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Spatiotemporal differences and convergence of urban industrial land use efficiency for China's major economic zones

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Abstract: Based on an SBM model, this paper first analyzes the spatial differences of urban industrial land use efficiency (UILUE) in the six main economic zones of China. Then, we analyze the dynamic changes in the urban industrial land's total factor productivity (UILTFP) by using the Malmquist productivity index approach, and we examine the UILTFP's convergence. The results show that the Pearl River Delta and the Yangtze River Delta have a higher UILUEs but show downward trends in UILTFPs. The other four zones, Beijing-Tianjin-Hebei, Chengdu-Chongqing, Guanzhong-Tianshui and the Central Plains, show poorer UILUEs but have upward trends in UILTFPs. A significant excess supply of industrial land and labor exists in all six zones, and the zones in economically developed areas perform better in industrial output. The results of the convergence test do not support σ-convergence but support conditional *β*-convergence for all zones. These results indicate that the gaps in the UILTFP of industrial land in all six zones, in fact, do not narrow, and the UILTFPs of cities will converge to their own steady states. The regression results of the influencing factors show that the urbanization rate should be increased in the Pearl River Delta and reduced in Beijing-Tianjin-Hebei. The Yangtze River Delta and Chengdu-Chongqing should pay more attention to the problem of industrial labor surplus, and the Pearl River Delta should reduce the proportion of industrial output. All zones should focus on improving the quality of the industrial economy and the land use intensity.

Keywords: industrial land; economic zone; efficiency; convergence; SBM model

1 Introduction

China has achieved rapid development in its industrial economy since the reform and opening up. China's industrial output value was 2.11 trillion yuan and accounts for more than 37% of GDP in 2012. On the other hand, the area of urban industrial land has been growing steadily. The total area of urban industrial land was 8712.44 km^2 in 2012 and shows an increase of 51.02% since 2002. The total area of urban industrial land also accounts for

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19.04% of the total area of the urban construction land, which ranks first in the types of production land. However, this ratio is typically not more than 10% in many developed countries and regions, which almost all show downward trends. Thus, it is important to analyze China's urban industrial land use efficiency (UILUE) and provide constructive suggestions (Meng *et al.*, 2008; Huang *et al.*, 2009).

Studies on industrial land can be traced back to the beginning of the 20th century (Weber, 1909). Since then, studies have considered more the industrial layout at the micro (Fetter, 1924; Losch, 1954; Isard, 1956) and macro levels (Beckman, 1968) and the price of industrial land (Hicks, 1985; Sato, 1995) and its estimation methods. The evaluations of intensive land use and efficiency have also attracted much attention in recent years (Fang, 2004; Wu, 2011; Li, 2014), which is important because of increasingly scarce urban industrial land resources. In recent years, much of the literature has focused on the evaluation of the UILUE from many aspects in modern day China. This evaluation includes the construction of an evaluation index system (Chen *et al.*, 2002; Wang *et al.*, 2006), evaluation models (Dong *et al.*, 1989; Luo *et al.*, 2003), the driving factors and their influencing mechanisms (Zhuang *et al.*, 2011; Guo *et al.*, 2014), and the spatiotemporal disparities among provinces (Chen *et al.*, 2014) and cities (Zhang *et al.*, 2014).

Regarding an evaluation index system, Liu *et al.* (2008) conducted an empirical analysis of the urban land use efficiency in Shandong Province. Efficiency is expressed as economic output per unit area of land, and other research has also employed this method to evaluate the efficiency of land use in some regions of China. However, Wu *et al.* (2011) argued that a single-factor index cannot adequately express the complex process of land use and factors such as labor and capital, and other factors from many aspects (e.g., society and environment) should also be considered. Since this study, a growing number of literature has adopted a multi-factor index system in the evaluation of land use efficiency (Xiong *et al.*, 2013; Guo *et al.*, 2014; Feng *et al.*, 2014).

Concerning methodology, many methods have been developed and applied in recent studies (e.g., the analytic hierarchy process (AHP), principal component analysis (PCA), and data envelopment analysis (DEA)). Hu *et al.*(2001) adopted the AHP in their study of land use efficiency in Zhongshan city; by setting four strategic targets and scoring the weight matrices, they calculated values and provided policy recommendations. Zhai *et al.* (2006) applied PCA to analyze intensive land use potential in typical urban development zones of Jiangsu Province. They established a complex index system to express a variety of land uses and create several levels of land use efficiency; thus, different regions can take corresponding measures to improve. In recent years, DEA has grown popular in efficiency evaluations (Wu *et al.*, 2011; Guo *et al.*, 2014; Feng *et al.*, 2014). The AHP and PCA are unsuitable for efficiency evaluation because the value of weights in the AHP method is decided by subjective scoring, and dimension reduction in PCA is accompanied by information compression. In contrast, DEA has the advantage of not needing to set specific functions and parameter weights (Charnes *et al.*, 1978). This model was improved later to obtain more scientific and reasonable evaluation results and was named the SBM (slack based model), which is realized by inserting slack variables directly in the objective function (Tone, 2001). Additionally, several studies have also analyzed efficiency disparities in industrial land use among regions (Lei *et al.*, 2009; Guo *et al.*, 2014), but almost all of them only provide some graph descriptions without a detailed analysis. Convergence is a useful tool to describe detailed inequality in the use of resources, but there is still no literature that employs the convergence test in studies on land use efficiency.

Significant differences exist regarding the selection of influencing factors in the literature. Per capita GDP, the structures of the labor force and the industrial layout are generally considered to have important influence on industrial land use (Shi, 2009). The price of land, the degree of industry openness and land policies are also considered in some studies (Guo *et al.*, 2014). When more factors are considered in studies, more scientific and reasonable conclusions can be made.

