

Urban Land Use Efficiency and Contributing Factors in the Yangtze River Delta Under Increasing Environmental Restrictions in China

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Abstract: Evaluating urban land use efficiency (ULUE) provides insights into the interactions between land use systems and their external environment. Specifically, changes in ULUE are important for monitoring urban transformation in developing countries. In this study, using a traditional input-output index model, we incorporated slack-based measurements and undesirable outputs into a SBM-UN (slack-based measure-undesirable) model to investigate ULUE within the context of increasing environmental restrictions in China. The model was used to estimate the ULUE of 26 cities in the highly developed urban agglomeration of the Yangtze River Delta from 2000 to 2018. The average ULUE in the Yangtze River Delta was relatively low compared to that of developed city regions in the European Union (EU) and North America and exhibited a U-shaped curve over the study period. Incorporating undesirable outputs, such as environmental pollution, into the model reduced ULUE by 19.06%. ULUE varied spatially, with the kernel density estimation exhibiting a bimodal distribution. Efficiency decomposition analysis showed that scale efficiency made a greater contribution to ULUE than pure technical efficiency. Based on our findings, recommended approaches to improve ULUE include optimizing factor allocation, reducing undesirable outputs, and increasing the effective output per land unit. The study suggests that ULUE and the SBM-UN model are useful planning tools for sustainable urban development.

Keywords: urban land use efficiency (ULUE); environmental restriction; efficiency decomposition; kernel density estimation; SBM-UN (slack-based measure-undesirable) model; Yangtze River Delta; China

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1 Introduction

Globally, land resource are an important factor in economic development and environmental protection, particularly in coastal areas characterized by high-density

cities and towns. land resource, whose sustainable management is one of the key goals in the nations' sustainable development goals, play a vital role in human development. During rapid urbanization in developing countries, urban land development takes two main

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forms: intensive land use and horizontal expansion (Barbosa et al., 2015; Zhao et al., 2018b). Intensive urban land use refers to intense socio-economic activity per unit of land, whereas horizontal expansion refers to extensive urban land use for non-agricultural activities (Huang et al., 2018). In China, in particular, rapid urbanization has led to the transformation and restructuring of urban land (Ding and Lichtenberg, 2011; Hegazy and Kaloop, 2015). Considering the importance, scarcity, and limitation of land resource, it is therefore necessary to improve urban land use efficiency (ULUE) in China (Yang et al., 2014; Lu et al., 2018). This is even more important that the supply of urban land is steadily declining because of the increased protection of agricultural and ecological land, with the consequent limitation of urban land expansion (Otto et al., 2015; Bagheri and Tousi, 2018; Liu et al., 2018).

In the Yangtze River Delta, which is one of China's most developed urban agglomerations, the area of urban construction land grew from 8552.3 km² to 22 515.8 km² from 2000 to 2018 (NBSC, 2019), corresponding to an average annual growth rate of 5.53%. This rapid expansion of construction land has led to a series of social and environmental problems, such as the loss of farmland, the reduction of biodiversity, and the urban heat island effect, which all have a negative impact on sustainable urban development (De Vos and Witlox, 2013; Mohajerani et al., 2017; Miller and Brewer, 2018; Lu et al., 2019; Masoudi et al., 2021). To achieve sustainable urban development, governments at various levels have advocated for endogenous urban growth with an intensive land use based on smart growth and compact development (Lee and Lim, 2018; Sciara, 2020). Thus, improving ULUE can increase sustainable urban development and unblock the bottleneck in urban land use.

ULUE describes the benefits produced per unit of urban land and reflects the ability of a region to promote the synergistic development of the society, economy, and environment (Luo et al., 2018; Zhu et al., 2019). Recent ULUE evaluations tend to involve multiple indicators, integrating environmental, social, economic, and other factors to better reflect the complex nature of ULUE (Xie and Wang, 2015; Chen et al., 2016; Wei et al., 2017; Kaur and Garg, 2019). Evaluations should also consider the undesirable outcomes of urban land development, such as environmental pollu-

tion (Huang et al., 2017; Zhu et al., 2019), whose impact can be characterized using non-parametric methods, such as the directional distance function (Wang et al., 2017) and slack-based measurement (SBM). Moreover, ULUE research has been conducted across multiple scales, such as the national, watershed, provincial and urban agglomeration scales, revealing significant spatial variability among regions (Chen et al., 2019). However, there are still many research gaps in the ULUE literature. First, most studies have focused on a limited number of desirable outputs (such as social welfare and economic benefits) and ignored undesirable outputs such as air pollution, carbon emissions, and industrial waste emissions. This may lead to distortion of the results. Second, few studies have decomposed ULUE into pure technical efficiency (PTE) and scale efficiency (SE). Technical and scale efficiencies can be used to determine the degree and direction of factors contributing to ULUE, which can enrich our understanding of ULUE. Third, few studies have explored the potential for improving ULUE while reducing the negative environmental inputs as much as possible. For this, it is important to determine the interaction between the improvement potential and efficiency level under given technical conditions. Therefore, we posed the following questions: 1) How can ULUE be accurately evaluated under the current environmental constraints in China? 2) What are the main contributors to changes in ULUE? 3) How can the ratio of input-to-output production factors be adjusted to improve ULUE?

