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Efficiency Evaluation of Urban Road Transport and Land Use in Hunan Province of China Based on Hybrid Data Envelopment Analysis (DEA) Models

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Abstract: Urban road transport and land use (RTLU) jointly promote economic development by concentrating labor, material, and capital. This paper presents an integrated RTLU efficiency analysis that explores the degree of coordination between these two systems to provide guidance for future adaptations necessary for sustainable urban development. Both a super efficiency Data Envelopment Analysis model and window analysis were used to spatiotemporally evaluate RTLU efficiency from 2012 to 2016 in 14 cities of Hunan province, central China. The Malmquist index was decomposed into technical efficiency and technology change to reveal reasons for changes in RTLU efficiency. These evaluation results show regional disparities in efficiency across Hunan province, with western cities being the least efficient. Eight cities showed an increasing trend in RTLU efficiency while Yueyang exhibited a decreasing trend. In 13 of 14 regions, productivity improved every year. At the same time, five regions had a decline in technical efficiency even though technical progress increased in all regions. Our analysis shows that greater investment in road transport and urban construction are not enough to ensure sustainable urban growth. Policy must instead promote the full use of current resources according to local conditions to meet local, regional, and national development goals.

Keywords: efficiency evaluation; road transport; land use; urban economy; data envelopment analysis

1. Introduction

Urbanization in China has accelerated since the implementation of economic reforms in 1978. The urban population has increased from 388.55 million to 813.45 million and the urban gross domestic product (GDP) has increased over ten times from 7.60 trillion RMB to 76.17 trillion RMB during the last 20 years. The scale of road construction in China has expanded dramatically with the rapid development of the urban economy. During the period of 2000 to 2018, the length of roads in China increased from 1.403 million km to 4.773 million km. At the same time, land use has also undergone tremendous changes as the built-up area increased from 39,758 to 55,155 km^2. Meanwhile, sustainable and collaborative development has become a central theme of urban planning and social management in China.

Land, transportation, and economy are three necessary components for continuous urbanization [1]. Land use and road transport are closely inter-connected and have a mixed interaction on urban economy by accumulation of labor, material resources, and capital. Urban land is accommodating increasing numbers of residents and workers attracted to industrial clusters in newly built-up areas, thus creating more demand for fast and efficient road transport. The large-scale construction of road networks increases accessibility between different regions, and accelerates the flow of labor and material resources, which will eventually result in the consumption of more land. Thus, the close connection between urban road transport and land use jointly promotes the growth of a local economy.

However, there are side effects from the development of industrial cities, since urban land usually displays a pattern of disorderly and inefficient expansion, while a road network is often over or under built and cannot match local travel demands. This has resulted in ineffective use of urban land and road transport resources, hindering economic growth and sustainability in urban regions. Hence, we aimed to use a quantitative evaluation of the combined urban road transport and land use (RTLU) efficiency to identify problems and issues in the allocation of road and land resources, thus providing rational guidance when planning road networks and land use for a balanced resource utilization and sustainable urban development.

In this study, the RTLU efficiency refers to the ability to achieve maximum urban economic output under the conditions of given road transport and land use input. A hybrid efficiency Data Envelopment Analysis (DEA) framework is proposed to assess efficiency of RTLU for 14 cities in Hunan province. In our method, super efficiency and window analysis DEA models were used to spatiotemporally evaluate the efficiency of 14 cities, and the Malmquist index was used to reveal the reasons for changes in efficiency. In China, Hunan province is one of the targets of the Belt and Road (B&R) policy. As a massive infrastructure-led economic integration plan, the B&R strategy advocates investing heavily in the infrastructure projects including roads and urban land in order to strengthen the economic coordination among the belt-road area [2]. However, our analysis yielded contradictory conclusions. Investment in land and roads (labor, material, capital) has a negative effect on RTLU efficiency, indicating an uncoordinated economic development, which is inconsistent with the original intention of the B&R policy. In addition, even in the same province, there are huge differences in economic efficiency among different cities, due to regional variations in the road transport and allocation of urban land resources. Furthermore, given continuous technological progress, the optimal allocation of human, capital, and material resources, together with the implementation of a corresponding level of management, have become drivers for productive efficient growth. Our conclusions will be a useful reference for policy-makers when coordinating economic development strategies in Hunan province as well as other belt and road areas. In theory, the RTLU efficiency evaluation framework including the indicators and hybrid models as proposed in this study can be applied to other parts of China as well as to foreign research areas. Findings from this study also may apply in areas where the road transport and land use context is similar to those in our research area.

The rest of this paper is organized as follows. Section 2 reviews the research both on the integration of road transport–land use and efficiency analysis with DEA models. Section 3 introduces the super efficiency DEA and window analysis as well as the Malmquist index. Section 4 presents the study area, data, and variables. Section 5 presents the analysis of the road transport–land use efficiency of 14 cities in Hunan province from 2012 to 2016. Conclusions are drawn in the final section.

2. Related Work

The interaction and integration between land use and road transport is considered an integral element for sustainable urban development. Various theoretical frameworks and models have been proposed for the integration of the two. For example, Dur and Yigitcanlar [3] assessed land use and transport integration via a spatial composite indexing model. Hrelja [4] explored how management and working practices among local authorities affected implementation of integrated land use and public transport planning. These theories and frameworks are qualitatively driven.

Various methods have been developed to evaluate efficiency, including the Analytic Hierarchy Process (AHP) [5], the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) [6], regression analysis [7], etc. Among these methods, one of the most widely used is the DEA model. In 1978, Charnes et al. [8] developed a novel methodology named Data Envelopment Analysis (DEA) to assess relative efficiencies of multi-input and multi-output production units, and then established improved DEA models to deal with the shortcomings of the basic model. The DEA model does not require any assumptions about the specific function form, and avoids inaccuracy caused by subjectivity during weight determination. In the past decades, DEA has gained popularity as a powerful methodology for evaluation of efficiency in various fields, including agricultural production [9], environment and energy [10], transportation [11], and education systems [12].

DEA models have been improved in different aspects to overcome the shortcomings existing in the traditional model [13]. In the basic Charnes–Cooper–Rhodes (CCR) DEA model [8], efficient decision-making units (DMUs) are simultaneously on the production frontier and thus share the same score of one, which leads to difficulty in further distinction and comparison. To address this problem, Andersen and Petersen [14] proposed an improved method called Super Efficiency DEA (SEDEA) to discriminate frontier DMUs and rank them. The SEDEA method has been applied in many studies [15–17]. Qiu et al. [18] used SEDEA to evaluate urban land use efficiency in 13 districts of Wuhan, China and sorted the 13 districts from a spatial perspective based on efficiency results.

Another problem in the basic DEA model is that it evaluates the performance of DMUs for one given timeframe and fails to measure the trend in efficiency of DMUs over time. To address this defect, a variation of the basic DEA approach called DEA window analysis [19] brings a reasonable solution to efficiency monitoring on time series. According to Asmild et al. [20] and Wang et al. [21], the major advantage of DEA window analysis is that it can make the efficiency comparable throughout the whole period and reflect the efficiency trend. Window analysis has been used in several studies to achieve dynamic efficiency assessment [22–24].

The Malmquist productivity index has been used for identifying the reason for change of efficiency. The Malmquist index was first introduced by Malmquist [25] for analyzing consumption efficiency. Improved by Cave et al. [26] and Fare et al. [27,28], the Malmquist productivity index refers to an index representing total factor productivity (TFP) growth of a DMU and consists of two components: technology frontier change (TC) and technology efficiency change (TEC) between two time periods. The former reflects the change in the technologic progress. The latter reflects progress or regression in technical efficiency and can be further decomposed into pure technical efficiency change (PEC) and scale efficiency change (SEC), reflecting managerial level and scale utilization, respectively.

