and others in the DRS stage are in another group. Finally, a four-quadrant classification is developed for sustainability analysis.

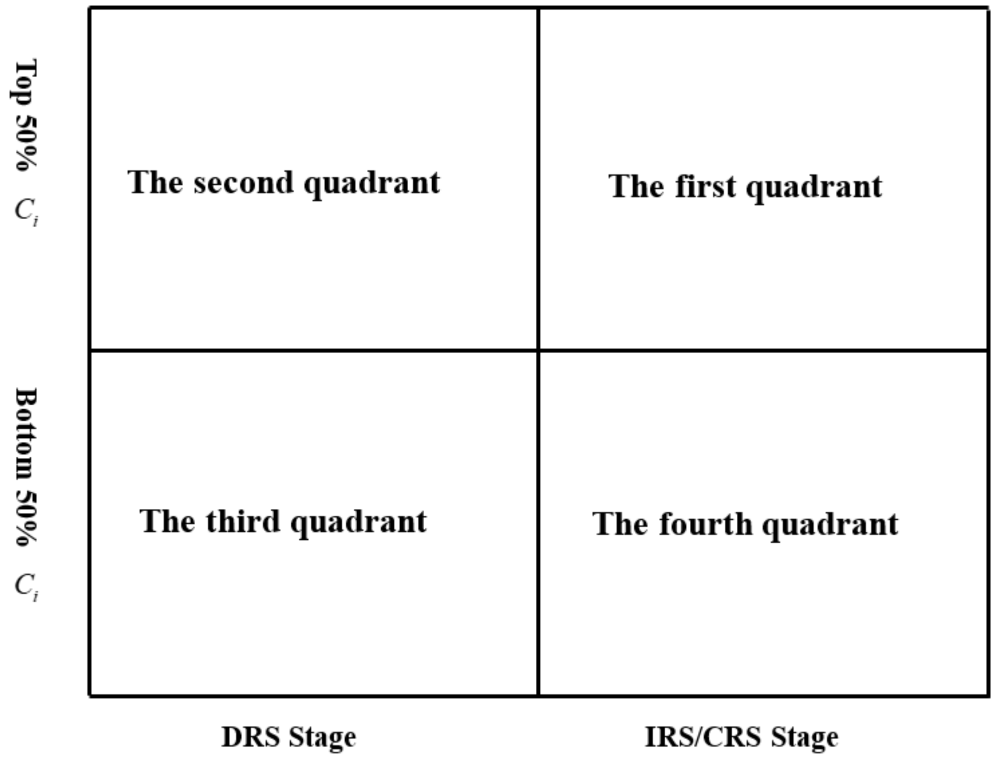


**Figure 2.** Four-quadrant classification for sustainability analysis.

(1) If the city's indicator $C_i$ ranks in the top 50% and it is in the IRS or CRS stage, that is, located in the first quadrant, then the sustainability of LUE for this city can be regarded as high. The city can adopt a strategy of increasing resource investment to improve outputs and LUE.
(2) If the city's indicator $C_i$ ranks in the top 50% and it is in the DRS stage, that is, located in the second quadrant, then the sustainability of LUE for this city can be regarded as being in the middle. The city should adopt a prudent strategy of increasing resource investment to improve sustainability.
(3) If the city's indicator $C_i$ ranks in the bottom 50% and it is in the IRS or CRS stage, that is, located in the third quadrant, then the sustainability of LUE for this city can be regarded as being in the middle. The city should first take measures to significantly and steadily increase LUE to improve sustainability and adopt a strategy of increasing resource investment to improve outputs.
(4) If the city's indicator $C_i$ ranks in the bottom 50% and it is in the DRS stage, that is, located in the fourth quadrant, then the sustainability of LUE for this city can be regarded as low. The city should take steps to significantly and steadily increase LUE and adopt a prudent strategy of increasing resource investment to improve sustainability.

It is worth noting that we set a threshold (50%) of indicator $C_i$ in the analysis. This is an easy and common sense classification. The threshold can be adjusted by the researchers for different sustainability analysis scenarios.

