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Article

Ecological Efficiency of Urban Industrial Land in Metropolitan Areas: Evidence from China

Lei Li, Chenzi Pan, Shuai Ling * and Mingqi Li

College of Management and Economics, Tianjin University, Tianjin 300072, China; lilei@tju.edu.cn (L.L.); cz12130@163.com (C.P.); 2020209247@tju.edu.cn (M.L.)
* Correspondence: lingshuai@tju.edu.cn

Abstract: Industrial land is an indispensable strategic resource in urban development that plays an indispensable role in ensuring the industrial space of urban construction and development. Measuring and analyzing the eco-efficiency of industrial land utilization (ECILU) can provide insights into how to maximize the input–output ratio of industrial land and ensure the sustainable development of land resources and economies. Based on the undesirable output slacks-based measure (SBM) model, choosing land, capital, and labor as input indicators, and the industrial added value and carbon emissions as desirable and undesirable output indicators, this study measured the ECILUs in 78 cities and 13 metropolitan areas in four Chinese major economic zones from 2007 to 2018, analyzed their spatial and temporal evolution characteristics and regional differences, and constructed a Tobit regression model to test the influence mechanism of each variable on the ECILUs in different regions. This has important theoretical and practical significance for the Chinese government in formulating relevant policies and realizing the green utilization of urban land in the future. Empirical results showed that the ECILUs in most cities were low and that the differences between regions were large. The ECILU in the Western Economic Zone was relatively high, followed by the Eastern, Central, and Northeastern Economic Zones. According to the ECILU value and urban synergy degree of each metropolitan area, this study divided the 13 metropolitan areas into four categories. The regression analysis results showed that the variables had different effects on the ECILUs of all cities and the four economic zones in China. It is suggested that all economic zones should reinforce the optimization of industrial structure, control industrial pollutant discharge, and solve the phenomenon of labor surplus. The Eastern Zone should maintain the growth of its economy while focusing on soil quality. The Central Zone should focus on the efficient use of infrastructure, and the Western, Northeastern, and Central Zones should balance the green coverage area and the industrial land area to ensure the efficient use of urban industrial land.

Keywords: ecological efficiency; urban industrial land; metropolitan area; undesirable output SBM model; influencing factors

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1. Introduction

Land is the most basic production factor for economic development and the material carrier necessary for developing the real economy [1]. From the perspective of developing countries around the world, industrialization is the only way for most countries to achieve modernization and promote rapid economic development. With the rapid development of industrialization and urbanization in many countries around the world, the level of industrialization in some developed countries and regions has been relatively mature, and most of the urban construction space has become saturated, which cannot continue to increase industrial economic output by expanding the area of industrial land, i.e., by increasing the volume of land. Therefore, improving the quality of industrial land to ensure the steady development of urban industry has become an important issue for most cities globally. Therefore, the Chinese government has made corresponding deployments according to the national conditions. In 2017, the "National Land Planning Outline (2016–2030)" emphasized the need to "reduce the proportion of industrial land and improve the input–output efficiency of industrial land." The 14th Five-Year Plan (2021–2025) also proposed that, in the future, efforts should be made to develop the real economy, promote the prosperity and efficiency of industrial land, and promote the use of new industrial land. It also emphasized the need to "optimize the spatial layout of land and promote regional coordinated development and new towns." These guidance suggestions further standardize the rational, efficient, and sustainable use of industrial land while providing an important policy basis for China to accelerate the construction of land and space planning systems and the construction of green, healthy, and ecological civilization cities [2].

The eco-efficiency of industrial land utilization (ECILU) will be used to evaluate the utilization rate of industrial land from both economic and ecological aspects. Its improvement is the key to China's economic transformation and ecological civilization construction, and it is an urgent task to be faced at this stage. At present, the Chinese urbanization process is rapidly developing. As the carrier of the industrial economy, industrial land has also shown a steady growth trend, but there remain widespread problems, such as disorderly use, idle waste, low floor area rate, and low output [3]. The land-use model with high extensiveness, high pollution, and low efficiency restricts the sustainable development of Chinese industries. Considering the vast Chinese territory and the differences between the realities of various economic zones, general administrative guidance at the national level is difficult to truly implement. Therefore, it is an urgent task at this stage to take effective governance measures for different places, improve the allocation mode of industrial land resources, and increase the ECILU to better alleviate the local problems of industrial land in different cities and metropolitan areas and realize intensive, economical, and efficient use of land and sustainable development throughout the country. In addition, China's original intention and goal of building a "resource-saving" and "environment-friendly" society also require us to embrace the industrialization of sustainable development that is oriented toward integrating ecological factors into the evaluation of industrial land efficiency while maintaining the economic output of steady national growth, thereby striving to reduce the negative external effects of resource waste and environmental pollution to improve economic output and social well-being to a greater extent while maintaining public interests [4,5].

In the context of further standardizing the ecological construction of industrial land in China's metropolitan areas and cities, accelerating the construction of green-livable cities, and promoting the construction of ecological civilization, this study explored the following issues: (1) How did the ECILUs of China's 13 metropolitan areas change from 2007 to 2018 and did it improve over that time? (2) Is there spatial heterogeneity in the changing trend of urban ECILUs in different metropolitan areas and economic zones? (3) Is the ECILU affected by certain factors in China and do these variables have similar effects on cities in different economic regions? In order to solve the above issues, this study measured and compared the temporal and spatial trends of the ECILUs based on the panel data of 78 cities and 13 metropolitan areas from 2007 to 2018 and explored the development process of China's prefecture-level cities and metropolitan areas. From a regional and holistic perspective, this paper presents its views and offers corresponding suggestions for improving the ECILU, promoting the optimal utilization of industrial land in Chinese cities, and realizing the high-quality development of the regional economy with metropolitan areas as the model in the 14th Five-Year Plan period. The rest of this paper is arranged as follows. The second part presents the relevant literature on the ECILU in academic circles. The third part expounds on the research samples and methods used in this study and the selection of variable data. The fourth part discusses the results of this empirical study, including the calculation and spatial-temporal difference analysis of industrial land ecological efficiency in China's metropolitan areas and prefecture-level cities, and the exploration of its influencing factors. The fifth part summarizes the significance and some enlightenment gained from this study.