This paper will make two main contributions to the studies on China's industrial land use. First, the static UILUE, and dynamic changes of the urban industrial land's total factor productivity (UILTFP) for China's major economic zones are evaluated by using an SBM model and the Malmquist productivity index for the first time. Second, disparities and trends of the UILUE among cities in China's major economic zones are first analyzed by a convergence test.

In this paper, the following questions will be addressed.

(1) What is the general UILUE of the major economic zones? Which are the top or bottom performers?

(2) What is the general situation and decomposition of the UILTFP?

(3) Do σ-convergence and β-convergence exist in the disparities of the UILTFP for the major economic zones?

(4) Which factors influence the UILTFP and what are the influencing mechanisms?

The remainder of this paper is organized as follows. Section 2 describes the general study area. Section 3 introduces the methods used in this paper, which consist of the SBM model, Malmquist production index and convergence test. Section 4 describes the indexes and data. Section 5 employs the above methods to analyze the general UILUE and UILTFP, the convergence test and an OLS regression of influencing factors. Section 6 concludes with some suggestions for future studies.

2 General study area

The study area in this paper includes six major economic zones, namely, the Yangtze River Delta, the Pearl River Delta, Beijing-Tianjin-Hebei, Chengdu-Chongqing, the Central Plains and Guanzhong-Tianshui. According to the latest classification of national economic zones, the GDP (trillion yuan), population (million persons) and cities of each economic zone are shown in Table 1, the distributions of economic zones and their cities are shown in Figures 1 and 2.

3 Method

3.1 SBM model

A meaningful conclusion in the DEA model is that there will always be a certain gap between actual resource allocation and optimal resource allocation, which can be called the slack variable and expressed as an input excess or output shortage of the observation. One

Table 1 General situation of China's six major economic zones in 2012

Economic zone	GDP	Population	Cities at prefecture level and above
Yangtze River Delta	11.96	157.66	All cities in Jiangsu and Zhejiang provinces, Shanghai, Hefei, Ma'anshan, Wuhu, Chuzhou and Huainan
Beijing-Tianjin-Hebei	5.2	74.92	Beijing, Tianjin, Shijiazhuang, Qinhuangdao, Tangshan, Langfang, Baoding, Cangzhou, Zhangjiakou and Chengde
Pearl River Delta	4.78	30.79	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Dongguan, Zhongshan, Huizhou and Zhaoqing
Chengdu-Chongqing	3.33	109.09	Chongqing, Chengdu, Deyang, Mianyang, Meishan, Ziyang, Suining, Leshan, Ya'an, Zigong, Luzhou, Neijiang, Nanchong, Yibin, Dazhou and Guang'an
Guanzhong-Tianshui	0.96	29.45	Xi'an, Baoji, Xianyang, Tianshui, Tongchuan, Weinan and Shangluo
Central Plains	4.52	179.43	All cities in Henan Province, Liaocheng, Heze, Xingtai, Handan, Huaibei, Suzhou, Bengbu, Bozhou, Fuyang, Yuncheng, Jincheng and Changzhi

Note: Chongqing city is merged into the Chengdu-Chongqing economic zone because of data availability.

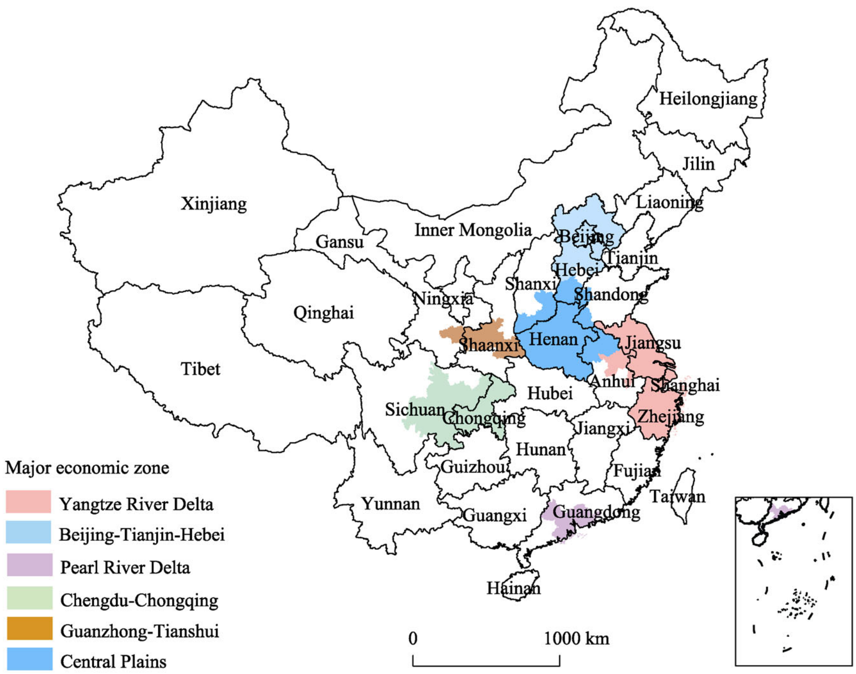

Figure 1 China's six major economic zones

problem of the traditional DEA model is that the slack variables are not considered in the objective function, which can lead to inaccurate results in efficiency evaluations. To overcome this problem, Tone has presented a non-radial and nonparametric SBM model (2001), which can incorporate slack variables in the objective function. The SBM model can be expressed as follows:

Suppose that there are n DMUs, and each DMU has M inputs (x) to produce J outputs (y). In this paper, they can be denoted by the vectors $x \in R^M$, $y \in R^J$, and then, we can define the matrices X and Y as $X = [x_{11}, \ldots, x_{Mn}] \in R^{M\times n}$, $Y = [y_{11}, \ldots, y_{Mn}] \in R^{J\times n}$, respectively. X>0, Y>0.