Recently, DEA models have been applied to study urban transport and land use from the view of economic efficiency. DEA models have been widely used to evaluate the performance of the transportation system in transport applications, including highway, air, port and maritime, and railway transportation [29]. Russo et al. [30] proposed the DEA approach to comparatively analyze the effectiveness of hub ports in the Mediterranean Sea. Wey and Huang [31] used the Taipei Metro Transit system as an empirical example to illustrate the application of DEA methods for transportation planning. Liu et al. [32] assessed construction level and investment efficiency of the municipal public infrastructure using the entropy method and a DEA model. Egilmez and McAvoy [33] used a DEA-Malmquist model to assess the relative efficiency and productivity in decreasing the number of road fatalities in the US from 2002 to 2008. Fancello et al. [34] compared performances of different urban road networks in Italy by using a DEA model. As for urban land use efficiency, Liang et al. [35] used a DEA model to analyze the spatial distribution characteristics of land use efficiency of 287 prefecture-level cities in China in 2011. Chen et al. [36] used a DEA model to analyze the changes in built-up land efficiency in 336 cities in China from 2005 to 2012 during the implementation of National General Land Use Plan (2006–2020). Yang et al. [37] employed DEA to obtain land use efficiency from an economic perspective in China. In addition, there are also many qualitative studies on the interaction between land use and road transport [38–40]. Zondag [41] even proposed an analytical instrument for the integrated modeling of land use, transport, and economy.

Although many theories and frameworks for the integration of urban road transport and land use have been established, little work directly addresses the efficiency of integrated urban road transport and land use quantitatively. The application of DEA in the field of transportation and land use is independent and separate, with little research on integrated efficiency. In addition, the RTLU efficiency analysis framework must be assessed in both the time and space dimensions; thus, exploring potential causes behind outcomes. Hence, this study aims to quantitatively explore the efficiency of the integration of road transport and land use from an economic perspective and an RTLU analysis framework based on the DEA methods is proposed. Our DEA-based efficiency assessment method combined with Geographic Information System (GIS) analysis will provide new ideas for integrated research on urban transport and land use.

3. Methodology

In our research, super efficiency DEA, DEA window analysis, and the Malmquist index are integrated to build a new evaluation model. Figure 1 shows an overview of the model structure in three steps. Section 3.1, Section 3.2, and Section 3.3 introduce these three steps in our methodology.

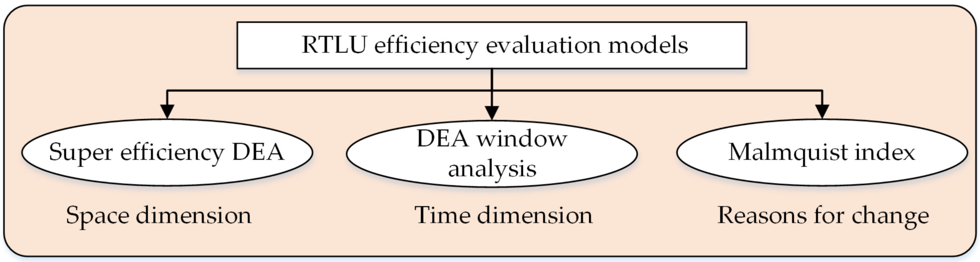

Figure 1. The urban road transport and land use (RTLU) efficiency evaluation models. DEA: Data Envelopment Analysis.

In the first step, we used the super efficiency DEA model to evaluate the efficiency of different cities in Hunan province each year. In the second step, the window analysis model was applied to reflect the efficiency trend over time. In the last step, the Malmquist index was decomposed into three parts to understand the reasons for efficiency changes.

3.1. Super Efficiency DEA Model

DEA is a non-parametric efficient frontier technique for evaluating the relative efficiency without any assumptions about the weights of the indicators. DEA usually deals with a unit k that has multiple inputs and multiple outputs,

$$X_k = (x_{1k}, x_{2k}, \ldots, x_{mk}) \tag{1}$$

x_{ik} refers to the i^{th} input, where $i = 1, \ldots, m$

$$Y_k = (y_{1k}, y_{2k}, \ldots, y_{sk})$$

y_{jk} refers to the j^{th} output, where $j = 1, \ldots, s$

These were incorporated into an efficiency measure: a ratio (E_k) of weighted outputs to weighted inputs [30].

$$E_k = \frac{\sum u_j y_{jk}}{\sum v_i x_{ik}} \tag{2}$$

E_k means the efficiency score of $\mathrm{DMU_k}$. This definition requires a set of factor weights v and u.

$$v = (v_1, v_2, \ldots, v_m)^T \tag{3}$$

v indicates the importance weight of m inputs

$$u = (u_1, u_2, \ldots, u_s)^T$$

u indicates the importance weight of s outputs

In the basic DEA model, known as the DEA-CCR model, the goal is to maximize the efficiency score E_k of the DMU. The basic CCR models can be divided into two types: input-oriented and output-oriented. Both can be used to evaluate efficiency. The results of the assessment are generally the same [42]. This study focuses on how to adjust the inputs of road transport and land resources to achieve constant high efficiency outputs. Therefore, the input-oriented model was chosen. The following formula shows the basic DEA-CCR model, used to assess DMU k_0, where $1 \le k_0 \le n$.

$$\begin{cases} \max E_{k_0} = \frac{u^T Y_0}{v^T X_0} \\ s.t. \frac{u^T Y_k}{v^T X_k} \le 1, k = 1, 2, \ldots, n \\ u \ge 0, v \ge 0, u \ne 0, v \ne 0 \end{cases} \tag{4}$$

The meaning of each symbol in Equation (4) is consistent with that in Equations (1)–(3). To simplify the calculation, we use Cooper–Cooper transformation to get an input-oriented form, as shown in Equation (5).

$$\begin{aligned} &\min \theta \\ &s.t. \begin{cases} \sum_{j=1}^{n} X_j \lambda_j \le \theta X_k \\ \sum_{j=1}^{n} Y_j \lambda_j \ge Y_k \\ \lambda_j \ge 0, j = 1, 2, \ldots, n \end{cases} \end{aligned} \tag{5}$$

where λ is the weight of each DMU, and θ refers to the efficiency score of DMUs. The efficiency score ranges from 0 to 1 where 1 refers to the efficient evaluated DMU relative to the other DMUs, while a DMU with a score less than 1 is identified as inefficient.

Based on the CCR model, super efficiency DEA (SEDEA) has been proposed to further distinguish among those DMUs sharing the same score of one and rank them. The difference from the traditional DEA-CCR model is that SEDEA evaluates the *k*th DMU by the linear combinations of all DMUs except the *k*th DMU. Thereby, an efficient DMU may increase the input proportionally while keeping its efficiency score unchanged, thus this DMU will have an efficiency score above one.

The input-oriented super-efficiency-CCR model is expressed as in Equation (6):

$$\begin{aligned} &\min \theta \\ &s.t. \begin{cases} \sum_{\substack{j=1 \\ j \ne k}}^{n} X_j \lambda_j \le \theta X_k \\ \sum_{\substack{j=1 \\ j \ne k}}^{n} Y_j \lambda_j \ge Y_k \\ \lambda_j \ge 0, j = 1, \ldots, n \end{cases} \end{aligned} \tag{6}$$

where $X_k = (x_{1k}, x_{2k}, \ldots, x_{mk})$, $Y_k = (y_{1k}, y_{2k}, \ldots, y_{mk})$ indicate the input and output vectors, respectively; λ is the weight of each DMU; and θ refers to the efficiency of DMUs. $\theta \ge 1$ means that the DMU will be considered efficient, while $0 < \theta < 1$ means that the DMU is inefficient.