2. Literature Review

The concept of "eco-efficiency," proposed by Schaltegger and Sturm [6], is in the process of product development; the efficiency of output results and ecological environment should be considered simultaneously to promote the sustainable development of enterprises, regions, and countries. In 1998, the World Economic Cooperation and Development (OECD) defined the concept of eco-efficiency as "the efficiency of using ecological resources to meet human needs." Mickwitz et al. believed that eco-efficiency is a tool for analyzing sustainable capacity, reflecting the relationship between economic activities and environmental costs, and environmental impacts [7]. Since eco-efficiency considers the input–output and ecological environment in the process of human production, scholars have introduced it into many fields in social and economic life, such as the calculation and analysis of organizational efficiency, the use of natural resources and industrial output, and to explore the degree of sustainable development. Korhonen and Luptacik used two different methods to measure the eco-efficiency of multiple power plants in European countries and obtained similar results [8]. Huang et al. found that geographic location, corporate attributes, government support, technological externalities, and international connections had impacts on the eco-efficiency of industrial land used by electronics companies in the Shanghai Development Zone [9]. Yu et al. analyzed the dynamic trend and convergence of the eco-efficiency of industrial companies in coastal provinces in China and found that eco-efficiency is unstable and scattered [10]. Georgopoulou et al. established an ecological efficiency evaluation method framework that explored the indicators that affect the ecological efficiency of the water system of the bottling plant, the textile printing and dyeing industry, and the dairy industry [11]. Thus, it can be seen that most of the existing studies on eco-efficiency mostly start from local enterprises and have a microscopic nature. In addition, there are also many other scholars who chose to start research on eco-efficiency from different types of industries or industrial parks. Gossling et al. used Rocky Mountain National Park and Amsterdam inbound tourism as cases to analyze and calculate the ecological efficiency of the local tourism industry and found that the source country and destination country, tourism culture, and holiday environment (cities, mountains, etc.) caused a huge difference in the eco-efficiency of the tourism industry [12]. Pai et al. measured 60 industrial parks in Taiwan and found that there was still a lot of room for improvement in eco-efficiency [13]. Therefore, it can be seen that when conducting research, scholars usually choose to measure the ecological efficiency of enterprises or specific industrial parks using land, labor, and capital as input indicators, and economic output as output indicators (Table 1). There are also a considerable number of scholars that have incorporated environmental variables into the efficiency calculation model to carry out research. This means that the academic circle still has room for optimization in the choice of index system and the level of research objects. This study explored eco-efficiency from the perspective of the macroscopic view and carried out comparative research with the industries of different cities, metropolitan areas, and large economic zones as the main body, and enriched the research level under this theme.

Table 1. Summary of inputs/outputs and methodology of total factor energy evaluation.

Inputs	Outputs	Method	Study
Land, labor, fixed-asset investment	Industrial GDP, wastewater, SO_2, smoke and dust	Slack-based model	Pu et al. [14]
Land, labor, fixed-asset investment	Industrial GDP, pollution	Slack-based model	Jiang [15]
Land, labor, fixed-asset investment	Industrial economic output	Slack-based model	Xie and Wang [16]
Land, labor, fixed capital, energy consumption	Industrial GDP, wastewater, SO_2, smoke and dust	SBM-undesirable model	Chen et al. [17]
Labor, energy, fixed capital	Industrial GDP, SO_2, CO_2, dust, smoke, and wastewater	SFA	Liu et al. [18]

Table 1. *Cont.*

Inputs	Outputs	Method	Study
Land, labor, the net value of fixed assets	Industrial GDP	SFA	Yan et al. [19]
Land, labor, the net value of fixed assets	Industrial GDP, exhaust, wastewater	SGDDF	Xie et al. [20]
/	Industrial GDP	Industrial GDP per unit land	Wang et al. [21]

At present, the academic research on "industrial land" mainly focuses on the policies of industrial land [22,23], the price of industrial land [24,25], the economical and intensive use of industrial land [26–28], and the efficiency of industrial land. The literature research on the efficiency of industrial land is relatively extensive, and there are many documents that measured the efficiency of industrial land use. On the one hand, the research objects of the academic circles on the measurement of industrial land efficiency are mainly concentrated in urban development zones, urban agglomerations, or provincial administrative regions. Liu et al. measured the eco-efficiency of water systems in 31 administrative regions of China and concluded that the northern coastal areas scored the highest, and the eco-efficiency value of North China was slightly higher than that of the south [29]. Shi et al. analyzed the temporal and spatial trends of the ecological efficiency of the Ningguo Port Industrial Park in eastern China and found that when the total value of the park's ecosystem services increases, the ecosystem services and economic value show a downward trend [30]. Zhang conducted a study on the industrial land efficiency of 19 typical enterprises in the Chengdu Technology Development Zone, showing that the overall level of land use by typical enterprises in the development zone is relatively high, but the industry differences are obvious [31]. It can be seen that the existing research shows that there are obvious differences in the efficiency of industrial land for different times and spaces. This preliminary evidence provides support for the smooth development of this research to a certain extent. On the other hand, Meng et al. found that the production characteristics of enterprises and the quantity, arrangement, and scheduling of land will produce the greatest differences in land-use efficiency of industrial enterprises in Shunyi, Beijing [32]. Tu et al. took Hangzhou, China, as an example and found that the impact of the industry type, land lease year, and land size was greater than that of government interventions on the efficiency of industrial land use [33]. Chen et al. found that the improvement of the industrial level has a significant positive impact on the utilization efficiency of industrial land [34]. Zhao et al. found that the utilization efficiency of industrial land in Chinese cities is positively correlated with the agglomeration of industries, labor, capital, and technology [35]. Ye et al. found that collective land with incomplete property rights would lead to inefficient land use by lower industrial enterprises. Different land lease periods are negatively correlated with the use efficiency of industrial land [36]. Chen et al. found that the regional economy, industrial structure, and technological level all have a positive effect on industrial land utilization efficiency, while labor structure and enterprise ownership structure have significant negative effects [37]. The academic circle has carried out relatively rich research on the influencing factors of land-use efficiency and reached a consensus on the influencing factors, such as economic scale, industrial structure, labor force, and land quality.

Summarizing the existing research writings, it can be found that current scholars have conducted relatively rich research in the fields of eco-efficiency and industrial land, but the academic circles have not yet formed a unified definition of the "eco-efficiency of industrial land utilization (ECILU)", more research is conducted with the "efficiency of industrial land utilization (EILU)" as the research object, and a unified industrial land efficiency measurement model and applicable method have not yet been formed. Based on the above premise, referring to the results of previous studies, this study innovatively introduced the concept of "ECILU" to a certain extent and defines it as "the degree of sustainable development and utilization of urban industrial land under the constraints of certain socio-economic output and resource and environmental costs" [38]. Using the undesirable output SBM model, this study included the ecological environment-related variables, and the research level of the ECILU was implemented to the two research levels of prefecture-level cities and metropolitan areas to calculate and analyze the ECILUs in 78 cities and 13 metropolitan areas in China. The regional differences and temporal and spatial trends in industrial land ecological efficiency were explored using horizontal comparisons and vertical analysis. In addition, considering the regional differences in China's economic zones, this study changed the original extensive regression analysis research model by considering the four major economic zones, making a more refined regression analysis of the factors affecting the ECILU in each city and exploring the regional heterogeneity of the regression results so that the calculation model is more comprehensive and credible.