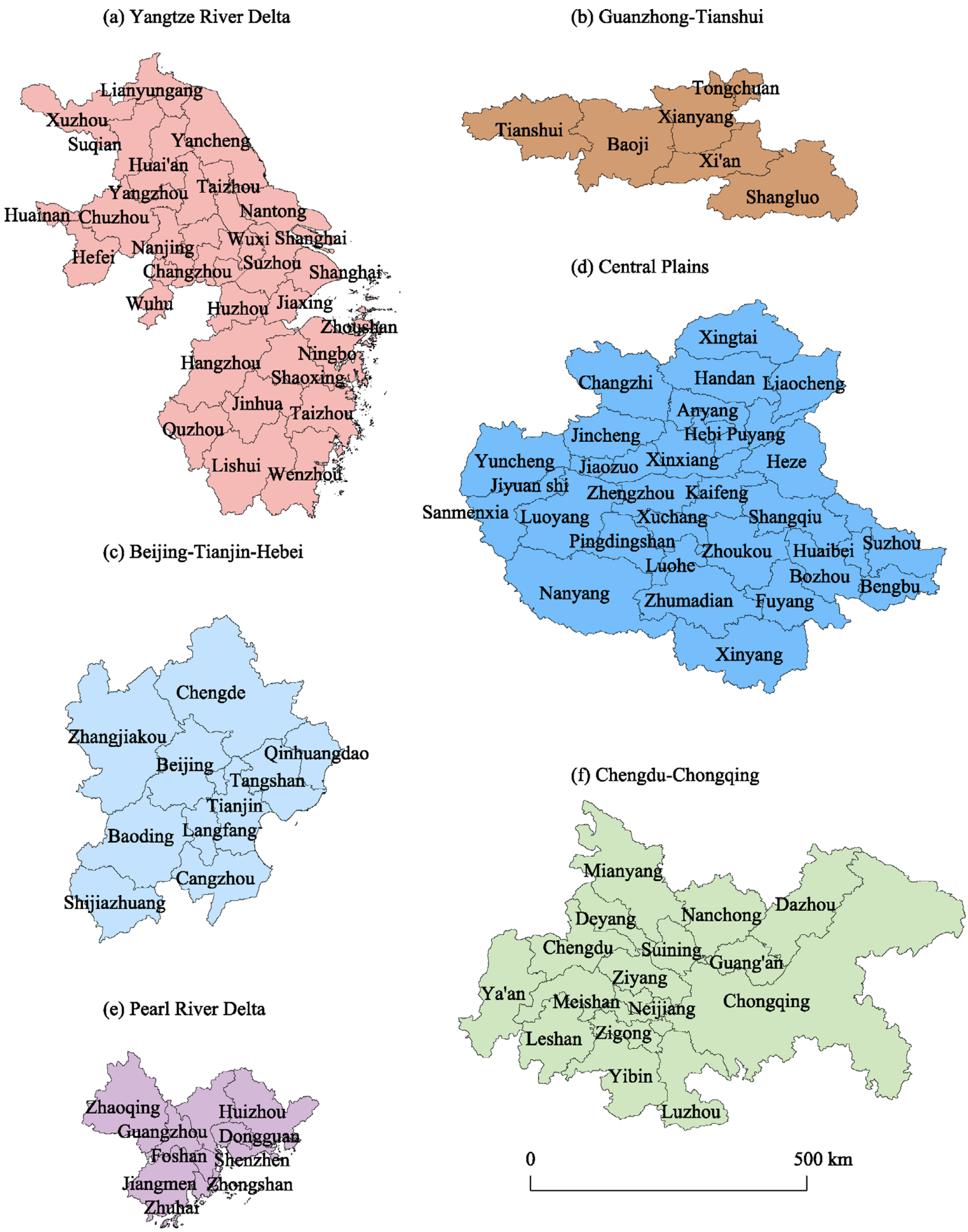

Figure 2 Distribution of cities in the six economic zones

In this way, production technology can be expressed as:

$$T = \{(x, y) |\ x \text{ can produce } y,\ x \geqslant X\lambda,\ y \leqslant Y\lambda, \lambda \geqslant 0\} \tag{1}$$

where T is always assumed to satisfy the production theory (Fare *et al.*, 2005). The objective function can be expressed as:

$$\rho = \min \frac{1 - \frac{1}{M}\sum_{m=1}^{M}\frac{s_{m0}^{x}}{x_{m0}}}{1 + \frac{1}{J}\sum_{j=1}^{J}\frac{s_{j0}^{y}}{y_{j0}}}$$
$$\text{S.T.}\begin{cases} x_0 = X\lambda + s_0^x \\ y_0 = Y\lambda - s_0^y \\ \lambda \geqslant 0,\ s_0^x \geqslant 0,\ s_0^y \geqslant 0 \end{cases} \tag{2}$$

where m and j represent the indexes of inputs and outputs, respectively. M and J represent the number of inputs and outputs, respectively. s^x and s^y represent the slack variables of inputs and outputs, respectively. The subscript 0 represents the DMU which is underestimated, and ρ represents its efficiency value. λ represents the nonnegative multiple vector.