3.2. Window Analysis

To compare RTLU efficiency over time, DEA window analysis was conducted to demonstrate dynamic performance in different regions of Hunan province in the period 2012–2016. This model treats the same DMU at different periods as different units, comparing the DMUs not only with the other DMUs in the same period but with themselves in other periods [43]. Thus, DEA window analysis can observe the efficiency from a temporal perspective and provide us more information about efficiency trends. A three-year window analysis is used as an example in Table 1. Here, E_{ij} means the efficiency score of the DMU over the j^{th} period in the i^{th} window.

Table 1. A three-year window analysis of a decision-making unit (DMU) from 2012 to 2016.

	2012	**2013**	**2014**	**2015**	**2016**
Window 1	E_{11}	E_{12}	E_{13}		
Window 2		E_{21}	E_{22}	E_{23}	
Window 3			E_{31}	E_{32}	E_{33}

In DEA window analysis, three variables are set to meet the specific experimental conditions, the time span (t), single window width (w) and the number of DMUs (n). In our study, 14 regions (n = 14) and a time span of five years (2012–2016) (t = 5) needed to be examined. Based on Charnes et al. [44], a window width of three or four time periods tends to produce an optimal balance of credibility and stable measures of efficiency. From this, a three-year window width was chosen (w = 3) and 14 cities were taken into account in our analysis. Each window contained 42 ($n \times w = 14 \times 3$) DMUs and the efficiency of these DMUs was calculated, w efficiency scores of each DMU were obtained. This model calculates dynamic efficiency on the principle of moving average. In our case the years of 2012, 2013, 2014 formed the first window. The window then moved on one-year periods and the analysis was performed on the next three-year set, dropping the original year and adding a new year. Therefore, the next three-year analytical results included the years 2013, 2014 and 2015. The process finally moved to the last window containing the years 2014, 2015 and 2016. Then, we calculated the average results of urban RTLU efficiency of each region in the same year to get an overall efficiency result for the 14 cities.

3.3. Malmquist Index Analysis

In addition to the super efficiency DEA model and window analysis described earlier, we also employed the Malmquist index to decompose the efficiency change into different factors. The non-parametric Malmquist productivity index [45] measures the total factor productivity (TFP) changes of a particular DMU and evaluates the efficiency change between the period $t + 1$ and the period t based on DEA. The index can be defined as Equation (7).

$$\begin{aligned} M &= \left[\frac{D^t\left[x^{t+1},y^{t+1}\right]}{D^t\left[x^t,y^t\right]}\frac{D^{t+1}\left[x^{t+1},y^{t+1}\right]}{D^{t+1}\left(x^t,y^t\right)}\right]^{1/2} \\ &= \frac{D^{t+1}\left(x^{t+1},y^{t+1}\right)}{D^t\left(x^t,y^t\right)} \times \left[\frac{D^t\left[x^{t+1},y^{t+1}\right]}{D^{t+1}\left[x^{t+1},y^{t+1}\right]}\frac{D^t\left[x^t,y^t\right]}{D^{t+1}\left(x^t,y^t\right)}\right]^{1/2} \\ &= \mathrm{TEC} \times \mathrm{TC} = \mathrm{PEC} \times \mathrm{SEC} \times \mathrm{TC} \end{aligned} \quad (7)$$

Here, M refers to Malmquist productivity index value, x indicates the input vector that can produce output vector y. $D^t(x^t, y^t)$ and $D^{t+1}(x^{t+1}, y^{t+1})$ are within-period distance functions. $D^t(x^{t+1}, y^{t+1})$ and $D^{t+1}(x^t, y^t)$ are the adjacent-period distance functions. In an input-oriented evaluation, $M > 1$ means the progress is in productivity, $M < 1$ reflects the regress is in productivity, and $M = 1$ indicates the status quo is in productivity. As the overall productivity change, the Malmquist index can be further decomposed into two exclusive parts: technical efficiency change (*TEC*) and technology change (*TC*).

TEC represents the change of technology efficiency from period t to $t + 1$ and indicates the degree of efforts the DMU attained to improve its efficiency. $TEC > 1$, $TEC = 1$, $TEC < 1$ represent the improvement, steadiness or decline of technical efficiency, respectively. *TEC* can be broken down into two components: pure efficiency change (*PEC*) and scale efficiency change (*SEC*). The pure efficiency denotes the level of management in utilizing given resources, while scale efficiency assesses the ability of exploiting scale economies for DMUs [46,47].

TC reflects the change in technology level by measuring the movement of the production frontier between periods. $TC > 1$ means a positive shift in frontier and shows the evidence of innovation, $TC < 1$ means a negative shift in frontier and technical backwardness, $TC = 1$ means no change in frontier.

4. Data and Indicators

4.1. Study Area and Data

Hunan province is located in the central south of China at 108°47′~114°13′E, 24°39′~30°08′N (as shown in Figure 2), with a total area of 211,800 km^2, 2.21% of total land area of China. It covers 14 cities and 122 counties. Hunan province is the core economic region and main inland transportation hub in China. As the central province of the Yangtze River Economic Belt, the government plans to make Hunan an economic affiliation of the "the Belt and Road", which will have an effect throughout the central, southern, and western regions in China. At the end of 2017, the population of Hunan province reached 68.60 million with an urban population of about 37.47 million. Since 2000, Hunan province has accelerated the construction of its road network and expanded the scope of urban built-up area. By 2017, the built-up region in Hunan province increased to 1709 km^2, the total length of road reached 239,724 km, and the GDP reached 3390 billion RMB.

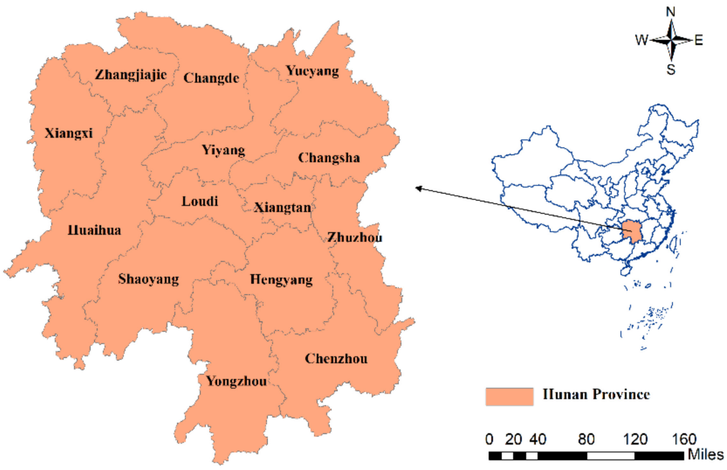

Figure 2. Map of Hunan province, China.

Over the past 40 years of reform and opening up, Hunan has made every effort to promote the construction of transportation infrastructure, and the road network system has become more optimized and complete. In 2018, the Hunan Provincial Road Work Conference revealed that the urban roads will continue to be the "main battlefield" for the province's transportation construction, with a planned investment of 46.4 billion yuan. In 2019, the Hunan Provincial Development and Reform Commission approved seven urban road projects, involving a total of 25.092 billion yuan. These infrastructure projects will strongly support the further development of the regional economy.

Limited by different terrain conditions, the distribution and development of the built-up area in Hunan province is uneven. The terrain in Hunan province is mountainous and hilly. The west is mainly mountainous, and the terrain is relatively high; the east is mainly flat, and the terrain is relatively low. Thus, the layout of construction land in the hilly and mountainous western areas is scattered, while in the flat eastern regions such as the Chang-Zhu-Tan urban agglomeration consisting of Changsha, Zhuzhou and Xiangtan built-up areas are relatively concentrated. The uneven development of urban land has caused the economic difference between the eastern and western regions.

With the rapid expansion of road transport within urban areas, the unbalanced distribution of built-up areas will increase disparity and imbalance in development levels between different localities, thus entail unpredictable consequences. This study used DEA models evaluate integrated RTLU efficiency in Hunan province to find the direction for road and land resource optimization in this region. To apply the DEA models described in Section 3, input–output indicators needed to be selected, which is presented in the following subsection.