3. Methodology

3.1. Sample Selection

The Chinese government set up a special fiscal expenditure level that was subject to environmental protection in 2007, which highlights the importance of the ecological environment in finance. Therefore, this study selected 2007–2018 as the research period to explore the evolution process of the ECILU over 12 years in China. In addition, considering the great differences in economies, geographical positions, resources, and other practical factors among different regions in China, it is difficult to conduct a comprehensive and holistic analysis. Therefore, this study selected some cities and metropolitan areas from the four economic zones of Eastern, Central, Western, and Northeastern China for empirical research. According to the planning documents jointly issued by the central and local Chinese governments and intergovernmental organizations, considering the availability of relevant analysis data, this study selected 13 metropolitan areas and 78 cities included in them as sample observation units from the 28 metropolitan economic areas currently under construction or already existing [39], including the capital economic circle (BJ), Shanghai metropolitan area (SH), Nanjing metropolitan area (NJ), Qingdao metropolitan area (QD), Xia–Zhang–Quan metropolitan area (XZQ), and Guangzhou metropolitan area (GZ) in the Eastern Economic Zone; Shenyang metropolitan area (SY) and Changji metropolitan area (CJ) in the Northeastern Economic Zone; Zhengzhou metropolitan area (ZZ), Wuhan metropolitan area (WH), and Changsha metropolitan area (CS) in the Central Economic Zone; and Chengdu metropolitan area (CD) and Xi'an metropolitan area (XA) in the Western Economic Zone. The prefecture-level cities included in each metropolitan area are as follows (Table 2, Figure 1).

Table 2. Description of metropolitan areas and their covered cities.

Name of Metropolitan Area	Symbol	Covered Cities
Capital economic circle	BJ	Beijing, Tianjin, Baoding, Tangshan, Langfang, Shijiazhuang, Cangzhou, Qinhuangdao, Zhangjiakou, Chengde, Handan, Xingtai, and Hengshui
Shenyang metropolitan area	SY	Shenyang, Anshan, Fushun, Benxi, Yingkou, Fuxin, Liaoyang, and Tieling
Changji metropolitan area	CJ	Changchun and Jilin
Shanghai metropolitan area	SH	Shanghai, Suzhou, Wuxi, Changzhou, Nantong, Jiaxing, Ningbo, Hangzhou, Zhoushan, and Huzhou
Nanjing metropolitan area	NJ	Nanjing, Zhenjiang, Yangzhou, Huaian, Maanshan, Chuzhou, Wuhu, Xuancheng, and Changzhou
Xia–Zhang–Quan metropolitan area	XZQ	Quanzhou, Xiamen, and Zhangzhou
Qingdao metropolitan area	QD	Qingdao and Weifang
Zhengzhou metropolitan area	ZZ	Zhengzhou, Kaifeng, Xinxiang, Jiaozuo, and Xuchang
Wuhan metropolitan area	WH	Wuhan, Huangshi, Ezhou, Huanggang, Xiaogan, and Xianning
Great Changsha metropolitan area	CS	Changsha, Zhuzhou, Xiangtan, Yueyang, Changde, Yiyang, Loudi, and Hengyang
Guangzhou metropolitan area	GZ	Guangzhou, Foshan, Zhaoqing, Qingyuan, Yunfu, and Shaoguan
Chengdu metropolitan area	CD	Chengdu, Deyang, Meishan, Ziyang, and Leshan
Xi'an metropolitan area	XA	Xi'an and Xianyang

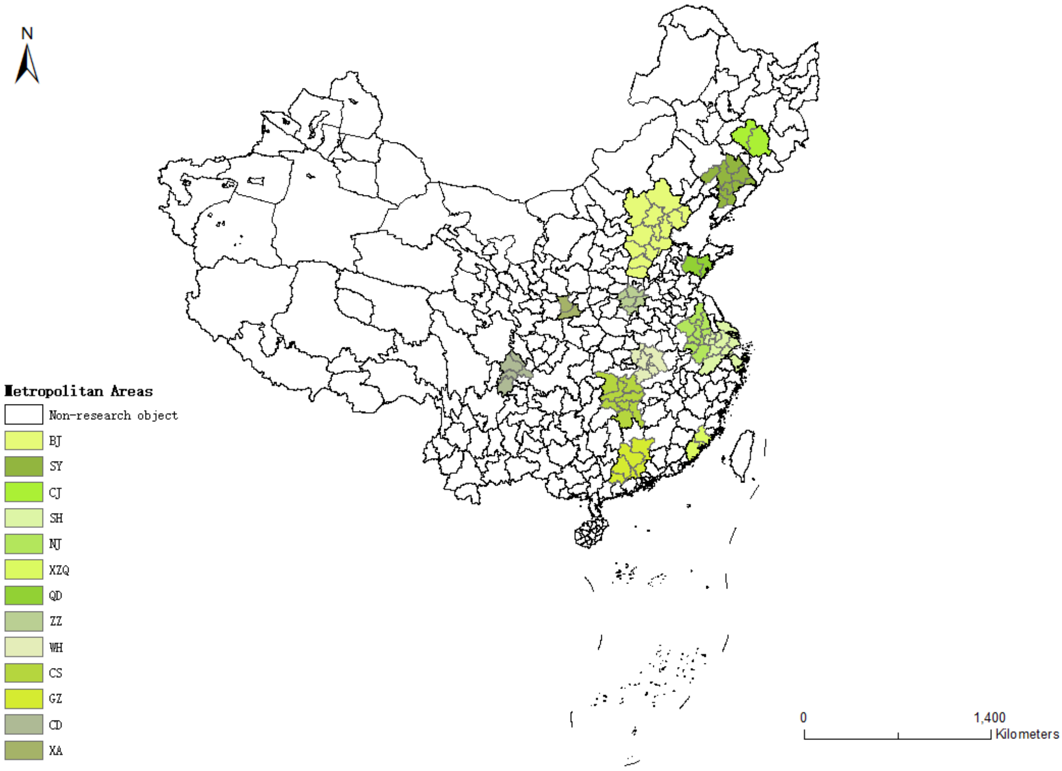

Figure 1. Distribution of the metropolitan areas.

3.2. SBM Model

The undesirable output SBM model, which is an expansion and extension of the DEA model, is a scientific evaluation method formed by scholars according to the continuous improvement and improvement of academic research and application practice. The DEA model assumes that there is a monotonic linear proportional relationship between input and output indexes; therefore, it can be used to determine the relative efficiency of production units using linear programming methods. The model has been applied to the efficiency evaluation of various fields since it was proposed by Charnes and Cooper in 1978 [40]. However, the traditional DEA model, which is based on the characteristics of radial measurement, makes it difficult to overcome its inherent defects because it cannot consider the influence of relaxation variables. To solve this problem, Tone introduced slack variables into the objective function and proposed non-radial SBM models [41]. Considering that in the process of social development and production, ecological environmental pollution will inevitably and unavoidably appear during production and management activities on industrial land, this study adopted the SBM model containing undesirable outputs [42]. The expression of the model is as follows:

$$
\begin{gathered}
\rho = \min \frac{1-\frac{1}{M}\sum_{i=1}^{M} s_i^x / x_{i0}}{1+\frac{1}{N+1}\left(\sum_{j=1}^{N} s_j^y / y_{j0} + \sum_{k=1}^{I} s_k^u / u_{k0}\right)} \\
\text{s.t. } \sum_{l=1}^{L} z_l x_{il} + s_i^x = x_{i0},\ i = 1, 2, 3, \ldots, M \\
\sum_{l=1}^{L} z_l y_{il} - s_i^y = y_{i0},\ i = 1, 2, 3, \ldots, N \\
\sum_{l=1}^{L} z_l y_{il} - s_k^u = u_{k0},\ k = 1, 2, 3, \ldots, I \\
\sum_{l=1}^{L} z_l = 1,\ z_l \geq 0;\ s_i^x,\ s_j^y,\ s_k^u \geq 0
\end{gathered} \tag{1}
$$

where x_{i0}, y_{i0}, and u_{k0} denote the value of inputs, expected outputs, and undesirable outputs of the decision-making unit, respectively; M, N, and I denote the number of decision-making units with inputs, expected outputs, and undesirable outputs redundancy, respectively; s_i^x, s_i^y, and s_k^u denote inputs and deficiencies of inputs, expected outputs, and undesirable outputs, respectively; and z_l denotes the weight of the decision-making unit.

ρ is the calculated efficiency value and $\rho \in (0,1]$. When $\rho = 1$, the decision-making unit is completely effective, that is, there is no shortage of surplus and expected output of input and non-expected output. When $\rho < 1$, the decision-making unit has an efficiency loss.

3.3. Tobit Regression

Since the interval of the ECILU measured by the SBM model is (0,1], this study selected the Tobit model to test the significance of the impact of various variables on the ECILU. The Tobit regression model was first proposed by James Tobin in 1958 [43]. It is an econometric model that uses the maximum likelihood method for the regression analysis of dependent variables when the dependent variable is a fragment value or a cut value. It can better solve the problem of inconsistent and biased parameter estimation and avoid the fact that the least-squares method cannot obtain consistent estimation results. Its mathematical expression is as follows:

$$\rho_i = \alpha_0 + \sum_{j=1}^{l} \alpha_j x_{ij} + \varepsilon_i \quad (2)$$

where ρ_i is the actual dependent variable observed by the regression model and $\rho_i \in (0,1]$. x_{ij} is the independent variable, l is the sample number, α_0 is the constant term, α_j is the correlation coefficient vector of the jth sample, and ε_i is independent and $\varepsilon_i \sim N(0,\sigma^2)$.

3.4. Data

3.4.1. Input and Output Indexes

According to the research ideas of previous literature, this study selected indicators from the two aspects of input and output in the process of measuring ECILU in prefecture-level cities and metropolitan areas:

- Input indicators. Land, capital, and labor are important input factors in social and economic construction activities. Considering this, this study selected the indicators from three aspects: First, land input. Industrial production activities do not require the quality of land; they only need to meet the supply of a certain area of input. Therefore, this study used the size of the available land area and selected the city's industrial land area as the indicator of land investment. Second, capital investment. Industrial production needs funds to start, run, complete production activities, and maintain the operation of industrial enterprises. Because the total amount of fixed assets can reflect the actual assets of industrial enterprises in the year, this study selected the total amount of fixed assets of industrial enterprises above the urban scale as the index of capital investment. Third, labor input. This study selected the number of employees in the urban secondary industry to represent the labor input index.
- Desirable output indicators. To a certain extent, industrial added value eliminates intermediate consumption in production activities, which can more accurately reflect regional industrial output. Therefore, this study selected the industrial added value of industrial enterprises above scale to represent economic benefits.
- Undesirable output indicators. This study selected carbon emissions as an undesirable output indicator to represent the total annual carbon dioxide emissions (million tons), which can reflect the impact on environmental changes when industrial production activities are carried out on land, to construct the ECILU measurement model.

3.4.2. Influencing Factor Variables

Based on the calculation of the ECILU, this study selected eight influencing factors from the perspectives of "industrial economics" and "ecology" to construct a Tobit regression model, and considered the various influencing factors of the ECILU (Table 3). To reduce multicollinearity between variables, this study log-transformed all variables in the model. The explanatory variables selected in the regression model were the following:

- Urban scale (gdp). The economy is an important aspect when judging the degree of development of a city. Provinces with higher per capita GDP levels are relatively more ecologically efficient [44]. The environmental Kuznets curve shows that when the economy develops to a higher level, environmental pollution will be improved [45], and cities with larger scales and higher levels of economic development are better able to cope with environmental challenges. Therefore, this study selected regional GDP as the proxy variable of urban scale that indicated the level of economic development in the region.

- Industrial structure (ic). The change in regional industrial structure will affect the ratio of input factors in industrial production and the change in resource utilization form. The higher the proportion of the tertiary industry, especially the service industry, the higher the eco-efficiency will be [46,47]. Therefore, this study selected the proportion of tertiary industry to GDP to measure the industrial structure of a region.
- Regional population quality (rpq). The agglomeration degree and potential development force of talents in the region are important driving forces for industrial growth, but they will also affect the local ecological quality [48]. Furthermore, mid-to-high-end labor can improve the efficiency of economic growth more than low-end labor [49]. This study selected the number of students in regional colleges and universities to measure the quality of the regional population.
- Degree of regional marketization (drm). The degree of marketization can reflect the allocation effect of the market on the elements needed for industrial production to a certain extent, thereby increasing the industrial output value and sales value and improving the ecological efficiency of local industrial land [50]. This study selected the total retail sales of social consumer goods to measure the marketization level.
- Infrastructure construction level (icl). Regional infrastructure level can provide development carriers and logistics support for the industrial and commercial economy [51]. This study used urban road areas to characterize the infrastructure levels.
- Regional green coverage (rg). The urban green coverage rate is an important indicator for the assessment of China's environmental protection model cities and the creation of civilized cities. In this study, the urban greening coverage area was used to characterize the ecological level and the degree of regional environmental protection to reflect local attention to environmental protection and the level of sustainable development and construction.
- Industrial wastewater pollution (wp). The discharge of industrial wastewater is significantly related to the quality of the local environment. Soil irrigated by industrial wastewater will have a substantial increase in heavy metal content [52,53]. This study selected industrial wastewater discharge as an ecological variable to measure the degree of regional ecological environmental pollution.
- Sulfur dioxide pollution (sp). Sulfur dioxide is an important indicator for evaluating pollution caused by industrial production [54]. The emission of industrial sulfur dioxide and other substances will inhibit the release of carbon dioxide and polycyclic aromatic hydrocarbons from the soil [55,56]. This study selected industrial sulfur dioxide emissions as another indicator to measure ecological pollution.

3.4.3. Data Sources

The statistics involved in the empirical analysis in this study were all collected from national and local statistical bureaus at all levels. For the missing data, the median filling method was used as a supplement. The data of the total fixed assets of industrial enterprises above scale, secondary industry practitioners, GDP, the number of students in ordinary colleges and universities, and total retail sales of social consumer goods were from "China City Statistical Yearbook 2008–2019". The data of the industrial land area, urban road area, and urban greening coverage area were from "China Urban Construction Statistical Yearbook 2007–2018" and "China Land and Resources Statistical Yearbook 2007–2018". The data of the proportion of tertiary industry in GDP and industrial added value were derived from local statistical yearbooks at all levels.