When ρ=1, s_0^x and s_0^y are all equal to 0, the DMU_0 is strongly efficient; and the DMU is weakly efficient when s_0^x and s_0^y are not all equal to 0. When ρ<1, the DMU is inefficient, and it is necessary to adjust the input-output structure. To make this DMU efficient, we should make adjustments such as $x_0 = X\lambda + s_0^x$ and $y_0 = Y\lambda - s_0^y$.

In contrast, we can obtain the optimization methods of efficiency by analyzing the slack variable ratios of inputs and outputs. The ratio of input excess to total input is computed by Eq. (3):

$$\overline{X} = \frac{1}{M}\sum_{m=1}^{M}\frac{s_{m0}^{x}}{x_{m0}} \tag{3}$$

The ratio of output shortage to maximum output is computed by Eq. (4):

$$\overline{Y} = \frac{1}{J}\left(\sum_{j=1}^{J}\frac{s_{j0}^{y}}{y_{j0}}\right) \tag{4}$$

3.2 Malmquist productivity index

The evaluation of the efficiency based on the SBM model is a type of static analysis, of which the results from different years cannot be compared with one another. To solve this problem, data envelopment analysis is combined with the Malmquist productivity index so that changes of total factor productivity (TFP) can be evaluated over time. This method has been improved by many scholars and widely used in the productivity measurements of various industries and resources (Fare *et al.*, 2005). Therefore, we employ TFP to analyze the dynamic changes of the efficiency. We can express the production technology as Eq. (1), and according to Shepherd’s distance functions, TFP can be defined by Eq. (5) (Zhang *et al.*, 2013):

$$\begin{aligned} TFP_i(y^{t+1}, x^{t+1}, y^t, x^t) &= \sqrt{\left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)}\right]\left[\frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^t, y^t)}\right]} \\ &= \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)}\sqrt{\left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})}\right]\left[\frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)}\right]} = TEC_i \times EC_i \end{aligned} \tag{5}$$

where x^t and x^{t+1} are defined as input vectors in time t and t+1, respectively. y^t and x^{t+1} are defined as output vectors in time t and t+1, respectively. Therefore, the productivity change of DMU_i between period t and t+1 can be defined by TFP_i. If the value of TFP_i is greater than 1, then the TFP of DMU_i has increased from t to t+1. If the value is less than 1, the TFP of DMU_i has decreased from t to t+1. In addition, TFP_i can be decomposed into two indexes named TEC_i and EC_i, which represent technology change and efficiency change, respectively. Technology change means the shift of production technology frontier, and efficiency change means a shift of DMU_i on the same technology frontier.

3.3 Convergence

The concept of convergence originates from neoclassical economics, which applies this tool to analyze the differences of per capita income among regions (Solow, 1953). In this paper, we apply this method to analyze the disparity of the UILTFPs among cities in the six major economic zones. There are usually two types of convergence, σ-convergence and β-convergence, and β-convergence also includes two types of convergence named absolute and conditional convergence. According to Eq. (6), σ-convergence can be measured by the standard deviation of the UILTFPs of cities in the six zones over time (Quah, 1993). σ-convergence exists if there is a clear decline of the standard deviation over time, which implies that the UILTFP gap among cities has been gradually narrowing. The measurement of absolute β-convergence can be observed in Eq. (7), which implies that the efficiencies of all cities converge to the same steady state if coefficient β is significantly negative. Because of the controversial absolute β-convergence's rationality, we choose σ-convergence here to analyze the absolute disparities among the UILTFP of cities in the six zones. In addition, the measurement of conditional β-convergence can be observed in Eq. (8), which implies that the UILTFP of cities in different zones converge to their own steady states if coefficient β is negative (Sala-I-Martin X, 1996).

σ-convergence:

$$\sigma_t = \sqrt{\left[\sum_{i=1}^{n}\left(\ln Y_{i,t} - \frac{1}{n}\sum_{i=1}^{n}\ln Y_{i,t}\right)^2\right]/n} \tag{6}$$

absolute β-convergence:

$$\frac{1}{T}\ln(Y_{i,t+T}/Y_{i,t}) = \alpha_0 + \beta_0 \ln Y_{i,t} + \varepsilon_{i,t} \tag{7}$$

conditional β-convergence:

$$\frac{1}{T}\ln(Y_{i,t+1}/Y_{i,t}) = \alpha_1 + \beta_1 \ln Y_{i,t} + \sum_{j=1}^{J}\gamma_j x_{i,t}^{j} + \varepsilon_{i,t} \tag{8}$$

where α_0 and α_1, are constants and i=1, …, n represents the cities. Y represents the UILTFP, and $x_{i,t}^{j}$ is the jth influencing factor of the ith city in period t. T is the study time period, and $\varepsilon_{i,t}$ is the stochastic error. Therefore, if the coefficients of absolute or conditional β-convergence are significantly negative, then absolute or conditional β-convergence exists.

4 Index and data

4.1 Input and output indexes

Industrial production comprises a series of complex activities; thus, the UILUE and UILTFP are affected by the factors of many aspects (e.g., economy and society) (Lee *et al.*, 2014). Therefore, according to the production function theory and data availability, we select land, labor and capital as inputs, which are represented by urban industrial land, industrial labor force, and industrial fixed asset investment. Industrial land sustains all industrial economic activities in the cities; industrial labor and capital are the bases of industrial production. Moreover, we select industrial economic output as the output factor, which can directly reflect the output of industrial development. Additionally, we select some of the following variables from the socioeconomic development, the structure of the industry and labor force, and the status of land use as driving factors to explore their effects on the UILTFP.

(1) The urbanization rate (UBR) is represented by the ratio of the population in a metropolitan area to the total population of the city. According to the experiences of developed countries, industrial production technology will be enhanced with the increase of the urbanization rate; therefore, we can assume that the urbanization rate is positively related to the UILTFP.