4.2. Indicator System and Data

This study defines the RTLU efficiency as the ability to achieve maximum urban economic outputs with given road transport and land use inputs. The high RTLU efficiency reflects reasonable allocation of road–land input resources and the coordinated urban economic development. Hence, the efficiency is measured from the aspects of road transport–land use inputs and urban economy outputs. Existing DEA studies on China's regional sustainability assessment tend to use capital, labor, and material as inputs and count GDP variables as outputs [15,48,49]. In this study, the road–land input variables are grouped into four types: capital, road, land, and labor resources. Investment in road construction, length of road network, and total number of transportation employees are chosen as road network inputs, while investment in urban land use, expanded built-up area, and total number of urban land employees are selected as urban land use inputs. The urban economy output variables used in the study are the GDP of the secondary and tertiary sector of the economy. Table 2 lists the chosen indicator system.

Table 2. List of input–output variables used in efficiency evaluation.

Types	First Level	Second Level	Third Level
Input Indicators	Road Transport	Capital	Investment in road (X_1)
		Road	Length of road network (X_2)
		Labor	Number of transportation employees (X_3)
	Land use	Capital	Investment in urban land use (X_4)
		Land	Expanded built-up area of each city (X_5)
		Labor	Total number of employees for land (X_6)
Output indicators	Economy	Urban economy	Second GDP (Y_1)
			Third GDP (Y_2)

The sample used in this study consisted of 14 cities in Hunan and was collected between 2012 and 2016. The 14 cities in Hunan are considered DMUs in the DEA models proposed in Section 2. The data were obtained from the annual reports of the Hunan Provincial Bureau of Statistics, including the Hunan Statistical Yearbooks 2012–2016 [50], Yearbook of Hunan Province Transportation and Communications 2012–2016 [51]. Descriptive statistics for the input and output variables are shown in Table 3. 'Mean' refers to the average of the 14 DMUs in each variable, 'Std. dev.' means standard deviation measuring how spread out variables are and how far from the normal, 'Max' and 'Min' refer to the maximum and the minimum value of each variable among 14 DMUs.

Table 3. Summary statistics of inputs and outputs (N = 14).

Year	Variable	Road Transport Inputs			Land Use Inputs			Economic Outputs	
		Capital	Road	Labor	Capital	Land	Labor	Second GDP	Third GDP
		billion RMB	km	10 k people	billion RMB	km^2	10 k people	billion RMB	billion RMB
2012	Mean	15.051	16,718.000	5.896	86.381	4.076	82.471	856.556	596.394
	Std. dev.	5.273	4899.969	3.716	59.355	2.964	49.365	859.807	584.224
	Max	26.330	22,960.000	16.395	193.970	11.000	204.820	3592.520	2535.080
	Min	6.880	7799.000	1.617	6.770	0.770	16.770	85.430	180.030
2013	Mean	16.243	16,814.000	6.088	111.078	3.062	87.009	938.913	683.459
	Std. dev.	5.044	4902.650	3.985	78.415	2.234	50.550	946.316	671.808
	Max	26.180	22,967.000	17.541	282.550	9.650	214.910	3946.970	2911.610
	Min	8.140	7788.000	1.619	6.700	1.080	17.620	92.890	207.140
2014	Mean	19.929	16,874.429	6.180	139.641	3.619	89.913	1012.802	777.581
	Std. dev.	5.576	4917.560	4.107	91.427	3.263	52.542	1017.240	755.012
	Max	28.610	23,022.000	18.060	341.320	12.450	221.090	4241.250	3271.660
	Min	6.880	7844.000	1.645	5.810	0.100	14.610	99.680	231.760
2015	Mean	23.600	16,920.286	6.079	183.819	3.860	40.176	1042.105	896.440
	Std. dev.	6.972	4926.752	4.109	127.809	5.021	28.824	1038.181	888.753
	Max	35.090	23,053.000	18.045	437.550	20.110	130.460	4333.580	3834.770
	Min	10.190	7844.000	1.640	18.270	0.320	8.670	101.890	262.870
2016	Mean	30.737	17,019.500	5.882	181.334	3.936	39.430	1070.540	1049.474
	Std. dev.	9.309	4934.720	3.588	125.574	3.540	26.429	1078.202	1038.844
	Max	52.390	23,166.000	16.094	457.520	11.530	120.930	4513.280	4472.680
	Min	16.020	7892.000	1.901	18.920	0.030	8.640	104.760	284.420

Table 3 shows that the mean investment in the road system and expanded urban land has experienced a significant increase, with a growth rate of 104.22% and 109.92% in RMB over the five-year period. The average count of workers employed in road transport and urban land management departments in Hunan showed a downward trend with a decline of 0.24% in transport and 109.16% in construction from 2012–2016. Meanwhile, the annual average GDP in the secondary sector grew by 24.98% and tertiary sector by 75.97% over time. These variables show that as transport and land use development consumed various resources, the secondary and tertiary sectors became engines of growth, these variables are the basis for our proposed model and case study of Hunan province.

5. A Case Study of Cities in Hunan Province from 2012 to 2016

The 14 cities in Hunan province from 2012 to 2016 were chosen as the empirical case to evaluate the proposed model discussed in Section 3, using the input and output data presented in Section 4. The super efficiency DEA model and window analysis were executed with the DEAP2.1 software. The EMS1.3 software product was used to calculate the Malmquist index. ArcGIS 10.2 software and Origin 9.1 software were used to visualize graphically the spatiotemporal distributions. The following three subsections show and discuss the efficiency results of SEDEA, window analysis, and the Malmquist index.

5.1. Efficiency Performance of Different Areas Based on SEDEA

The super efficiency scores and ranks for 14 cities in Hunan from 2012–2016 are shown in Table 4. 'Score' refers to the RTLU efficiency reflecting the degree of coordination between road transport–land use and economic development. An efficiency score equal to or greater than one reflects an efficient development, while less than one indicates an inefficient development. We used the CCR formulation for SEDEA because the RTLU efficiency for each year was calculated separately. The process is a constant return to scale each year so the input can be increased proportionally to obtain the same ratios in the output, regardless of the scale of the input. To make a comparison intuitive, we ranked the performance of the 14 cities based on their efficiency values. Rank was statistically tested by the Kendall's Coefficient of Concordance (W). The test of Kendall's W showed $p < 0.001$, rejected the null hypothesis and was statistically significant. Meanwhile, the score of Kendall's W was 0.738, indicating that our five-year efficiency assessment for the 14 cities is highly consistent.

Table 4. Ranking based on the super efficiency DEA model (2012–2016).

Cities	2012		2013		2014		2015		2016	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Changsha	3.694	1	3.927	1	3.405	2	3.445	1	3.075	1
Zhuzhou	0.894	8	0.890	8	1.028	7	1.723	3	0.779	10
Xiangtan	1.373	4	1.242	4	1.228	4	1.904	2	1.790	3
Hengyang	0.688	11	0.731	10	0.787	9	0.878	9	0.773	11
Shaoyang	0.587	13	0.351	14	0.304	14	0.494	14	0.472	14
Yueyang	1.307	5	1.230	5	1.102	5	1.027	8	0.929	7
Changde	0.972	7	0.900	7	0.920	8	1.181	7	0.848	9
Zhangjiajie	2.135	2	2.372	2	4.996	1	1.691	4	2.054	2
Yiyang	0.610	12	0.794	9	1.082	6	1.640	5	1.490	5
Chenzhou	0.983	6	1.033	6	0.659	11	1.285	6	1.080	6
Yongzhou	2.096	3	0.635	13	1.577	3	0.635	13	0.582	13
Huaihua	0.844	9	1.251	3	0.709	10	0.800	11	1.528	4
Loudi	0.791	10	0.637	12	0.656	12	0.812	10	0.870	8
Xiangxi	0.515	14	0.702	11	0.642	13	0.697	12	0.736	12
Mean [1]	1.249		1.192		1.364		1.301		1.215	
< Mean	9		9		11		9		9	
> 1	5		6		7		8		6	

[1] 'Mean' refers to the average efficiency of the 14 cities each year.