Table 3. Description of explanatory variables of the Tobit regression model.

Explanatory Variable	Symbol	Unit	Definition
Urban scale	gdp	10,000 CNY	Regional GDP, taken as a logarithm
Industrial structure	ic	%	The proportion of tertiary industry in regional GDP (gross domestic product), taken as a logarithm
Regional population quality	rpq	People	The number of students in regional colleges and universities, taken as a logarithm
Degree of regional marketization	drm	10,000 CNY	The total retail sales of social consumer goods, taken as a logarithm
Infrastructure construction level	icl	10,000 m^2	Urban road area, taken as a logarithm
Regional green coverage	rg	ha	Urban greening coverage area, taken as a logarithm
Industrial wastewater pollution	wp	10,000 tons	Volume of industrial wastewater discharged, taken as a logarithm
Sulfur dioxide pollution	sp	ton	Volume of industrial sulfur dioxide emissions, taken as a logarithm

4. Results and Discussions

4.1. Measurement Results of the ECILU

4.1.1. Comparison of the ECILU

After the integration and analysis of the data, this study used DEA-SOLVER Pro 5.0 to operate and uses the undesirable output SBM model to measure the ECILUs in 78 cities from 2007 to 2018. According to the calculation results, the efficiency values could be divided using the equal width method according to the regional difference of a city's ECILU [57]: low efficiency (≤0.25), medium-low efficiency (0.25~0.50), medium-high efficiency (0.50~0.75), and high efficiency (≥0.75), where the number of cities in different levels is presented below (Table 4).

Table 4. Statistics of ECILUs from 2007 to 2018.

Year	Mean	Maximum	Minimum	ECILU Levels			
				Low	Medium–Low	Medium–High	High
2007	0.2699	1.0000	0.1024	49	23	2	4
2008	0.2709	1.0000	0.0942	50	20	5	3
2009	0.2432	0.7068	0.0891	56	16	6	0
2010	0.2574	1.0000	0.1056	52	21	3	2
2011	0.2475	1.0000	0.0998	49	26	2	1
2012	0.2876	1.0000	0.0863	44	27	5	2
2013	0.2707	0.6887	0.0810	45	26	7	0
2014	0.2804	0.7620	0.0953	34	38	5	1
2015	0.3026	0.8825	0.1111	35	34	8	1
2016	0.3169	1.0000	0.1773	33	37	6	2
2017	0.3574	1.0000	0.1613	24	44	5	5
2018	0.4103	1.0000	0.1239	17	42	11	8

By counting the efficiency values and grade proportions of prefecture-level cities, this study analyzed the classification and temporal variation characteristics of the ecological efficiency value of industrial land in each city (Figure 2). First, throughout the period, the average ECILU improved from 0.2699 to 0.4103. Second, the average ECILU showed characteristics of increasing during this period. It decreased from 2007 to 2008, and from 2009 to 2018; although there was no significant increase, the overall trend showed the evolutionary characteristics of fluctuating growth. Finally, the number of cities with low ECILUs decreased yearly, and gradually evolved to the level of medium and high efficiency. There were 49 inefficient cities in 2007 and 17 in 2018, and the proportion of cities with medium-high efficiency also increased from 7.69% in 2007 to 24.36% in 2018. It can be seen that although the number of medium-high-efficiency cities increased yearly, the ECILUs in most cities in China were still at a low level.

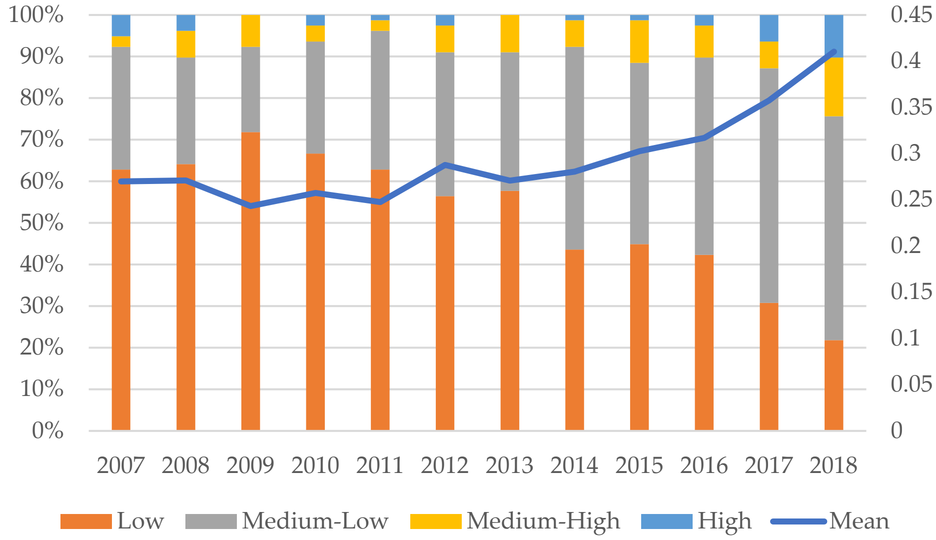

Figure 2. Evolution trend of the ECILUs in 2007–2018.

To understand the distribution of the ECILUs in different regions more intuitively, this study found the average change trend of the ECILU in all cities and cities in the four major economic zones over the years based on the results above. Figure 3 shows that the ECILUs in China and the four major economic zones showed steady yearly increases in the time dimension, and the ECILUs in the four major economic zones from high to low were the Western, Eastern, Central, and Northeastern Economic Zones. Moreover, it can be seen from Figure 3 that the line of "All samples" was below the "Western Economic Zone" and "Eastern Economic Zone" and above the "Central Economic Zone" and "Northeastern Economic Zone" throughout the period from 2007 to 2018. This means that the ECILUs in the Western Economic Zone and the Eastern Economic Zone were higher than the average efficiency of all cities over the 12 years, and the ECILUs in the Central and Northeastern Economic Zones were lower than the average efficiency of all cities. In addition, at the regional dimension level, the ECILUs in the Western Economic Zone reached its peak in 2008 and 2012, and the Eastern Economic Zone reached its peak in 2010 and 2012; then, both of them decreased for one year and increased steadily. The ECILU in the Central Economic Zone steadily increased from 2007 to 2017, but the growth rate in 2018 was significantly accelerated, while the ECILU in the Northeastern Economic Zone decreased in 2016, but increased again in the next year.

4.1.2. Spatial and Temporal Differences in ECILUs in Metropolitan Areas

To further analyze the changes in the ECILUs in different metropolitan areas over the assessed 12 years, this study analyzed the spatial and temporal differences of 78 cities' ECILUs in 13 metropolitan areas by using averaging and variance operations. First, this study took three years as a cycle and selected the grouping data of the years 2007, 2009, 2011, 2013, 2015, and 2017 for comparative analysis (Figure 4).