### *3.5. Measure for Efficiency Improvement*

In DEA theory, the projected point on the production frontier is the most efficient target for each inefficient DMU to achieve. Hence, the DEA method can be used to set the optimization targets of inputs and outputs to improve efficiency. With the process of urbanization, it is difficult for major cities to reduce population and fixed asset investment, while $SO_2$ emission is mainly determined by the industrial sector. Therefore, in this study, we focus on analyzing improvements in the land area input and GDP output of inefficient cities. Based on Model (2), the optimization target of the land area can be obtained by the following equation:

$$TL_i^t = \sum_{j=1}^{n} \lambda_{1j} XL_j^t \ \ (t = 1, 2, \ldots, T) \tag{4}$$

where $\sum_{j=1}^{n} \lambda_{1j} XL_j^t$ represents the optimal input attached to land area. The target land area input is expressed at a minimum level under the optimal LUE. Therefore, the index of potential land use improvement can be defined as the ratio of the difference between the actual value and the target value to the actual value. The equation is as follows:

$$PL_i^t = \frac{XL_i^t - TL_i^t}{XL_i^t} \ (t = 1, 2, \ldots, T) \tag{5}$$

Similarly, the optimization targets of GDP output of inefficient cities can be calculated by the following equation:

$$TG_i^t = \sum_{j=1}^{n} \lambda_{1j} YG_j^t \ (t = 1, 2, \ldots, T) \tag{6}$$

Similar to Equation (5), the improvement potential of GDP output can be also defined as the ratio of the difference between the target value and actual value to actual value, as expressed by Equation (7):

$$PG_i^t = \frac{TG_i^t - YG_i^t}{YG_i^t} \ (t = 1, 2, \ldots, T) \tag{7}$$

Based on the above equations, the improvement potential of land area input and GDP output can be calculated to enhance urban LUE for sustainable development.

## 4. Empirical Analysis

In this paper, we used the proposed approach to estimate the LUE of major cities in China. The country has had rapid development in urbanization in the past decades, and it has become more important to detect the LUE. Due to data availability, 34 major cities were selected for observation in this empirical case over the period 2015 to 2017. The major cities are spread across most areas in China. These cities are municipalities directly under the central government, provincial capitals, or cities with good economic development levels, which can reflect the process of urbanization and land use in China. Three years is a suitable time period in terms of the balance of informativeness and stability of the performance evaluation of the DEA model [47].

### *4.1. Data Source*

The sample data on population, capital, land area, GDP, and $SO_2$ emission were collected from China City Statistical Yearbooks. The data on capital and GDP were converted based on 2015 prices to avoid the effect of price. According to the locations of major cities, the samples were divided into three areas: eastern, central, and western areas, as shown in Table 1. The descriptive statistics of the data are provided in Table 2. From Table 2, it can be seen that $SO_2$ emission declined rapidly in all three years, indicating that more environmental protection equipment was used for desulfurization and the emissions were transferred to non-major cities with the transfer of polluting industries.

**Table 1.** Sample cities and categorization.

| Area | Cities |
|---|---|
| Eastern | Beijing, Tianjin, Shijiazhuang, Shenyang, Dalian, Shanghai, Nanjing, Hangzhou, Ningbo, Fuzhou, Xiamen, Jinan, Qingdao, Guangzhou, Shenzhen, Haikou |
| Central | Taiyuan, Changchun, Harbin, Hefei, Nanchang, Zhengzhou, Wuhan, Changsha |
| Western | Hohhot, Nanning, Chongqing, Chengdu, Guiyang, Kunming, Xi'an, Lanzhou, Yinchuan, Urumqi |

**Table 2.** Descriptive statistics.

| | | Input | | | | Output |
|---|---|---|---|---|---|---|
| Year | Indicator | Population ($10^6$ People) | Fixed Asset Investment ($10^9$ CNY) | Land Area ($km^2$) | GDP ($10^9$ CNY) | $SO_2$ ($10^3$ tons) |
| 2015 | Maximum | 21.29 | 102.15 | 1401.01 | 2483.84 | 426.80 |
| | Minimum | 1.09 | 2.37 | 152.40 | 89.33 | 2.52 |
| | Average | 4.97 | 28.26 | 522.31 | 682.29 | 72.62 |
| | Std. Dev. | 4.16 | 22.21 | 316.51 | 617.83 | 70.09 |
| 2016 | Maximum | 24.49 | 117.65 | 1419.66 | 2709.93 | 174.05 |
| | Minimum | 1.13 | 2.45 | 140.59 | 96.95 | 0.59 |
| | Average | 5.26 | 30.21 | 549.39 | 743.92 | 33.40 |
| | Std. Dev. | 4.58 | 24.05 | 326.67 | 675.37 | 32.32 |
| 2017 | Maximum | 24.51 | 129.87 | 1445.54 | 2861.33 | 139.88 |
| | Minimum | 1.16 | 4.59 | 140.59 | 102.53 | 0.50 |
| | Average | 5.55 | 31.22 | 571.84 | 814.98 | 22.76 |
| | Std. Dev. | 4.60 | 26.60 | 336.33 | 712.83 | 24.54 |

Note: CNY is Chinese yuan.