(2) The per capita GDP (PGDP) represents the level of local economic development, but its impact on the UILTFP cannot be certain because we are unsure whether the development mode in these zones is extensive or intensive.

(3) The ratio of industrial workers to total labor force (LP3) represents the structure of the local labor force.

(4) The degree of industrialization (IND) is represented by the ratio of industrial economic output to total local GDP. According to the Petty-Clark theorem, the centers of labor and industrial distribution will transfer from the primary industry to the secondary industry and then to the tertiary industry with the development of the economy. Because China is roughly in the middle and late stages of industrialization, the LP3 and IND should be negatively related to the UILTFP.

(5) Industrial land use intensity (USE) is represented by industrial output per unit of land area and can satisfactorily exhibit the status of land use. Clearly, higher economic output per unit of land area indicates better intensive use of industrial land; therefore, the USE should be positively related to the UILTFP.

4.2 Data

In this paper, the data come from the *China City Statistical Yearbook* (2003–2013), the *Regional Economic Statistical Yearbook* (2003–2013) and the *China Statistical Yearbook* (2003–2013). Because the data of some cities cannot satisfy the study parameters, 270 cities at the prefecture level and above are selected, which account for more than 85% of the total number of cities in China. To exclude the impact of price, the values of industrial fixed asset investment and industrial economic output are converted to constant prices based on 2000, according to the deflectors of fixed assets and GDP, respectively.

5 Empirical results

5.1 Urban industrial land use efficiency

An efficiency evaluation by an SBM model is a static analysis of each year, which means the result in one year cannot be compared with the results in other years. Therefore, we use the average values of the UILUEs of all cities during the study period to exhibit the overall situation in Table 2.

Table 2 The UILUEs of China's six major economic zones from 2002–2012

Economic zone	Average UILUE of zones	UILUEs of all cities
Pearl River Delta	0.675	Foshan (1)*, Dongguan (1), Zhongshan (0.971), Guangzhou (0.55), Huizhou (0.53), Jiangmen (0.501), Zhaoqing (0.441), Zhuhai (0.406)
Yangtze River Delta	0.592	Suzhou (1), Lishui (1), Taizhou (0.862), Wuxi (0.837), Shaoxing (0.802), Changzhou (0.775), Zhoushan (0.699), Taizhou (0.692), Hangzhou (0.675), Nantong (0.671), Yancheng (0.66), Yangzhou (0.641) , Jinhua (0.635), Suqian (0.6), Wenzhou (0.559), Ningbo (0.548), Chuzhou (0.529), Huzhou (0.528), Xuzhou (0.516), Zhenjiang (0.497), Wuhu (0.479), Nanjing (0.455), Jiaxing (0.455), Huai'an (0.452), Hefei (0.42), Lianyungang (0.389), Quzhou (0.382), Ma'anshan (0.297), Huainan (0.124)
Chengdu-Chongqing	0.534	Ziyang (0.96), Guang'an (0.874), Nanchong (0.804), Neijiang (0.636), Yibin (0.597), Zigong (0.545), Dazhou (0.533), Meishan (0.524), Suining (0.49), Deyang (0.481), Luzhou (0.414), Mianyang (0.389), Ya'an (0.369), Leshan (0.328), Chengdu (0.32), Chongqing (0.275)
Beijing-Tianjin-Hebei	0.473	Langfang (0.765), Cangzhou (0.693), Tianjin (0.565), Shijiazhuang (0.552), Baoding (0.437), Chengde (0.416), Beijing (0.386), Tangshan (0.378), Qinghuangdao (0.323), Zhangjiakou (0.215)
Central Plains	0.458	Luohe (0.795), Sanmenxia (0.697), Zhoukou (0.695), Xuchang (0.644), Heze (0.628), Liaocheng (0.603), Jiaozuo (0.49), Anyang (0.48), Zhumadian (0.48), Puyang (0.478), Shangqiu (0.463), Zhengzhou (0.455), Yuncheng (0.449), Xingtai (0.448), Xinyang (0.445), Handan (0.441), Bozhou (0.44), Hebi (0.436), Nanyang (0.418), Kaifeng (0.412), Xinxiang (0.403), Luoyang (0.392), Fuyang (0.369), Bengbu (0.366), Suzhou (0.322), Pingdingshan (0.312), Changzhi (0.288), Jincheng (0.241), Huaibei (0.183)
Guanzhong-Tianshui	0.436	Shangluo (1), Tianshui (0.463), Baoji (0.358), Weinan (0.288), Tongchuan (0.257), Xi'an (0.247)

* The numbers in parentheses represent the values of urban industrial land efficiency.

According to Table 2, out of 98 cities, only 5 cities, namely, Foshan, Dongguan, Suzhou, Lishui and Shangluo, were consistently efficient during the study period, and they account for 5.1% of the total number of cities. Clearly, most cities are inefficient in industrial land use, and they have significant room for improvement.

For the individual zones, the Pearl River Delta shows the best UILUE with an average value of 0.675 and is followed by the Yangtze River Delta, with an average value of 0.592. These values indicate that the UILUEs in the two zones could increase by 32.5% and 40.8%, respectively, if industrial production activities are performing efficiently for all cities in the two zones. Additionally, the zones of Chengdu-Chongqing, Beijing-Tianjin-Hebei, the Central Plains and Guanzhong-Tianshui show poorer performance, with average values of 0.534, 0.473, 0.458 and 0.436, respectively. Notably, of the 6 cities in Guanzhong-Tianshui, only Shangluo continuously had an efficiency value of 1, whereas the average value of the other 5 cities is only 0.323. These results indicate a significant UILUE gap among cities in this zone.