As shown in Table 4, the percentage of efficient regions (efficiency score >1) in Hunan province was lower than 50% from 2012 to 2016, indicating an imbalance between these two systems and urban economic growth. Changsha, Xiangtan and Zhangjiajie kept their RTLU efficiency above 1, indicating an enhancement in road–land resource conservation and economic growth. Yueyang, which was in a state of coordinated development in most years, also exhibited high efficiencies above 1 except in 2016. More than nine cities showed low RTLU efficiency below average. Among them, Shaoyang and Xiangxi showed much lower efficiency than the average. Only Changsha and Zhangjiajie had efficiencies that were greatly above the average every year.

We further explored the reasons behind these results for Changsha and Zhangjiajie (the top two cities). As the capital of Hunan, Changsha development policy directs more funding to land and road infrastructure development. Changsha is a central transportation hub of the country. In 2014, road transport took up 76.6% of passenger traffic and 89% of freight traffic in Changsha [50]. In 2012–2016, the average length of road in Changsha reached 15,945km. At the same time, the level of urbanization in Changsha was far ahead of the other cities in Hunan province, as the built-up area expanded from 319.96 to 350.63 km^2 during that period [50]. Convenient transportation and sufficient urban land have promoted the upgrades of the urban industrial structure, keeping this city's GDP the highest in Hunan province. Hence, the input in land and road transport is well matched with the high level of local economic development, which explains the high efficiencies in Changsha. In Zhangjiajie, the level of investment in road and land is not as high as that in Changsha, but it is enough to meet the developing needs of the area. In addition, as the largest tourist city, the rich tourism resources in Zhangjiajie have driven the growth of GDP, thus this city had a higher efficiency value.

We also analyzed the results of the two cities with lowest efficiency scores, Shaoyang and Xiangxi. Shaoyang is surrounded by mountains on three sides. Due to terrain restrictions, the city has a slow expansion rate; local rugged mountains make road construction difficult and costly. Our results show that the slow urbanization process and inadequate road infrastructure might cause the economy in Shaoyang to lag behind other cities in Hunan, leading to its low efficiency. Xiangxi is located in the northwestern edge of Hunan province. The financial input of the road network is actually high in this city. However, the local population base is small and the labor serving for the efficient construction of road and land is insufficient, likely resulting in a lack of road transport facilities and the tiny built-up area, only 35 km^2 in 2016 [50], less than 1/10 of that in Changsha.

For brevity, we used the performance of the 14 cities in 2015 as an example, as depicted in Figure 3. From Figure 3, the Chang-Zhu-Tan urban agglomeration shown in red, had higher efficiency scores than the other 11 cities, indicating the development of road transport and urban land use is well adapted to the urban economy, which is consistent with our expectations. However, the western region including Xiangxi, Huaihua, Shaoyang, Yongzhou, and Loudi had efficiency scores much lower than 0.85, reflecting a development imbalance between RTLU and the local economy.

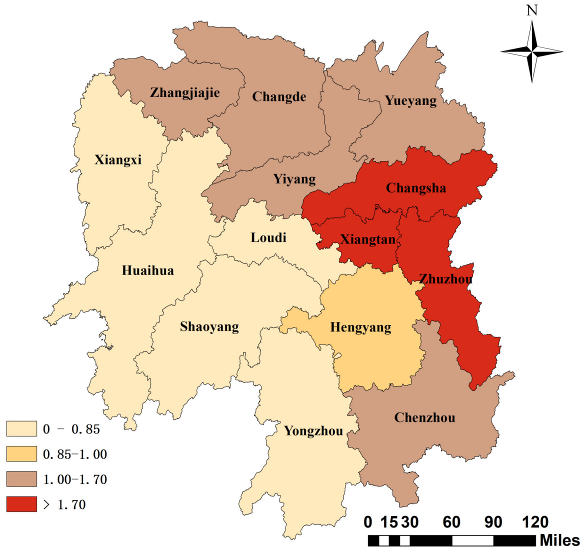

Figure 3. Efficiency distribution map of 14 cities in 2015 based on Super Efficiency DEA (SEDEA).

The high efficiency found in the cities of Changsha, Zhuzhou, and Xiangtan in 2015 can be attributed to scientific road guidance as well as open economic policies. Changsha, Zhuzhou and Xiangtan form the Chang-Zhu-Tan urban agglomeration along the middle reaches of the Yangtze River. Since 2012, Chang-Zhu-Tan urban agglomeration has advocated the "Transportation integration" project [52], promoting road construction between the connected cities. The connecting road forms a network that extends in all directions, and the transit time between the three cities was shortened to less than 30 minutes. Convenient transportation promotes close economic cooperation between the three cities and the coordinated development of urbanization. As for the western regions (such as Huaihua, Yongzhou, and Shaoyang), mountainous terrain limits the intercommunication of the area with other areas. Limited passenger and freight traffic means less use of the local road and land infrastructure. Thus, redundant road and land resource inputs caused local inefficiencies. To narrow the performance gap between the western region and eastern region in Hunan effectively, and strengthen cooperation between different cities, local authorities in western regions should focus on the full use of road transport-urban land resources and economic growth.

5.2. Dynamic Efficiency Performance Based on Window Analysis

Window analysis was used to find the trend in efficiency for the period 2012–2016 (t = 5, w = 3, n = 14). The initially detailed results of window analysis are shown in the Appendix A (Table A1). Table 5 shows the average efficiency of window analysis from 2012–2016. The performance trend for the 14 cities over the five years is depicted in Figure 4, based on the results shown in Table 5.

Table 5. Average efficiencies of window analysis.

Category	Cities	2012	2013	2014	2015	2016	Average
Group 1	Changsha	1.270	1.272	1.244	1.425	1.502	1.343
	Xiangtan	1.034	1.007	1.071	1.406	1.299	1.163
	Yueyang	1.307	1.221	1.056	0.982	0.929	1.099
	Zhangjiajie	0.813	0.872	3.872	1.192	1.913	1.733
Group 2	Zhuzhou	0.894	0.853	0.934	1.178	0.779	0.927
	Hengyang	0.600	0.662	0.706	0.762	0.773	0.700
	Shaoyang	0.339	0.279	0.292	0.450	0.472	0.366
	Changde	0.710	0.771	0.839	1.064	0.848	0.847
	Yiyang	0.575	0.703	0.843	1.293	1.132	0.909
	Huaihua	0.779	0.857	0.644	0.706	1.528	0.903
	Yongzhou	0.595	0.501	0.977	0.573	0.582	0.646
	Huaihua	0.779	0.857	0.644	0.706	1.528	0.903
	Loudi	0.590	0.606	0.631	0.759	0.812	0.679
	Xiangxi	0.463	0.593	0.608	0.663	0.702	0.606

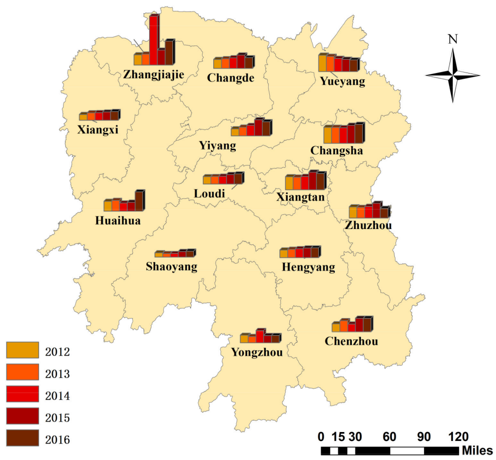

Figure 4. Efficiency trend in 14 cities of Hunan provinces.