### 4.2. Efficiency Analysis

Based on the data collected for 2015, 2016, and 2017, LUE scores were acquired by Model (2). The results are provided in Table 3.

**Table 3.** Results generated by Model (2).

| Area | Cities | 2015–2017 | 2015 | 2016 | 2017 | Cities | 2015–2017 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|
| Eastern | Beijing | 0.8282 | 0.8113 | 0.8434 | 0.8300 | Ningbo | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Tianjin | 0.9454 | 0.9610 | 1.0000 | 0.8752 | Fuzhou | 0.9301 | 1.0000 | 0.7902 | 1.0000 |
| | Shijiazhuang | 1.0000 | 1.0000 | 1.0000 | 1.0000 | Xiamen | 0.5391 | 0.5591 | 0.5409 | 0.5174 |
| | Shenyang | 0.8275 | 0.9455 | 0.7615 | 0.7754 | Jinan | 0.6915 | 0.7876 | 0.6623 | 0.6245 |
| | Dalian | 1.0000 | 1.0000 | 1.0000 | 1.0000 | Qingdao | 0.6792 | 0.9792 | 0.5493 | 0.5090 |
| | Shanghai | 1.0000 | 1.0000 | 1.0000 | 1.0000 | Guangzhou | 0.8416 | 0.9150 | 0.8205 | 0.7894 |
| | Nanjing | 0.6691 | 0.6810 | 0.6771 | 0.6492 | Shenzhen | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Hangzhou | 0.8514 | 0.8114 | 0.8394 | 0.9035 | Haikou | 0.3937 | 0.3507 | 0.4148 | 0.4156 |
| Central | Taiyuan | 0.6565 | 0.6955 | 0.6513 | 0.6228 | Nanchang | 0.5287 | 0.4990 | 0.4943 | 0.5928 |
| | Changchun | 0.5702 | 0.6184 | 0.5556 | 0.5365 | Zhengzhou | 0.7038 | 0.7187 | 0.7640 | 0.6287 |
| | Harbin | 0.7753 | 0.9154 | 0.7226 | 0.6879 | Wuhan | 0.7747 | 0.7835 | 0.7698 | 0.7708 |
| | Hefei | 0.5243 | 0.5771 | 0.5026 | 0.4931 | Changsha | 0.7567 | 0.7551 | 0.7967 | 0.7182 |
| Western | Hohhot | 1.0000 | 1.0000 | 1.0000 | 1.0000 | Kunming | 0.9467 | 1.0000 | 0.9581 | 0.8819 |
| | Nanning | 0.4566 | 0.4623 | 0.4350 | 0.4724 | Xi'an | 0.5261 | 0.6692 | 0.5101 | 0.3990 |
| | Chongqing | 0.8406 | 0.8423 | 0.8451 | 0.8343 | Lanzhou | 0.5663 | 0.5791 | 0.5510 | 0.5687 |
| | Chengdu | 0.5104 | 0.6028 | 0.4607 | 0.4678 | Yinchuan | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Guiyang | 0.8542 | 1.0000 | 0.5625 | 1.0000 | Urumqi | 0.6581 | 0.8541 | 0.4219 | 0.6983 |
| Overall | | 0.7602 | 0.8051 | 0.7324 | 0.7430 | Central | 0.6613 | 0.6953 | 0.6571 | 0.6314 |
| Eastern | | 0.8248 | 0.8626 | 0.8062 | 0.8056 | Western | 0.7359 | 0.8010 | 0.6744 | 0.7322 |

It can be found that during the study period, the overall average efficiency score of the 34 major cities is 0.7602. The efficiency value is 1.0000 for seven cities: Shijiazhuang, Dalian, Shanghai, Ningbo, Shenzhen, Hohhot, and Yinchuan. These cities can be considered efficient. In addition, 11 cities have a higher efficiency score than the overall average: Beijing (0.8282), Tianjin (0.9454), Shenyang (0.8275), Hangzhou (0.8514), Fuzhou (0.9301), Guangzhou (0.8416), Harbin (0.7753), Wuhan (0.7747), Chongqing (0.8406), Guiyang (0.8542), and Kunming (0.9467). The efficiency scores of the remaining 16 cities are below the overall average. That is to say, LUE in many cities is still low, and there is the potential for improvement.