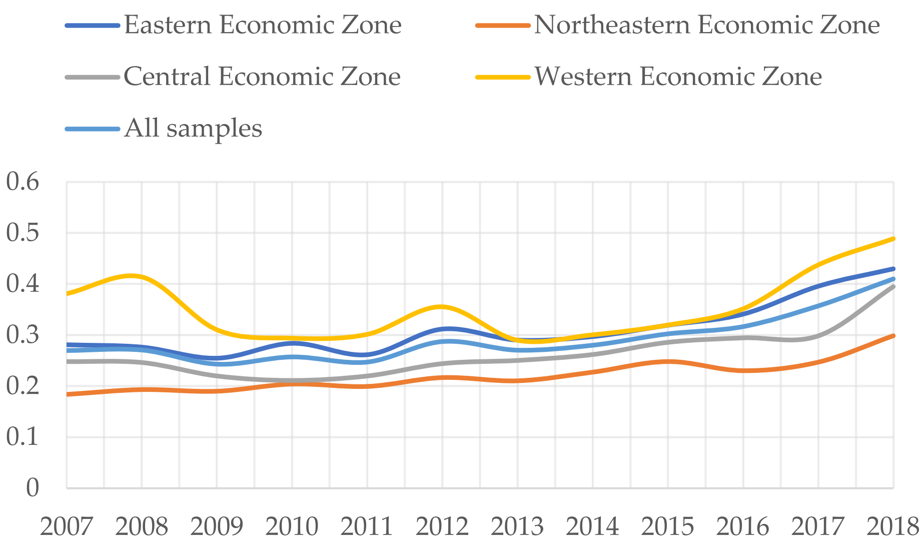

Figure 3. Evolution trend of the ECILUs in 2007–2018.

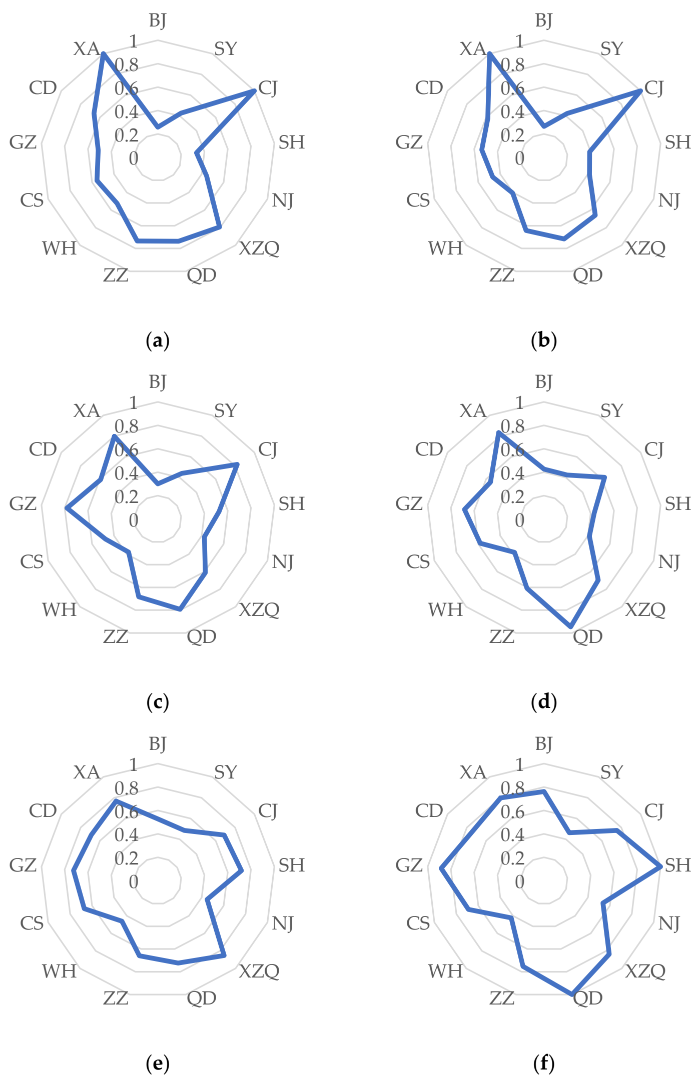

Figure 4. Comparison of the ECILUs in metropolitan areas: (**a**) 2007, (**b**) 2009, (**c**) 2011, (**d**) 2013, (**e**) 2015, and (**f**) 2017.

The results showed that the ECILUs in XA and CJ decreased significantly, and the ECILUs of the other 11 metropolitan areas showed a fluctuating upward trend from 2007 to 2018. The ECILUs in CJ, XZQ, QD, ZZ, GZ, and XA reached more than 0.5, showing a high level. The ECILUs of SY and WH were generally concentrated in 0.3~0.5, and the efficiency was low. It can be seen that the size distribution of the ECILU was not divided by the economic development level of the economic zone it belonged to. For example, although the economic development levels of BJ and NJ in the Eastern Economic Zone were relatively high, there were only a few years when the ECILUs were more than 0.5. Although SY and CJ are both in the Northeastern Economic Zone, the ECILU was obviously in the opposite state of one high and one low, and the reason for this phenomenon is worth further discussion.

Based on comparing the ECILUs in 13 metropolitan areas, this study investigated the close degree of the relationship between the cities in different metropolitan areas using the variance of the ECILUs between cities covered by the metropolitan area to judge the overall unity and synergy of each metropolitan area in the development of industries. That is, the smaller the variance index value, the higher the degree of synergy between cities in the metropolitan area, and the greater the index value, the greater the differences between cities and the lower the synergy. The 100-fold variance index for ECILU for each metropolitan area is shown below (Table 5, Figure 5).

Table 5. Variance indexes of the ECILUs in the metropolitan areas from 2007 to 2018.

Year	BJ	SY	CJ	SH	NJ	XZQ	QD	ZZ	WH	CS	GZ	CD	XA
2007	0.83	0.56	0.01	5.65	6.03	0.30	0.09	0.65	1.18	0.16	8.94	9.70	0.14
2008	1.06	0.49	0.01	2.40	5.98	0.39	0.06	0.41	1.70	0.27	4.51	11.8	0.37
2009	0.98	0.40	0.01	1.42	1.76	0.38	0.08	0.26	1.36	0.18	2.71	4.81	0.21
2010	5.31	0.42	0.01	0.90	1.66	0.48	0.07	0.31	0.39	0.09	4.89	3.33	0.13
2011	0.39	0.33	0.07	1.18	0.35	0.29	0.01	0.32	0.12	0.07	8.17	1.81	0.06
2012	1.23	0.60	0.09	1.95	0.33	15.2	0.08	0.88	0.23	1.05	7.97	2.48	0.03
2013	1.39	0.74	0.04	1.40	0.27	5.70	0.20	0.89	0.21	1.52	2.77	1.99	0.00
2014	1.10	0.96	0.02	0.71	0.42	7.15	0.00	1.17	0.47	1.74	2.90	1.63	0.00
2015	1.56	1.27	0.01	1.10	0.50	9.50	0.01	1.68	0.18	2.52	3.47	1.49	0.01
2016	1.91	0.30	0.00	1.21	0.64	12.8	0.00	1.47	0.23	1.70	4.24	1.77	0.03
2017	5.79	0.27	0.00	3.88	0.96	0.90	0.01	2.23	0.56	0.62	4.66	6.57	0.00
2018	6.89	0.77	0.01	4.68	0.82	1.43	5.24	6.34	8.89	0.77	6.99	5.73	0.00