Figure 4 shows an improvement in the efficiency for Changsha, Loudi, Zhangjiajie, Hengyang, Shaoyang, Yiyang, Xiangxi, and Xiangtan. Among them, Changsha can be considered as a steadily efficient city from 2012–2016 since its efficiencies never fell below 100% (Table 5). It kept growing over the study period, indicating that the urban road and land use were in a state of coordinated development and had a positive impact on urban economy. Yueyang had a decreasing trend over the years, while the efficiency scores for Zhuzhou, Huaihua, Changde, Chenzhou, and Yongzhou fluctuated. Overall, most cities showed an upward trend in road transport and land use efficiencies, demonstrating that Hunan province is building a resource-conserving and sustainably developing society, and has achieved efficient use of road transport and land use resources.

The rows in Table 5 reflected the performance trend of the 14 cities. The column "Average" in Table 5 showed a comprehensive performance of each city during the study period. The 14 cities can be divided into two groups based on the average RTLU efficiency of window analysis. The first group consisted of four regions (Changsha, Xiangtan, Yueyang, Zhangjiajie) which had high average efficiencies, higher than 100% during the entire analysis period. The rest of the cities (Zhuzhou, Hengyang, Shaoyang, Changde, Yiyang, Chenzhou, Yongzhou, Huaihua, Loudi, Xiangxi) that had lower values ranging from 0.366 to 0.927 formed the second group.

In the first group, the rich tourism resources are the main reason for the efficiency of Yueyang and Zhangjiajie. A large number of tourists in Yueyang make full use of road transportation resources and promote local economic development. In 2016, the GDP of Yueyang ranked second to the provincial capital Changsha [50]. Zhangjiajie is the kind of city with "less input, less output and higher efficiency". It has rich natural resources and is known as the "National Forest City". In order to protect regional ecological resources, the city limits the development of urban land and roads. Though it has insufficient road construction and small-scale built-up areas, relying on tourism resources, the economy has developed. This city restricts overexploitation, protects natural resources, and adapts to local natural conditions, which is conducive to sustainable development, while achieving high efficiency development at the same time. This will provide a reference for the cities that are inefficiently developed due to natural factors such as the western regions in Hunan. For those inefficient cities in the second group, redundant input of road resource and low level of economic output are the main reasons for the imbalances in development. Taking the performance of Shaoyang in 2013 as an example, the efficiency for 2013 was equal to 0.279, the road investment and employees reached 2.02 billion RMB with 100,964 people. In both investment and people this city ranked second among the 14 cities, while its secondary and tertiary industry GDP was only 43.95 and 43.65 billion RMB, ranking 12th and ninth in these industries, respectively [50,51]. The high input into road construction has not brought about rapid economic development, so the average efficiency is in a low state.

5.3. Efficiency Change Decomposition Based on the Malmquist Index

In this study, the five-year productivity changes of 14 cities were computed using input-oriented Malmquist index. The average Malmquist index (MI) was 1.169, and 0.3% resulting from an increase in technical efficiency and 16.6% from an increase in technology, as shown in Table 6.

Table 6. Efficiency averages of 14 cities in Malmquist index (MI). TEC: technical efficiency change; TC: technology change; PEC: pure technical efficiency change; SEC: scale efficiency change.

Cities	MI	TEC	TC	PEC	SEC
Changsha	1.110	1.000	1.110	1.000	1.000
Zhuzhou	0.967	0.966	1.002	0.971	0.995
Xiangtan	1.225	1.000	1.225	1.000	1.000
Hengyang	1.235	1.029	1.199	1.040	0.990
Shaoyang	1.160	0.947	1.226	0.964	0.983
Yueyang	1.075	0.982	1.095	0.984	0.998
Changde	1.140	0.967	1.180	0.984	0.983
Zhangjiajie	1.278	1.000	1.278	1.000	1.000
Yiyang	1.204	1.132	1.064	1.039	1.089
Chenzhou	1.269	1.004	1.264	1.000	1.004
Yongzhou	1.215	0.874	1.390	0.924	0.946
Huaihua	1.281	1.043	1.228	1.031	1.012
Loudi	1.115	1.024	1.088	1.000	1.024
Xiangxi	1.141	1.094	1.043	1.079	1.014
mean	1.169	1.003	1.166	1.000	1.002

This table illustrates the change in Malmquist productivity and its decomposition by city, 13 out of the 14 cities had an average MI above 1, indicating positive productivity growth. The only remaining city, Zhuzhou had a negative growth, of which 0.2% resulted from an increase in technological development and 3.4% from a decrease in technical efficiency related management and scale utilization. In terms of TC, all the cities showed growth. In terms of TEC, six cities showed an increasing efficiency, three cities had constant efficiency and five cities exhibited a decline in technical efficiency performance, which resulted from both decreased technical efficiency and decreased scale efficiency. To improve the TEC in these cities, the resource allocation capability, management level and scale optimization should be taken into consideration.

The annual average Malmquist productivity and decomposition change between 2012 and 2016 are shown in Table 7. The average MI was greater than 1, suggesting increasing efficiency. TC also exhibited a constantly increasing trend for all of the years. However, in terms of TEC, the results fluctuated over time, which indicates non-stable performance in the management and scale of the transport and land systems in Hunan province. Specifically, growth was negative in all periods except for 2014–2015. The decreasing technical efficiency from 2012 to 2013 was caused largely by the decreasing scale efficiency, while the decline in technical efficiency from 2013 to 2014 was caused by decreasing pure technical efficiency. The negative TEC during 2015–2016 can be attributed to a 4.7% decrease in scale efficiency. Therefore, the decreasing TEC during the three periods could alert local authorities to a need in these cities for substantial improvement in management and scale utilization levels.

Table 7. Efficiency averages of Malmquist index against years.

Year	MI	TEC	TC	PEC	SEC
2012–2013	1.123	0.969	1.159	1.025	0.945
2013–2014	1.117	0.995	1.123	0.906	1.099
2014–2015	1.226	1.078	1.137	1.058	1.019
2015–2016	1.215	0.972	1.25	1.019	0.953
mean	1.169	1.003	1.166	1	1.002

6. Conclusions

In this study, we analyzed the joint efficiency of road transport and land use through a RTLU efficiency evaluation in a hybrid DEA framework in 14 cities from 2012–2016 in Hunan province, China. A super efficiency DEA model was built to make a comparison of different cities for each year. We also compared the trend in efficiency for each city over the entire study period using DEA window analysis. We explored the changes in efficiency using three components decomposed from the Malmquist index.

Our spatial, temporal, and decomposed efficiency analyses show that coordination between land use, roads, and economic development is uneven across Hunan province. The spatial RTLU efficiencies of the 14 cities in Hunan province are unevenly distributed, as the efficiency of cities in southwestern Hunan was generally lower than that in the eastern region. Changsha, Zhangjiajie, and Xiangtan had the highest RTLU efficiency scores, implying close coordination between the road transport–land use pattern and the urban economy, while Shaoyang, Xiangxi, and Loudi show an uncoordinated development with the lowest efficiency. The temporal RTLU efficiencies show that eight cities such as Hengyang, Loudi, and Changsha have an increasing efficiency trend while Yueyang has a continuous decline in efficiency over the five years. The analysis of the Malmquist index shows increasing technological development in Hunan, but with a decreasing trend in technical efficiency, pure efficiency, and scale efficiency in five cities including Zhuzhou, Shaoyang, Yueyang, Changde, and Yongzhou, dispersed across the province.

These results provide a reference for local authorities to balance the development of land and road systems in Hunan.