From the areal perspective, for the eastern cities, the average efficiency value is 0.8248. Among these 16 cities, five cities have an efficiency value of 1.0000, six cities perform better than the overall average, and five cities have a lower value than the overall average. For the central area, the average efficiency value is 0.6613. Among these eight cities, only two cities are above the overall average, and the other six cities are below the overall average. It is evident that the average efficiency value of the central cities is lower than that of the eastern cities. Hence, it is more urgent for cities in central China to enhance LUE. Interestingly, the western cities performed better than the central cities. For the western area, the average efficiency score is 0.7359. Among the 10 cities, two cities have an efficiency value of 1.0000, three cities are above the overall average, and the other five cities are below the overall average. This is most likely due to the efficient utilization of resources in the western cities in terms of larger GDP output and less $SO_2$ emissions. In conclusion, there are significant disparities in urban LUE among the three areas. Specifically, the eastern area has the best efficiency, followed by the western and central areas.

According to the literature, China's first-tier cities include Beijing, Shanghai, Guangzhou, and Shenzhen [48]. From the perspective of urban attributes, among these four first-tier cities, two of them have an efficiency value of 1.0000, and two cities have a higher value than the overall average. Meanwhile, among 30 non-first-tier cities, five cities have an efficiency value of 1.0000, nine cities are above the overall average, and the other 16 cities are below the overall average. The average efficiency score of first-tier cities is higher than that of non-first-tier cities, at 0.9175 and 0.7392, respectively. This may be because first-tier cities have more developed economies and high-quality professionals and can take more effective management and technological measures to enhance urban LUE.

### *4.3. Sustainable Analysis*

The dynamically changing trend of LUE reflects its sustainability. Figure 3 displays the dynamic changes in efficiency. During the observed period, the overall average efficiency of major cities shows a fluctuating decreasing trend. It declined from 0.8051 in 2015 to 0.7324 in 2016 and then rose slightly to 0.7430 in 2018. This high volatility reveals that the sustainability of LUE is in a weak state. In terms of area, the average efficiency value of the western area shows the same trend, decreasing from 0.8010 to 0.6744, and then rising to 0.7322, while that of the eastern and central areas declined. Specifically, in the eastern area, the value dropped from 0.8626 to 0.8062, and then declined slightly to 0.8056. In the central area, the value fell from 0.6953 to 0.6571, and then declined slightly to 0.6314. In terms of the amplitude of variation, as a whole, the efficiency change was smaller in the eastern cities (0.0570) than in the central cities (0.0639) and western cities (0.0688).

For specific inefficient cities, the proposed indicator of change intensity $C_i$ and the RTS stage were taken together to analyze the sustainability of LUE reasonably. Table 4 lists the results of indicator $C_i$ and RTS, and Figure 4 shows the distribution of inefficient cities.

It can be observed that 10 cities (Shenyang, Fuzhou, Qingdao, Haikou, Harbin, Nanchang, Nanning, Guiyang, Xi'an, and Urumqi) belong to the first quadrant. This demonstrates a high level of sustainability of LUE in these cities. There are three cities in the second quadrant (Beijing, Tianjin, and Hangzhou), which means that they have a middle level of sustainability of efficiency. Since these cities are in the DRS stage, an expansion of resource inputs would not produce a proportionate increase in outputs. They should reasonably control the expansion of resource inputs, strengthen the integration of existing resources, improve the allocation efficiency of resources, and then improve the overall LUE. Eleven cities (Nanjing, Xiamen, Jinan, Taiyuan, Changchun, Hefei, Zhengzhou, Wuhan, Changsha, Chengdu, and Lanzhou) belong to the third quadrant, showing that they have a middle level of sustainability of LUE. Considering that these cities are in the IRS/CRS stage, moderate expansion of resource inputs could improve their outputs. The most important thing for these cities is that they should improve efficiency as much as possible with little fluctuation, since all of them had a decline in efficiency during the observed period. Three cities are in the fourth quadrant (Guangzhou, Chongqing, and Kunming), demonstrating that they have a low level of sustainability of efficiency. They should smoothly improve LUE and reduce efficiency fluctuation. In addition, they should strengthen the utilization of existing resources and prudently increase resource inputs as they are in the DRS stage.