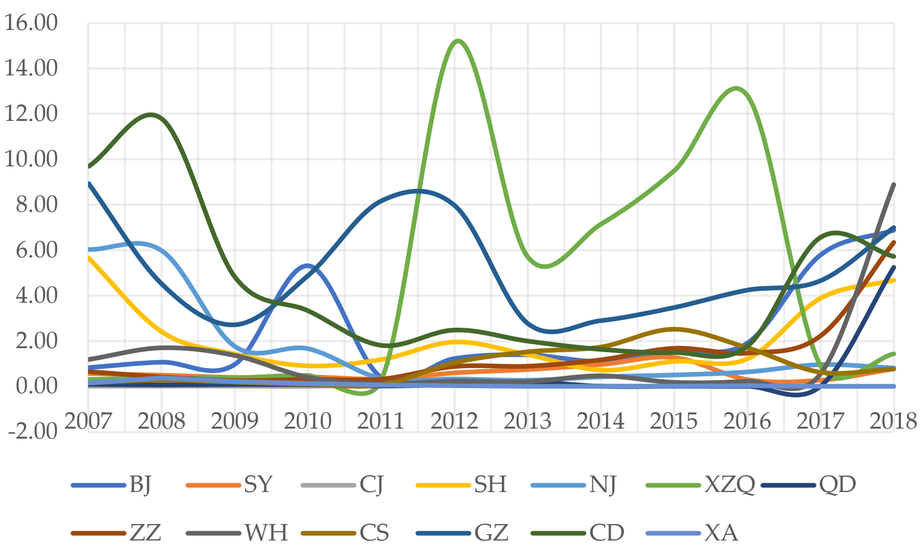

Figure 5. Variance indexes of ECILUs in the metropolitan areas 2007–2018.

According to Table 5 and Figure 5 above, during the 12 years from 2007 to 2018, the variance indexes of XZQ, GZ, and NJ were significantly larger than those of other metropolitan areas, and the degree of urban synergy was also relatively low. The variance indexes of SH and CD showed a trend of first decreasing and then increasing. The variance index of the cities in CD reached its peak in 2008. Then, like SH, CD's variance index decreased steadily in 2010 and increased yearly from 2016. BJ reached its first peak in 2010, then decreased in the following year, and then had stable fluctuations for nearly six years, but increased again after 2017. The variance index of XZQ had two peaks, namely, in 2012 and 2016, indicating that there was a large gap in the ECILUs between cities within the metropolitan area and that urban synergy was reduced. The index value of QD was low in the first 11 years but rose to the middle level of the 13 metropolitan area samples in 2018.

In general, the ECILUs can allow observers to see the degree of industrial development in a region from a quantitative perspective. However, concurrently, the degree of synergy between cities is also an important factor when measuring the sustainable development of a metropolitan area. Based on the comprehensive consideration of ECILUs in the metropolitan areas and cities above, and taking the average value and variance index as the reference, this study divided the 13 metropolitan areas into four categories: First, the high efficiency–high synergy metropolitan areas were represented by CS, QD, ZZ, and CS. Second, the high efficiency–low synergy metropolitan areas were represented by SH, XZQ, GZ, and CD. Third, the low efficiency–high synergy metropolitan areas were represented by SY, NJ, and WH. Fourth, the low efficiency–low synergy metropolitan area was represented by BJ.

4.2. Analysis of the Influencing Factors of the ECILU

This study used the SBM model to effectively measure the ECILU in each city and metropolitan area and undertook a comparative analysis and summary. Furthermore, this study investigated all kinds of factors and mechanisms that affect efficiency. Based on the Tobit regression model of the maximum likelihood estimation method and panel data of 78 prefecture-level cities from 2007 to 2018, this study conducted an empirical analysis according to the classification of the four economic zones, namely, the Eastern, Northeastern, Central, and Western regions. The specific effects of each variable are shown in Table 6.

Table 6. Tobit regression analysis results of the ECILUs.

Explanatory Variable	**Explained Variable: the ECILU**				
	All Samples	**Eastern Zone**	**Northeastern Zone**	**Central Zone**	**Western Zone**
gdp	0.1213337 *** (0.000)	0.1320097 *** (0.000)	0.0770858 *** (0.001)	0.0926126 *** (0.000)	−0.0573272 (0.447)
ic	−0.0038424 (0.870)	−0.0825258 ** (0.035)	0.0622304 (0.124)	0.0453927 (0.215)	0.2991415 ** (0.002)
rpq	−0.0528232 *** (0.000)	−0.0590623 *** (0.000)	−0.0501857 *** (0.000)	−0.0332701 ** (0.002)	−0.0572474 *** (0.000)
drm	−0.0325802 ** (0.021)	−0.0325819 (0.120)	−0.0128263 (0.578)	−0.0378645 * (0.073)	0.0424439 (0.561)
icl	−0.0240317 ** (0.007)	−0.0254135 ** (0.039)	0.0209241 (0.138)	−0.0972003 *** (0.000)	−0.0121398 (0.758)
rg	−0.0053223 (0.427)	0.0112974 (0.302)	−0.010946 ** (0.073)	0.0767977 *** (0.000)	−0.0562089 ** (0.049)

Table 6. *Cont.*

Explanatory Variable	Explained Variable: the ECILU				
	All Samples	Eastern Zone	Northeastern Zone	Central Zone	Western Zone
wp	−0.0019175 (0.692)	−0.0157632 ** (0.025)	−0.0131907 * (0.084)	−0.0221559 ** (0.026)	0.0305218 (0.129)
sp	−0.0245648 *** (0.000)	−0.0253258 *** (0.000)	−0.0245787 ** (0.002)	−0.0136374 * (0.058)	−0.0451033 ** (0.004)

Note: *, **, *** respectively indicate that the variables were significant at the levels of 10%, 5%, and 1%, and the values in brackets are *p*-values.