(1) The cities with high RTLU efficiency should continue to rely on their own local road transport and land use resource advantages to create economic benefits.
(2) The western cities with low RTLU efficiency still have great potential for efficiency gains by exploiting their unique natural resources to help with economic growth.
(3) Excessive investment can cause a decline in efficiency, but scientific allocation of resources and improved resource utilization can help sustainable development.
(4) In addition to resource inputs, improvements in management sufficiency and scale utilization are an intangible measure to boost efficiency growth.

The three cities with high RTLU efficiency, Changsha, Xiangtan, and Zhangjaijie, should continue to rely on their own local road transport and land use resource advantages to attract funds and technology, thus achieving a steady increase in urban economic through rational development and use of resources. Reducing regional imbalance contributes to urban sustainability. Inefficient cities are mainly located in southwestern Hunan. The local governments in these cities should scientifically allocate resources and investments, and efficiently exploit their unique natural resources for local economic development and sustainability. The 14 cities in Hunan province should scientifically allocate road transport and land use resources according to local conditions to enhance urban RTLU efficiency, rather than blindly building road networks, expanding urban areas, or aimlessly increasing investment; labor, material, and capital resources must be balanced based on actual demands. Sustainable urban development is closely related to productivity, improvement in technical innovation, level of management, and scale utilization will drive productivity growth.

Although the current study framework only evaluated the integration efficiency of past road and land use patterns, it could be used for ex-ante evaluation to support transport and land use planning [53]. By simulating the planning data of transportation and land, we can further calculate the efficiency under different planning schemes, and explore the optimal scheme based on the evaluation results. This study currently focuses on the supervision of the regions from labor, capital and material, but does not consider the impact of local policy. In China, road transport and land use are inseparable from policies and regulations. In the future, research needs to quantify policy factors and incorporate them into the evaluation indicator system to provide a more accurate assessment. In addition, we need to identify the driving factors in inefficient regions, thus some methods such as logistic regression and multiple linear regression will be integrated in our future research.

Author Contributions: The first author T.Y., had the initial idea for the study, performed the experiments, conducted analysis and wrote the manuscript. The second author X.G. (corresponding author), supervised the whole process of writing the paper, came up with the key suggestions on experiments and revised the manuscript over time. The third and fourth authors, Y.Q., W.X., H.W. investigated the current research status, collected demand data and visualized the experimental results.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Dynamic DEA efficiencies of 14 cities for years 2012–2016 using window analysis.

Cities	Window	2012	2013	2014	2015	2016
Changsha	1	1.269	1.266	1.116		
	2		1.278	1.088	1.803	
	3			1.527	1.047	1.502
Zhuzhou	1	0.894	0.855	0.900		
	2		0.851	0.906	1.239	
	3			0.996	1.117	0.779
Xiangtan	1	1.034	1.006	1.179		
	2		1.007	1.029	1.821	
	3			1.005	0.992	1.299
Hengyang	1	0.600	0.668	0.787		
	2		0.656	0.701	0.858	
	3			0.629	0.665	0.773
Shaoyang	1	0.339	0.277	0.286		
	2		0.281	0.287	0.494	
	3			0.304	0.407	0.472
Yueyang	1	1.307	1.212	1.092		
	2		1.229	1.084	1.025	
	3			0.994	0.939	0.929

Table A1. *Cont.*

Cities	Window	2012	2013	2014	2015	2016
Changde	1	0.710	0.810	0.920		
	2		0.733	0.853	1.181	
	3			0.743	0.947	0.848
Zhangjiajie	1	0.813	0.874	4.512		
	2		0.871	4.512	1.379	
	3			2.592	1.004	1.913
Yiyang	1	0.575	0.694	0.751		
	2		0.713	0.863	1.270	
	3			0.915	1.315	1.132
Chenzhou	1	0.636	0.979	0.659		
	2		0.794	0.621	1.130	
	3			0.588	1.034	1.078
Yongzhou	1	0.595	0.515	1.493		
	2		0.488	0.753	0.635	
	3			0.684	0.510	0.582
Huaihua	1	0.779	0.792	0.646		
	2		0.923	0.629	0.800	
	3			0.656	0.612	1.528
Loudi	1	0.590	0.612	0.656		
	2		0.599	0.629	0.788	
	3			0.608	0.731	0.812
Xiangxi	1	0.463	0.557	0.599		
	2		0.629	0.596	0.697	
	3			0.630	0.629	0.702

References

1. Hoover, E.M.; Giarratani, F. *An Introduction to Regional Economics*; Knopf: New York, NY, USA, 1971.
2. Du, J.; Zhang, Y. Does one belt one road initiative promote Chinese overseas direct investment? *China Econ. Rev.* **2018**, *47*, 189–205. [CrossRef]
3. Dur, F.; Yigitcanlar, T. Assessing land-use and transport integration via a spatial composite indexing model. *Int. J. Environ. Sci. Technol. (Tehran)* **2015**, *12*, 803–816. [CrossRef]
4. Hrelja, R. Integrating transport and land-use planning? How steering cultures in local authorities affect implementation of integrated public transport and land-use planning. *Transport. Res. A Policy* **2015**, *74*, 1–13. [CrossRef]
5. Fan, G.; Zhong, D.; Yan, F.; Yue, P. A hybrid fuzzy evaluation method for curtain grouting efficiency assessment based on an AHP method extended by D numbers. *Expert Syst. Appl.* **2016**, *44*, 289–303. [CrossRef]
6. Barros, C.P.; Wanke, P. An analysis of African airlines efficiency with two-stage TOPSIS and neural networks. *J. Air Transp. Manag.* **2015**, *44*, 90–102. [CrossRef]
7. Kiadaliri, A.A.; Jafari, M.; Gerdtham, U.-G. Frontier-based techniques in measuring hospital efficiency in Iran: A systematic review and meta-regression analysis. *BMC Health Serv. Res.* **2013**, *13*, 312. [CrossRef]
8. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
9. Ohe, Y. Assessing Managerial Efficiency of Educational Tourism in Agriculture: Case of Dairy Farms in Japan. *Sustainability* **2017**, *9*, 1931. [CrossRef]
10. Mardani, A.; Zavadskas, E.K.; Streimikiene, D.; Jusoh, A.; Khoshnoudi, M. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renew. Sustain. Energy. Rev.* **2017**, *70*, 1298–1322. [CrossRef]
11. Marchetti, D.; Wanke, P. Brazil's rail freight transport: Efficiency analysis using two-stage DEA and cluster-driven public policies. *Socio-Econ. Plan. Sci.* **2017**, *59*, 26–42. [CrossRef]