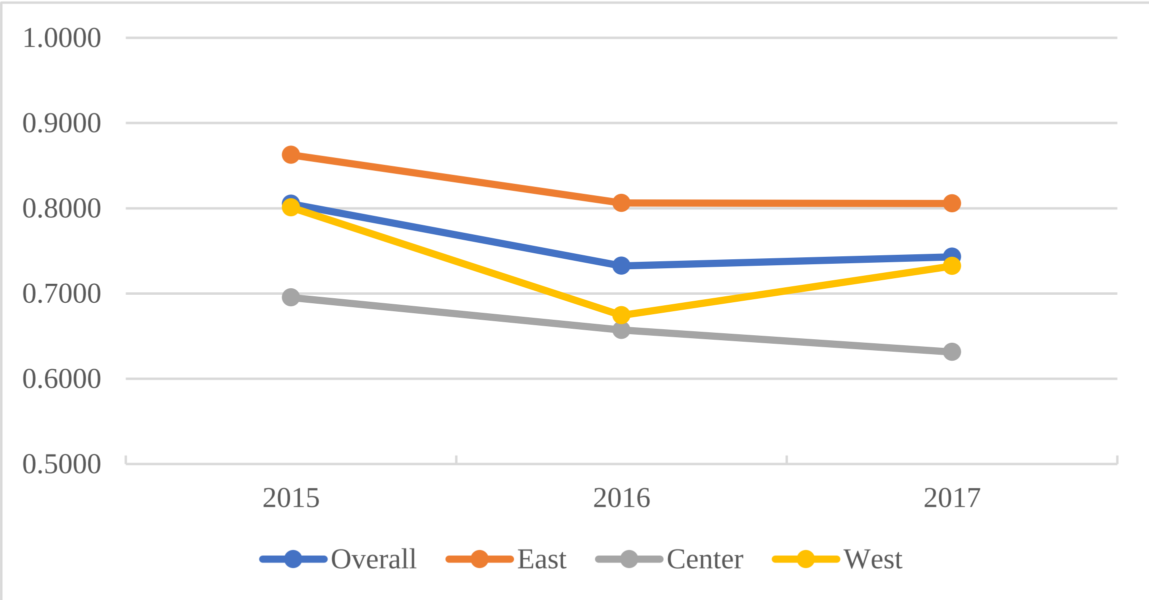


**Figure 3.** Change trend in land use efficiency during 2015–2017.


**Figure 4.** Distribution of inefficient cities.

**Table 4.** Results of indicator and RTS.

| Area | Cities | $C_i$ | $\sum\lambda_j^*$ | RTS (2017) | Quadrant |
|---|---|---|---|---|---|
| Eastern | Beijing | 132.70 | 1.3486 | DRS | 2 |
| | Tianjin | −32.85 | 1.6578 | DRS | 2 |
| | Shenyang | −25.72 | 0.8744 | IRS | 1 |
| | Nanjing | −232.33 | 0.7851 | IRS | 3 |
| | Hangzhou | 76.36 | 1.0547 | DRS | 2 |
| | Fuzhou | 0.00 | 1.0000 | CRS | 1 |
| | Xiamen | −255.97 | 0.2207 | IRS | 3 |
| | Jinan | −42.63 | 0.5896 | IRS | 3 |
| | Qingdao | -10.60 | 0.3649 | IRS | 1 |
| | Guangzhou | −48.14 | 1.2965 | DRS | 4 |
| | Haikou | 200.22 | 0.0667 | IRS | 1 |
| Central | Taiyuan | −116.88 | 0.3354 | IRS | 3 |
| | Changchun | −108.28 | 0.5257 | IRS | 3 |
| | Harbin | −24.82 | 0.5796 | IRS | 1 |
| | Hefei | −103.18 | 0.4262 | IRS | 3 |
| | Nanchang | 91.29 | 0.4471 | IRS | 1 |
| | Zhengzhou | −39.59 | 0.8194 | IRS | 3 |
| | Wuhan | −417.64 | 0.6702 | IRS | 3 |
| | Changsha | −47.45 | 0.2916 | IRS | 3 |
| Western | Nanning | 87.25 | 0.3045 | IRS | 1 |
| | Chongqing | −454.76 | 4.0854 | DRS | 4 |
| | Chengdu | −52.39 | 0.6103 | IRS | 3 |
| | Guiyang | 0.00 | 1.0000 | CRS | 1 |
| | Kunming | −49.39 | 1.1776 | DRS | 4 |
| | Xi'an | −32.83 | 0.2940 | IRS | 1 |
| | Lanzhou | −132.44 | 0.5951 | IRS | 3 |
| | Urumqi | −5.71 | 0.9599 | IRS | 1 |