To answer these questions, taking the Yangtze River Delta as an example, the aim of this study was to measure ULUE and estimate the contributing factors. First, undesirable outputs (e.g., pollution) were incorporated into the data envelopment analysis (DEA) analysis method to build a complete and reliable evaluation model of ULUE based on slack-based measure-undesirable (SBM-UN) model. Second, the SBM-UN model was used to measure the comprehensive efficiency of land use, PTE, and SE. Through this method, the main reasons for the change of ULUE can be found out quantitatively. Third, the improvement potential of ULUE was determined by exploring the degree of input redundancy, desirable output insufficiency, and undesirable output excess. We then reported the spatial-temporal variation of ULUE in the Yangtze River Delta and determined the relative contributions of PTE and SE to

ULUE. Last, we suggested ways to improve ULUE. Through this, we can fully understand the current situation of urban land use, which is conducive to achieve intensive and efficient use of urban land resource and provide scientific evidence for high-quality development in the Yangtze River Delta.

2 Materials and Methods

2.1 Study area

The Yangtze River Delta, is located on the east coast of China and belongs to the core region of China’s urbanization (Fig. 1). Covering Shanghai City, Jiangsu Province, Zhejiang Province, and Anhui Province, the Yangtze River Delta includes 26 closely-linked prefecture-level cities. It is also at the nexus of two national strategies, namely, the One Belt One Road Initiative and the Yangtze River Economic Belt Development Strategy, both of which play important roles in enhancing China’s participation in international markets. Since the 21st Century, rapid urbanization and industrialization in the Yangtze River Delta have resulted in the excessive expansion of construction land and a subsequent reduction of ecological space (Yang et al., 2014; Luo et al., 2018; Yuan et al., 2020). In 2018, the Yangtze River Delta covered an area of 211 700 km², with a GDP of 17.86 trillion yuan RMB and a permanent population of 154 million people, accounting for 2.21%, 19.84%, and 11.04% of the total area, GDP, and population of the whole country, respectively (NBSC, 2019). Thus, the growing demand for construction land

in the area may cause increasing conflict between regional development and environmental protection.

2.2 ULUE indicators

To calculate ULUE, we considered the comprehensive land use benefits to the development of economy, society, and environment. Negative environmental effects were also included in the index system (Luo et al., 2018; He et al., 2020; Kuang et al., 2020; Table 1). Following the Cobb-Douglas production function (Huang et al., 2017), the selected input indicators were the urban construction land area, fixed asset investment, and number of employees in secondary and tertiary industries. The output indicators were divided into two groups of desirable and undesirable outputs. The desirable output indicators reflected positive outputs in the city’s production and operation activities within a certain period of time. These included economic, social, and environmental benefits, and more specifically, the added value of secondary and tertiary industries, the average wages of employees, and green land coverage in built-up areas, respectively. Undesirable output indicators included wastewater discharge, industrial SO₂ emissions, and smoke discharge, which were used to characterize negative environmental effects in the process of urban socio-economic development.

2.3 Methodology

2.3.1 SBM-UN model

The SBM model is proposed by Tone (2001), which was derived from non-radial and non-angle models. It

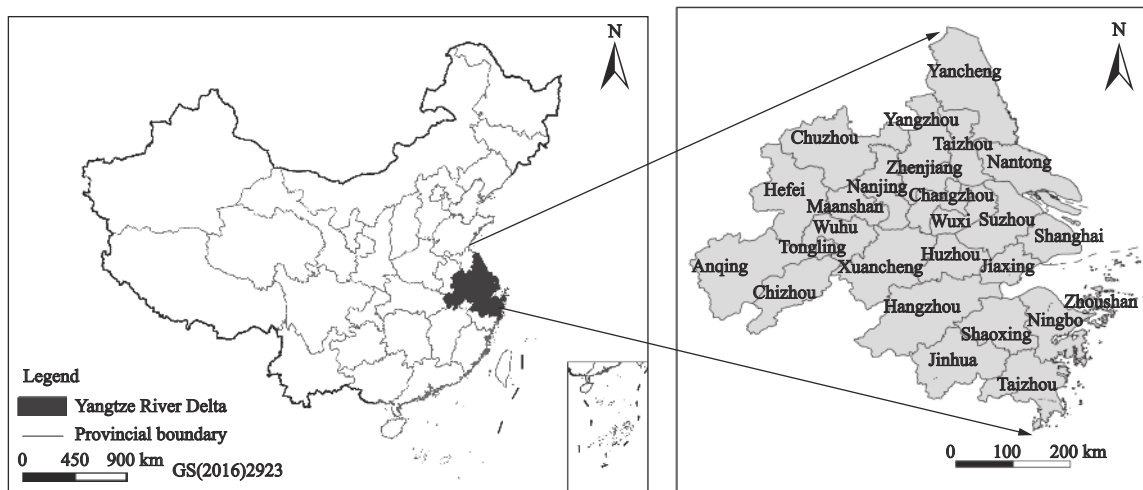


Fig. 1 Location of the Yangtze River Delta, China

Table 1 Evaluation index system used to measure urban land use efficiency (ULUE)