12. Wolszczak-Derlacz, J. An evaluation and explanation of (in) efficiency in higher education institutions in Europe and the US with the application of two-stage semi-parametric DEA. *Res. Policy* **2017**, *46*, 1595–1605. [CrossRef]
13. Cook, W.D.; Seiford, L.M. Data envelopment analysis (DEA)–Thirty years on. *Eur. J. Oper. Res.* **2009**, *192*, 1–17. [CrossRef]
14. Andersen, P.; Petersen, N.C. A procedure for ranking efficient units in data envelopment analysis. *Manage. Sci.* **1993**, *39*, 1261–1264. [CrossRef]
15. Yang, L.; Ouyang, H.; Fang, K.; Ye, L.; Zhang, J. Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA. *Ecol. Indic.* **2015**, *51*, 13–19. [CrossRef]
16. Mousavi, M.M.; Ouenniche, J.; Xu, B. Performance evaluation of bankruptcy prediction models: An orientation-free super-efficiency DEA-based framework. *Int. Rev. Financ. Anal.* **2015**, *42*, 64–75. [CrossRef]
17. Ab Rahim, R. Ranking of Malaysian commercial banks: super-efficiency data envelopment analysis (DEA) approach. *AAMJAF* **2015**, *11*, 123–143.
18. Qiu, Y.; Sheng, J.; He, X. Evaluation Model of Urban Land Use Efficiency Based on Super-Efficiency-DEA. In Proceedings of the 2016 4th International Conference on Sensors, Mechatronics and Automation (ICSMA 2016), Harbin, China, 7–10 August 2016.
19. Charnes, A.; Clark, C.T.; Cooper, W.W.; Golany, B. A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the US air forces. *Ann. Oper. Res.* **1984**, *2*, 95–112. [CrossRef]
20. Asmild, M.; Paradi, J.C.; Aggarwall, V.; Schaffnit, C. Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *J. Prod. Anal.* **2004**, *21*, 67–89. [CrossRef]
21. Wang, K.; Yu, S.; Zhang, W. China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Math. Comput. Modell.* **2013**, *58*, 1117–1127. [CrossRef]
22. Cuccia, T.; Guccio, C.; Rizzo, I. UNESCO sites and performance trend of Italian regional tourism destinations: A two-stage DEA window analysis with spatial interaction. *Tour. Econ.* **2017**, *23*, 316–342. [CrossRef]
23. Al-Refaie, A.; Hammad, M.; Li, M.-H. DEA window analysis and Malmquist index to assess energy efficiency and productivity in Jordanian industrial sector. *Energy Effic.* **2016**, *9*, 1299–1313. [CrossRef]
24. Gamassa, P.K.P.O.; Chen, Y. Comparison of port efficiency between Eastern and Western African ports using DEA Window Analysis. In Proceedings of the 2017 International Conference on Service Systems and Service Management, Dalian, China, 16–18 June 2017.
25. Malmquist, S. Index numbers and indifference surfaces. *Trab. Estad.* **1953**, *4*, 209–242. [CrossRef]
26. Caves, D.W.; Christensen, L.R.; Diewert, W.E. The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica* **1982**, *50*, 1393–1414. [CrossRef]
27. Fare, R.; Färe, R.; Fèare, R.; Grosskopf, S.; Lovell, C.K. *Production Frontiers*; Cambridge University Press: Cambridge, UK, 1994.
28. Färe, R.; Grosskopf, S.; Lindgren, B.; Roos, P. Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *J. Prod. Anal.* **1992**, *3*, 85–101. [CrossRef]
29. Mahmoudi, R.; Emrouznejad, A.; Shetab-Boushehri, S.-N.; Hejazi, S.R. The origins, development and future directions of Data Envelopment Analysis approach in transportation systems. *Socio-Econ. Plan. Sci.* **2018**. [CrossRef]
30. Russo, F.; Rindone, C. Container maritime transport on an international scale: Data envelopment analysis for transhipment port. *WIT Trans. Ecology Environ.* **2011**, *150*, 831–843. [CrossRef]
31. Wey, W.-M.; Huang, J.-Y. The Application of Data Envelopment Analysis for Transportation Planning based on the Viewpoint of Economic Efficiency. *JABE* **2018**, 20. [CrossRef]
32. Liu, Q.; Wang, S.; Zhang, W.; Li, J.; Zhao, Y.; Li, W. China's municipal public infrastructure: Estimating construction levels and investment efficiency using the entropy method and a DEA model. *Habitat Int.* **2017**, *64*, 59–70. [CrossRef]
33. Egilmez, G.; McAvoy, D. Benchmarking road safety of US states: A DEA-based Malmquist productivity index approach. *Accid. Anal. Prev.* **2013**, *53*, 55–64. [CrossRef] [PubMed]
34. Fancello, G.; Uccheddu, B.; Fadda, P. Data Envelopment Analysis (DEA) for urban road system performance assessment. *Procedia Soc. Behav. Sci.* **2014**, *111*, 780–789. [CrossRef]
35. Liang, L.T.; Zhao, Q.L.; Chen, C. Analysis on the characters of spatial disparity of urban land use efficiency and its optimization in China. *China Land* **2013**, *27*, 48–54. [CrossRef]

36. Chen, Y.; Chen, Z.; Xu, G.; Tian, Z. Built-up land efficiency in urban China: Insights from the General Land Use Plan (2006–2020). *Habitat Int.* **2016**, *51*, 31–38. [CrossRef]
37. Yang, X.; Wu, Y.; Dang, H. Urban land use efficiency and coordination in China. *Sustainability* **2017**, *9*, 410. [CrossRef]
38. Soria-Lara, J.A.; Aguilera-Benavente, F.; Arranz-López, A. Integrating land use and transport practice through spatial metrics. *Transport. Res. A Policy* **2016**, *91*, 330–345. [CrossRef]
39. Szeto, W.; Jiang, Y.; Wang, D.; Sumalee, A. A sustainable road network design problem with land use transportation interaction over time. *Netw. Spat. Econ.* **2015**, *15*, 791–822. [CrossRef]
40. Acheampong, R.A.; Silva, E. Land use–transport interaction modeling: A review of the literature and future research directions. *J. Transp. Land Use* **2015**, *8*, 11–38. [CrossRef]
41. Zondag, B. Joint Modeling of Land-Use, Transport and Economy. Ph.D. Thesis, Delft University, Delft, The Netherlands, 2007.
42. Xie, L.; Chen, C.; Yu, Y. Dynamic Assessment of Environmental Efficiency in Chinese Industry: A Multiple DEA Model with a Gini Criterion Approach. *Sustainability* **2019**, *11*, 2294. [CrossRef]
43. Chen, X.; Gao, Y.; An, Q.; Wang, Z.; Neralić, L. Energy efficiency measurement of Chinese Yangtze River Delta's cities transportation: A DEA window analysis approach. *Energy Effic.* **2018**, *11*, 1941–1953. [CrossRef]
44. Charnes, A.; Cooper, W.W.; Lewin, A.Y.; Seiford, L.M. *Data Envelopment Analysis: Theory, Methodology, and Applications*; Springer: Berlin, Germany, 1994.
45. Färe, R.; Grosskopf, S. Malmquist productivity indexes and Fisher ideal indexes. *Econ. J.* **1992**, *102*, 158–160. [CrossRef]
46. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manage. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
47. Chen, N.; Xu, L.; Chen, Z. Environmental efficiency analysis of the Yangtze River Economic Zone using super efficiency data envelopment analysis (SEDEA) and tobit models. *Energy (Oxf.)* **2017**, *134*, 659–671. [CrossRef]
48. Sueyoshi, T.; Yuan, Y.; Li, A.; Wang, D. Social sustainability of provinces in China: A data envelopment analysis (DEA) window analysis under the concepts of natural and managerial disposability. *Sustainability* **2017**, *9*, 2078. [CrossRef]
49. Zhang, A.; Li, A.; Gao, Y. Social sustainability assessment across provinces in China: An analysis of combining intermediate approach with Data Envelopment Analysis (DEA) window analysis. *Sustainability* **2018**, *10*, 732. [CrossRef]
50. Hunan Provincial Bureau of Statistics. *Hunan Statistical Yearbook 2012–2016*; China Statistics Press: Beijing, China, 2012–2016. Available online: http://tjj.hunan.gov.cn/tjsj/tjnj/ (accessed on 5 April 2017).
51. Hunan Provincial Department of Transportation. *Hunan Transportation and Communications Yearbook 2012–2016*; Hunan People's Publishing House: Changsha, China, 2012–2016.
52. Li, X.; Sun, B. Regional Integration of the Yangtze River Middle Reaches Urban Agglomerations: Measuring and Comparison. *Resour. Environ. Yangtze. Basin.* **2013**, *22*, 996–1003.
53. Musolino, G.; Rindone, C.; Vitetta, A. Evaluation in Transport Planning: A Comparison between Data Envelopment Analysis and Multi Criteria Decision Making Methods. In Proceedings of the 31st Annual European Simulation and Modelling Conference 2017 (ESM 2017), Lisbon, Portugal, 25–27 October 2017; pp. 238–243.