### *4.4. Improvement Potential Analysis*

After analyzing LUE, inefficient cities can be identified. The inefficiency is mainly due to the existence of more inputs, less desirable outputs, and more undesirable outputs. Actually, with the process of urbanization, it is difficult for major cities to reduce population and fixed asset investment, while $SO_2$ emission is mainly determined by the industrial sector. So this paper focuses on analyzing improvements in land area input and GDP output of inefficient cities. By calculating Equations (4)–(7), the adjustment potential of land area and GDP can be obtained, as shown in Table 5.

In terms of land area, it can be determined that all inefficient cities have the potential for further improvement, with an average improvement potential of 33.41%. That is to say, local authorities need to take measures to reduce land input; in other words, they should make better use of the land to produce more output. For example, compared with the best benchmark, Haikou, Nanning, Xi'an, Chengdu, Hefei, Urumqi, Nanchang, Xiamen, Qingdao, Changchun, and Lanzhou should reduce their proportion of land area by 60.75, 54.35, 52.99, 49.92, 49.65, 48.59, 47.03, 46.15, 45.64, 44.96, and 43.80%, respectively. Nine cities (Nanjing, Jinan, Guangzhou, Taiyuan, Harbin, Zhengzhou, Guiyang, Changsha, and Wuhan) should reduce their land area by 20 to 40%, and the other seven cities (Beijing, Tianjin, Shenyang, Hangzhou, Fuzhou, Kunming, and Chongqing) should reduce their land area by less than 20%. In terms of area, the average improvement potential of western inefficient cities is 38.73%, which is higher than that of eastern inefficient cities (28.15%) and central inefficient cities (35.32%). This indicates that it is more urgent to improve land use in western inefficient cities to increase efficiency.

With regard to GDP output, it can be determined that 17 cities have improvement potential. This indicates that the GDP of most cities does not reach an ideal level. For eastern cities, the growth potential of Beijing, Guangzhou, and Fuzhou is 0.35, 0.47, and 0.17%, respectively, while that of Tianjin, Nanjing, and Haikou is 0.12, 0.03, and 0.03%, respectively. For central cities, the growth potential of Taiyuan is greater than the average (5.83 vs. 0.55%), while that of Harbin, Zhengzhou, Wuhan, and Changsha is between 0.10 and 0.30%. For western cities, the growth potential of Lanzhou, Kunming, and Chongqing is 4.14, 2.09, and 0.71%, respectively, while that of Nanning, Guiyang, and Urumqi is 0.23, 0.05, and 0.05%, respectively. At a holistic level, the average GDP growth potential of eastern inefficient cities is 0.11%, while that of central and western inefficient cities is 0.80 and 0.91%, respectively.

The potential to optimize the land area and GDP should be realized by most cities exerting more effort to strengthen LUE and consequently achieve sustainability in the future. To summarize, the sustainable utilization of urban land is important for urban economic development, while LUE still needs to be improved.