In general, it is crucial to improve the UILUE. According to Eqs. (3) and (4), we can find the optimization methods by calculating the ratios of input excesses and output shortages.

According to Table 3, input excesses and output shortages exist in all six major economic zones. Regarding the input factors, Beijing-Tianjin-Hebei ranks first in the excess ratios of industrial land and capital, with values of 63.6% and 26.5%, respectively. These values indicate that Beijing-Tianjin-Hebei can save 63.6% of industrial land and 26.5% of capital. Guanzhong-Tianshui shows the greatest ratio of 60.69% in labor excess and can save 60.69% of its industrial labor force with the same outputs. Moreover, all the excess ratios of land and labor in the six zones are greater than 30%, which indicates a significant waste of industrial resources in all six zones. Concerning the output factor, the Pearl River Delta, the Yangtze River Delta and Beijing-Tianjin-Hebei show lower ratios of output shortage of 9.18%, 21% and 24.43%, respectively. On the contrary, Guanzhong-Tianshui ranks first in the shortage ratios with a surprising value of 113.51%, which indicates that Guanzhong-Tianshui can increase industrial GDP by 113.51% with the same inputs. In addition, the zones in economically developed eastern China (e.g., the Pearl River Delta and the Yangtze River Delta) perform significantly better in industrial output than the zones in less developed central and western China (e.g., Guanzhong-Tianshui and the Central Plains).

Table 3 Optimization of urban industrial land use efficiency in China's six major economic zones

Economic zone	Excesses (%)			Shortages (%)
	Land	Labor	Capital	GDP
Pearl River Delta	32.24	49.6	6.44	9.18
Yangtze River Delta	46.86	36.54	5.03	21
Chengdu-Chongqing	63.13	54.92	12.62	53.79
Beijing-Tianjin-Hebei	63.6	51.44	26.5	24.43
Central Plains	43.43	46.31	6.16	58.96
Guanzhong-Tianshui	56.44	60.69	1.89	113.51

In general, 1450 square kilometers of industrial land, 8.82 million laborers and 672.3 billion yuan of industrial fixed asset investment can be saved. Moreover, an increase of 3.18 trillion yuan of industrial economic output could have been realized every year during the study period if all cities were efficient in industrial production. Therefore, the rational use of resources should be considered to improve input and output efficiency.

The previous efficiency evaluation based on the SBM model is a type of static analysis that cannot be used to study dynamic changes over time. Therefore, the Malmquist productivity index is applied in this paper to analyze the dynamic changes of the UILTFP during the study period. Table 4 shows the decomposition of the Malmquist productivity indexes. The average value of the UILTFP from 2002–2012 is 1.008 considering all six zones as a whole, which means that the UILTFP for all the six zones increased by 0.8% every year.

According to Eq. (5), the UILTFP can be decomposed into two indexes that are called the efficiency change index (EC) and the technology change index (TEC). As Table 4 shows, the average value of EC during the study period is 1.024, which is greater than 1, and it indicates an increase in efficiency of industrial land use. However, the average value of TEC is 0.985, which is less than 1, and it indicates receding technology for industrial production.

Table 4 Decomposition of the Malmquist productivity indexes during 2002–2012

Year	UILTFP	EC	TEC
2002–2003	1.195	0.998	1.198
2003–2004	1.106	1.132	0.977
2004–2005	1.006	1.008	0.997
2005–2006	0.974	0.929	1.048
2006–2007	0.99	1.089	0.91
2007–2008	0.99	0.996	0.995
2008–2009	0.834	0.976	0.855
2009–2010	1.04	1.001	1.039
2010–2011	0.864	0.929	0.93
2011–2012	1.134	1.213	0.935
Average	1.008	1.024	0.985

Table 5 shows the decompositions of the UILTFP for the individual zones. Chengdu-Chongqing's UILTFP shows the highest average value of 1.033, which indicates that the UILTFP in Chengdu-Chongqing increases 3.3% annually. The values of the UILTFPs in the Central Plains, Guanzhong-Tianshui, and Beijing-Tianjin-Hebei are also greater than 1, which indicate that the UILTFPs in these zones show upward trends. In contrast, the UILTFPs of the Yangtze River Delta and the Pearl River Delta are only 0.985 and 0.958, respectively, which are less than 1 and indicate that the UILTFPs in these two zones show downward trends.

Table 5 Decomposition of the Malmquist productivity indexes for China's six major economic zones

Economic zone	UILTFP	EC	TEC
Chengdu-Chongqing	1.033	1.047	0.986
Central Plains	1.03	1.045	0.985
Guanzhong-Tianshui	1.021	1.05	0.972
Beijing-Tianjin-Hebei	1.015	1.025	0.99
Yangtze River Delta	0.985	1	0.985
Pearl River Delta	0.958	0.977	0.981
Average	1.007	1.024	0.983

Regarding the decomposition indexes, the TEC values in all zones are less than 1, which indicate backward technology in industrial production in all zones. Therefore, industrial production technology urgently requires improvement. The EC values in all zones are greater than 1, except the Yangtze River Delta and the Pearl River Delta; in particular, the EC value in the Pearl River Delta is only 0.977, which implies a decrease in the UILUE. The UILUE in the Yangtze River Delta and the Pearl River Delta is higher than in the other four zones. Therefore, a better use of industrial land is shown in the Pearl River Delta and the Yangtze River Delta, whereas the other four zones are catching up and even overtaking them.