The regression results of the factors affecting the ECILUs in various cities from 2007 to 2018 showed that, in the empirical study, from the perspective of all the samples, the variables of urban scale, regional population quality, degree of regional marketization, infrastructure construction level, and sulfur dioxide pollution had significant effects on the ECILUs in various prefecture-level cities selected in the sample, and the influencing coefficients were 0.1213337, −0.0528232, −0.0325802, −0.0240317, and −0.0245648, respectively. From the perspective of the economic zones:

- The urban scales of the Eastern, Central, and Northeastern Economic Zones had an appreciable impact on their ECILUs, and the regression coefficients were all positive. The industrial economy affected the ecological efficiency of industrial land by providing support for ecological environment protection, but there were significant differences in the effects of different regions [58], which may have been the reason why the urban scale did not have a significant impact on the Western Economic Zone. Therefore, each economic zone should pay attention to the positive role of urban scale, and strengthen the introduction of regional factors and industrial upgrading by expanding the economic scale of cities.
- Industrial structure had a negative correlation with the Eastern Economic Zone and a positive correlation with the Western Economic Zone. Within a certain range, the improvement in the industrial structure level will affect the allocation mode of various resources and transfer them in the direction conducive to industrial development. However, when the industrial structure level reaches a certain standard under the combined effect of the siphon effect and the negative externality of environmental pollution, it may hinder the improvement of ECILU. Existing research showed that large cities mainly improve eco-efficiency by influencing the tertiary industries, and other small- and medium-sized cities mainly improve eco-efficiency via the secondary industries [59]. Therefore, it is suggested that the Western Economic Zone should strengthen industrial and ecological construction in the construction of metropolitan areas, and also innovate the internal inter-city cooperation mechanism [60].
- Regional population quality had a significant impact on the ECILUs of all economic zones, and the impact coefficients were all negative. The allocation of labor among industries and regions is a direct manifestation of the efficiency of economic operation [61]. The negative correlation shown in the regression results may have been due to the existence of a large surplus of industrial labor, which had a negative impact on the ECILUs [16]. It is recommended that the economic zones appropriately reduce the proportion of industrial labor to slow down the phenomenon of labor surplus.
- The degree of regional marketization had an appreciable impact on the ECILU only in the Central Economic Zone, and the regression coefficient was −0.0378645. The vitality of the market is crucial to industrial efficiency [62]. Industrial agglomerations and transfers have become the main ways for China to improve industrial efficiency [63]. However, when the negative crowding effect caused by industrial agglomeration brought by the marketization level is greater than the positive scale effect, it will have a negative impact on the ECILU.
- There was a significant negative correlation between the level of infrastructure construction and ECILU in the Eastern and Central Economic Zones. Cross-regional

transportation and other infrastructure construction provide logistic guarantees for local industrial agglomerations, and industrial agglomerations can also promote the use of urban land resources and reduce the total cost of industrial activities through external economies of scale [64,65]. However, in fact, the eastern and central parts of China are flat and the spatial distribution of public transportation services is uneven [66]. This study suggests that scientific planning of road transportation and other infrastructure should be strengthened, road utilization should be improved, and an efficient connection between public transportation and land use should be established [67].

- The area of regional green coverage had a negatively correlated and significant impact on the Northeastern and Western Economic Zones, and a positively correlated impact on the Central Economic Zone. Compared with the Central and Eastern Economic Zones, it can be explained that the more green areas in the Northeastern and Western Economic Zones may compress industrial land and limit the growth of the industrial economy, while the green areas in the Central Economic Zone may greatly improve the local ecology. Improving ECILU entails the common development of "economy" and "ecology." Therefore, each economic zone should jointly promote industrial economic growth and environmental protection and realize their harmony.
- The regression coefficients of industrial wastewater pollution and sulfur dioxide pollution for ECILU were both negative. This is consistent with existing research. Industrialization has brought serious pollution problems to the ecological environment, resulting in the decline of water and air quality, soil structure destruction, etc., and has severely weakened the ecosystem service functions of concentrated industrial areas [68]. Therefore, strengthening the city's management of industrial production factors and reducing pollutant emissions is one of the important ways to improve ECILU on the basis of building a sustainable city [69].

5. Conclusions

Evaluating ECILU can show the utilization efficiency and sustainable development level of industrial land in various cities in China to a certain extent. It has practical significance and reference value for urban economic and intensive land use, metropolitan circle coordination, and industrial innovation and optimization development. With 13 metropolitan areas, including 78 cities selected and relevant indicators collected as samples from 2007 to 2018, this study used the undesirable output SBM model to measure the ECILUs in various prefecture-level cities and metropolitan areas and a Tobit regression model was constructed to explore the factors affecting the ECILUs in different economic zones. We conclude the following:

From the ECILU calculated results, the average ECILU in the statistical period was only 0.293, and the differences between the 78 cities were very large. The ECILUs of the cities in the Western Economic Zone were the highest over the 12 years studied, followed by the Eastern and Central Economic Zones, and the efficiency of the Northeastern Economic Zone was the lowest. In addition, the calculation of metropolitan areas showed that the ECILUs of cities in most metropolitan areas varied greatly, and the degree of urban coordination was low, which may have been due to more opportunities for industrial land expansion in the central cities of the metropolitan area, inhibiting the development of other cities and widening the gap between cities in the metropolitan area.

From the regression results of the influencing factors, each factor had obvious regional heterogeneity. Urban scale had a positive impact on the ECILU in the whole sample, the Eastern Economic Zone, Northeastern Economic Zone, and Central Economic Zone. Industrial structure had a significant negative impact in the Eastern Economic Zone and a positive impact in the Western Economic Zone. Regional population quality and Sulfur dioxide pollution had appreciable negative correlations with the ECILU in the whole sample, as well as the four economic zones. Regional green coverage significantly impacted the other economic zones, except the Eastern Economic Zone. Industrial wastewater pollution had a negative correlation with ECILU in the Eastern Economic Zone, the Northeastern Economic Zone, and the Central Economic Zone. Therefore, as for cities with different geographical locations and different levels of economic development, corresponding countermeasures should be adopted to improve or optimize the input of factors according to the influential effects of different variables in the region. For example, the Eastern Economic Zone, with its rapid economic development and strong talent re-serves, should emphasize the important role of economic scale in ecological governance, and attention should also be paid to problems such as labor surplus and soil pollution. For the Western Economic Zone, it is necessary to carry out regional industrial upgrades and structural optimization. For the Central and the Northeastern Economic Zone, attention should not only be paid to the optimization of the industrial structure but also balancing the relationship between the green area coverage and the industrial land area. Only by using urban land resources efficiently and promoting the economical and intensive use and effective protection of natural resources can the improvement of the regional ecological environment be promoted [70], the emission of industrial pollution can be reduced, and the ECILU can be improved.

In summary, the ECILU was not the same as the level of local industrial economic development; therefore, ECILU evaluation based on economic benefits as the output index will no longer apply to the needs of high-quality urban development. In the future, when evaluating ECILU, the local government should establish a better evaluation system that includes economic, social, ecological, and other factors, rather than blindly pursuing economic development and sacrificing social and environmental benefits. Meanwhile, in order to increase the growth of the industrial economy and the ECILU while ensuring environmentally friendly development, it is necessary to reinforce the flow of resources and factors between cities and promote coordination between cities in the metropolitan area to truly implement the policy guidance of local governments in improving the utilization of industrial land, optimizing the spatial layout of urban land, and promoting the coordinated and high-quality development of cities.

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