**Table 5.** Adjustment potential for land area and GDP based on three observed years.

| Area | Cities | Improvement Rate of Land Area | Improvement Rate of GDP |
|---|---|---|---|
| Eastern | Beijing | 17.17% | 0.35% |
| | Tianjin | 6.94% | 0.12% |
| | Shenyang | 18.35% | 0.00% |
| | Nanjing | 33.12% | 0.03% |
| | Hangzhou | 14.61% | 0.00% |
| | Fuzhou | 13.90% | 0.17% |
| | Xiamen | 46.15% | 0.00% |
| | Jinan | 32.63% | 0.00% |
| | Qingdao | 45.64% | 0.00% |
| | Guangzhou | 20.44% | 0.47% |
| | Haikou | 60.75% | 0.03% |
| Central | Taiyuan | 36.15% | 5.83% |
| | Changchun | 44.96% | 0.00% |
| | Harbin | 27.69% | 0.12% |
| | Hefei | 49.65% | 0.00% |
| | Nanchang | 47.03% | 0.00% |
| | Zhengzhou | 30.04% | 0.12% |
| | Wuhan | 22.55% | 0.23% |
| | Changsha | 24.47% | 0.10% |
| Western | Nanning | 54.35% | 0.23% |
| | Chongqing | 15.96% | 0.71% |
| | Chengdu | 49.92% | 0.00% |
| | Guiyang | 27.63% | 0.05% |
| | Kunming | 16.56% | 2.09% |
| | Xi'an | 52.99% | 0.00% |
| | Lanzhou | 43.80% | 4.14% |
| | Urumqi | 48.59% | 0.05% |
| Overall | | 33.41% | 0.55% |

## 5. Conclusions

This study proposes a dynamic DEA model to investigate LUE in Chinese cities from a sustainability angle. In this study, the LUE of a city refers to the conversion efficiency of the input system relative to the output system, incorporating the contributions of land use and undesirable output. Moreover, methods for judging and analyzing the sustainability of LUE and estimating the improvement potential for outputs are proposed based on the optimal solutions. Finally, the proposed model is applied to China's cities and the effectiveness of the method is verified.

Based on the Chinese urban situation, this study analyzes urban LUE from a sustainability angle. The important conclusions are as follows. First, the land use efficiency of most cities has room for improvement. Second, a distinct difference in efficiency was found among the three areas in the study period. Specifically, the average efficiency of eastern cities was higher than that of central and western cities. Third, the sustainability of LUE in most inefficient cities was weak. Fourth, inefficient cities have great improvement potential to optimize the land area and GDP by exerting more effort to strengthen efficiency. In addition, some management implications can be provided for improving urban LUE, as follows:

(1) First, measures should be enacted by government agencies to reduce the redundancy of land input and strengthen the intensive utilization of urban land. As redundant land use in China's cities is serious, LUE can be enhanced by the rational allocation of input factors. Government agencies should formulate a coordinated regulation policy for population, economy, and land use, including developing compact cities, improving land use intensity, and avoiding land destruction and idleness. Moreover, it is essential to establish an effective incentive and constraint regulation mechanism to change the current land use modes, for example, by reducing extensive urban expansion and motivating local authorities to fully utilize potential built-up land.
(2) Second, local authorities should reach a trade-off between land use and environmental protection. The uncoordinated relationship between land utilization and environmental protection constrains the improvement of LUE [1]. Attention should be paid to issues related to undesirable outputs in the land use process. Local authorities should develop innovative green urban land use models. It is recommended to improve the industrial structure, promote transformation and upgrading, facilitate the application of advanced production technologies, and improve the governance of industrial pollution reduction and environmental protection. Moreover, a green land use mode based on natural resource endowment should be established to balance economic development and ecological protection.
(3) Third, increasing investment in advanced technology could strengthen the dynamic supervision and macro planning of urban land use, improving the management level of land resources. The application of new technologies, such as global positioning and remote sensing technology, could realize rapid and accurate dynamic monitoring of local land use and capture real-time land use changes. Moreover, scientific urban planning using big data analytical tools and simulation methods is an important component of monitoring or improving land use [49].
(4) Fourth, establishing a regular exchange platform could facilitate the sharing of successful land management techniques and promote the exchange of advanced technologies and cooperation among cities. Due to the significant LUE gap between cities, those with lower LUE (such as Nanning and Hefei) should learn from those with higher LUE (such as Shanghai and Ningbo). The former could acquire more useful management experiences via an exchange platform, which would be conducive to promoting intensive land use and reducing the efficiency gap.

The limitations of this study should also be pointed out. First, the analysis was based on data from 34 cities during a specific period, 2015–2017. Future studies could extend the observation period to reveal the LUE of more cities over many years. More samples with a longer observation period could provide more valuable management implications. Second, the influence factors of LUE are not further explored in this study. Third, methods could be developed to compute the efficiency of massive cities in the big data environment, which is expected to reveal more insights. All of these could be areas of future research.

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