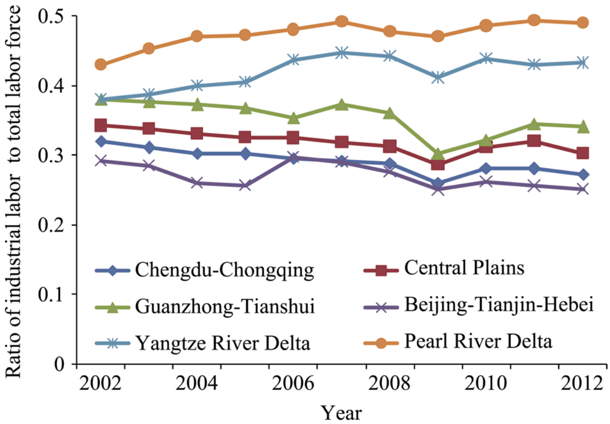

Figure 3 Ratio of industrial labor force to total labor force for each economic zone during 2002–2012

Considering that China's industrial economy is transitioning from labor intensive to technology intensive, an industrial labor surplus may be an important factor that negatively influences land use efficiency and the improvement of production technology. Figure 3 shows the changes in the ratios of industrial labor force to total labor force in each economic zone during the study period. The ratios in the Pearl River Delta and the Yangtze River Delta are on average more than 50% and 40%, respectively, and they trend upward during the study period. In contrast, the ratios in the other four zones are much less and show declining trends, especially in Beijing-Tianjin-Hebei where the ratios are even consistently less than 30%. Therefore, a serious industrial labor surplus has impeded improvements to the UILTFP. Moreover, from the land price perspective, industrial land resources in the Pearl River Delta and the Yangtze River Delta account for more than half of the total of the six economic zones, whereas the land prices in these locations are relatively low. In 2012, the average industrial land prices in Shanghai, Suzhou and Guangzhou were approximately 500, 684 and 674 yuan per square meter, respectively. In contrast, the price in Beijing was as high as 984.75 yuan per square meter in the same year. These results imply that a relative abundance of resources and low prices can easily cause an inability to improve the UILTFP; therefore, an appropriate increase in industrial land price should positively impact industrial land use.

5.2 Convergences

According to Eq. (6), the UILTFP's standard deviations in China's six major economic zones can be calculated, and the trends of the UILTFP's standard deviations are shown in Figure 4. Similarly, according to Eq. (8), the results of conditional β-convergence are shown in Table 6.

5.2.1 σ-convergence

According to Figure 4, the results do not support σ-convergence for all zones during the study period; the UILTFP gaps in all zones have fluctuated continuously, and the gaps do not disappear in the study period. The standard deviation of the UILTFPs in Chengdu-Chongqing ranks first with

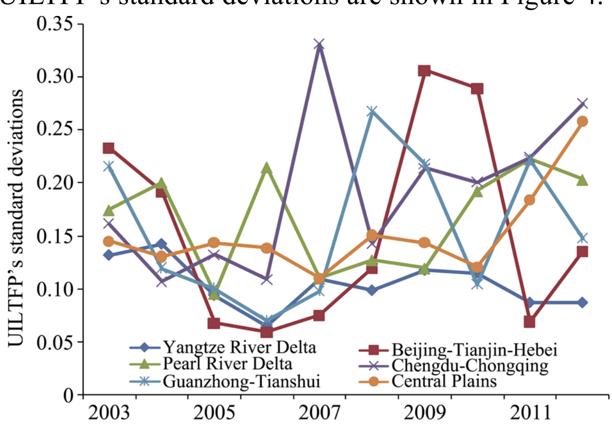

Figure 4 Trends of the UILTFP's standard deviations in China's six major economic zones

Table 6 Conditional β-convergence results of the UILTFP

	Yangtze River Delta	Beijing-Tianjin-Hebei	Pearl River Delta	Chengdu-Chongqing	Guanzhong-Tianshui	Central Plains
Constant	–0.102*	–0.108	0.178	0.036	0.022	–0.055
	(1.889)	(–0.963)	(1.456)	(0.198)	(0.126)	(–1.018)
β_1	–1.017***	–1.382***	–1.149***	–1.221***	–1.095***	–1.211***
	(–21.21)	(–15.256)	(–11.035)	(–12.924)	(–7.904)	(–19.419)
γ_{j1}	0.015	–0.377*	0.28**	0.241	0.061	–0.024
	(0.466)	(–2.39)	(2.491)	(0.306)	(0.432)	(–0.271)
γ_{j2}	–9.1E-07**	–5.61E-06*	–3.8E-06*	–2.28E-06	–4.99E-06	–3.74E-07
	(–2.446)	(2.391)	(–2.252)	(–0.669)	(–1.462)	(–0.293)
γ_{j3}	–0.112*	–0.419	–0.266	–0.546*	–0.002	–0.041
	(–1.918)	(–1.368)	(–1.478)	(–2.042)	(–0.003)	(–0.434)
γ_{j4}	0.002*	0.003	–0.003	0.001	0.0002	0.0005
	(1.846)	(0.999)	(–1.004)	(0.138)	(0.034)	(0.377)
γ_{j5}	1.74E-08*	3.09E-8*	5.23E-08*	8.05E-08***	8.24E-08	5.53E-08***
	(2.017)	(1.814)	(2.089)	(4.687)	(1.293)	(9.711)
Adjusted-R^2	0.771	0.737	0.731	0.579	0.644	0.712

Note: *, ** and *** represent the significance level of 10%, 5% and 1%, respectively. The values in the parentheses refer to t-values.

0.19, and the Yangtze River Delta ranks last with only 0.1. These results indicate that the UILTFP gaps in Chengdu-Chongqing is greater than in other zones, which may be caused by economic imbalances. The UILTFP gaps in the Yangtze River Delta is the least, which may be attributed to adequate and balanced regional economic development.

5.2.2 Conditional β-convergence

Table 6 shows that the results support conditional β-convergence for all zones during the study period. All zones' coefficients β are significantly negative, which indicates that the UILTFPs in all cities will converge to their own steady level states over time. Therefore, the cities with low UILTFPs may not be able to catch up to cities with higher UILTFPs, which implies that the UILTFP gaps among the cities have always been there but because of σ-convergence.

Concerning individual influencing factors, the coefficients of the urbanization rate are only statistically significant in Beijing-Tianjin-Hebei and the Pearl River Delta, with negative and positive signs, respectively. Therefore, an increase and decrease of urbanization rates in the two zones, respectively, can enhance the UILTFP. This conclusion may be because the urbanization rates in 2012 for Beijing and Tianjin, which are located in Beijing-Tianjin-Hebei, were as high as 94% and 81.8%, respectively, whereas the number was only 68.5% in the Pearl River Delta at the same time.

Moreover, the coefficients of per capita GDP are significantly negative in the Yangtze River Delta, Beijing-Tianjin-Hebei and the Pearl River Delta, whereas the coefficients in the other zones are not statistically significant. This result indicates a negative relation between per capita GDP and the UILTFP. Although ignoring the quality of development is common in these zones, a possible explanation may be that the pursuits of industrial economic output cause a negative relation between per capita GDP and the UILTFP.

The coefficients of the ratio of industrial workers to the total labor force are significantly negative in the Yangtze River Delta and Chengdu-Chongqing; the signs of the coefficients in the other four zones are also negative although not statistically significant, which is consistent with the assumptions. A significant labor force surplus may already exist in these zones, which has impeded the transformation of the industrial development model from labor intensive to technology intensive and caused adverse effects on the UILTFP.

The signs of the coefficients of the degree of industrialization are positive in all zones except in the Pearl River Delta, and the coefficient is statistically significant in only the Yangtze River Delta, which is not consistent with the assumptions. A possible explanation may be because these zones have not entered the middle and late stages of industrialization except the Pearl River Delta. Therefore, the ratios of industrial economic output to total local GDP in these areas must be further increased.

Finally, the coefficients of industrial land use intensity are significantly positive in all zones, which is consistent with the assumptions. This result indicates that the industrial output per unit of land area must be further increased to improve the UILTFP.

6 Conclusions

Based on the SBM model, this paper analyzes the general situation of the UILUE in China's main economic zones. Then, in order to analyze dynamic changes of industrial land use efficiency, a Malmquist productivity index approach is applied to analyze the dynamic changes of the UILTFPs. We also conduct a convergence test to analyze the trends of the cities' UILTFPs. The empirical results are as follows.

(1) Of the 98 cities in the six zones, only 5 cities were always efficient in industrial land use during the study period, whereas other cities were inefficient or efficient in only several single years. The efficiencies of the Pearl River Delta and the Yangtze River Delta are superior to the efficiencies of Beijing-Tianjin-Hebei, Chengdu-Chongqing, the Central Plains and Guanzhong-Tianshui. The results of optimization show that a significant waste of industrial land and labor exists in all zones. And the zones in economically developed eastern China show smaller output shortages than the zones in less developed central and western China.

(2) Overall, the average value of the UILTFP is 1.008, which indicates that the UILTFP increased by 0.8% per year during the study period. The results of the decompositions show that the increase of the UILTFP is mainly attributed to the improvement of efficiency, whereas production technology in all zones shows different degrees of decline. In contrast to efficiency, the UILTFP in the Pearl River Delta ranks last, and the UILTFP in the Yangtze River Delta is somewhat higher; however, both UILTFPs are less than 1, which indicate that the UILTFPs in these two zones are declining. This decline may be caused by a surplus of industrial labor force and a lower price of industrial land in the two zones. On the contrary, the UILTFPs in other zones are greater than 1, which indicate an increasing trend of the UILTFPs in these four zones and imply gaps of land use efficiency among the zones that are narrowing.

(3) The results of the convergence tests do not support σ-convergence for all zones; thus, the gaps of UILTFP in the six zones do not disappear. The gaps among cities in Chengdu-Chongqing rank first, and the gaps in the Yangtze River Delta are the smallest. In addition,

conditional β-convergence exists in all six zones; therefore, the UILTFPs of all cities will converge to their own steady level states over time, which indicates stable development of the UILTFPs in each city.

(4) The regression results of the influencing factors show that the urbanization rate should be increased in the Pearl River Delta and reduced in Beijing-Tianjin-Hebei. A significant industrial labor surplus exists in the Yangtze River Delta and Chengdu-Chongqing, and only the Pearl River Delta has entered the middle and late stages of industrialization. These results indicate that the focus of development should be transferred to the service industry from industry. The per capita GDP in all zones shows a negative relation to the UILTFP and indicates a focus on industrial economic development and increasing GDP rather than the quality of development. Finally, the industrial output per unit of land area must be further increased in all zones.

Several limitations exist in this paper. First, the study period is somewhat short, from 2000–2012, because of data availability; therefore, further studies can consider a longer time period to make the results more reasonable. In addition, the index system can be made more comprehensive in future studies, which will better reflect reality. For example, environmental pollutants, such as industrial wastewater, industrial waste gas and industrial solid waste, can be considered. Additionally, according to the production function of new classical economics and the realities of industrial development in many countries and regions, human capital is an important input element in the process of industrial production that is separated from capital and labor. Therefore, the mutual influence between human capital and industrial land use efficiency would be a suitable topic for future studies.

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