Criterion layer	Factor layer	Indicator layer	Unit
Input	Land input	Urban construction land area	km ²
	Capital input	Investment in fixed assets	100 million yuan RMB
	Workforce input	Number of employees in secondary and tertiary industries	10 000 persons
Desirable output	Economic benefit	Added value of secondary and tertiary industries	100 million yuan RMB
	Social benefit	Average wage of employees	Yuan RMB
	Environmental benefit	Green coverage of built-up area	%
Undesirable output	Negative environmental effect	Wastewater discharge	10 000 t
		Industrial SO ₂ emissions	t
		Smoke discharge	t

comprehensively considers the input and output of each decision-making unit (DMU), but does not take into account undesirable outputs such as the environmental negative effects due to urban land use. That is, the relaxation variable is directly put into the objective function to solve the problem of input-output slacks. In other words, we used this concept to develop the SBM-UN model, which additionally considers undesirable outputs, resulting in more accurate ULUE evaluations in the context of increasing environmental restrictions.

The principle of the model is as follows. Supposing there are n decision making units (DMU), each consumed m inputs and produced s_1 desirable outputs and s_2 undesirable outputs, expressed as $x \in R_m$, $y^g \in R_{s_1}$, and $y^b \in R_{s_2}$, respectively (Liu et al., 2017; Chen et al., 2020). Additionally, X , Y^g , and Y^b are defined as $X = (x_1, x_2, \dots, x_n) \in R_{m \times n}$, $Y^g = (y_1^g, y_2^g, \dots, y_n^g) \in R_{s_1 \times n}$, and $Y^b = (y_1^b, y_2^b, \dots, y_n^b) \in R_{s_2 \times n}$, respectively. Based on the actual input-output, assuming $X > 0$, $Y^g > 0$, and $Y^b > 0$, the set of production possibilities is P . That is, all combinations of desirable and undesirable outputs produced by the input factor x is defined as follows:

$$P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \geq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\} \tag{1}$$

According to this definition, the SBM-UN model with undesirable outputs is defined as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b} \right)} \tag{2}$$

$$s.t. \begin{cases} x_0 = X\lambda + s^-; y_0^g = Y^g\lambda - s^g; y_0^b = Y^b\lambda + s^b \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{cases} \tag{3}$$

where s_i^- is the input slack, and s_r^g and s_r^b are the desirable and undesirable output slacks, respectively; λ is the weight variable that determines the scale effect of each DMU. ρ^* is the comprehensive efficiency of DMU; $0 < \rho^* \leq 1$. When $0 < \rho^* \leq 1$, all slacks satisfy $s_i^- = s_r^g = s_r^b = 0$, and the DMU is efficient. If $\rho^* < 1$, the DMU is inefficient, and the input and output should be improved, the values of slack variables X , Y^g , and Y^b could be used to determine potential approaches to improve ULUE. The model is a nonlinear programming model; however, it can be transformed into a linear programming model using the transformation method of Charnes-Cooper (Lu et al., 2018; Yu et al., 2019).

2.3.2 Kernel density estimation

Kernel density estimation (KDE) is an important non-parametric estimation method that is often used to quantify the disparity of quantitative elements in economics. KDE obtains continuous density curves by measuring the probability density, which can describe the distribution of random variables (Katkovnik and Shmulevich, 2002; Xu et al., 2015). Specifically, if $f(x)$ is the probability density function estimated according to the value of ULUE, and x_1, x_2, \dots, x_n are samples of continuous X , the KDE estimation formula is:

$$f(x) = \frac{1}{nh} \sum_i^n K\left(\frac{x - x_i}{h}\right) \tag{4}$$

where $K(\cdot)$ is the kernel function, h is the bandwidth, n is the number of samples, and $i = 1, 2, \dots, n$. To ensure the rationality of the KDE estimation results, the kernel function should satisfy $K(x) \geq 0$, $\int_{-\infty}^{+\infty} K(x)dx = 1$. Moreover, $K(\cdot)$ should fit the morphological characteristics of the density function. Considering that the accuracy of the estimation results is rarely affected by the kernel

function, this study used the common Epanechnikov kernel function (Kuang et al., 2020).

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \quad (5)$$

The kernel density function is sensitive to the choice of bandwidth (h) (Katkovnik and Shmulevich, 2002). At higher bandwidth, the variance of KDE is smaller, and the density function curve is smoother. However, the smoothness of the curve may mask the characteristics of the data and reduce the accuracy of the evaluation results (Kuang et al., 2020). When the bandwidth is low, the variance of the KDE is large. As it is difficult to remove noise in the random error, the curve is not smooth, but the results can be more accurate. Therefore, it is important to use as low a bandwidth as possible. When h is a function of n , $h(n)$ needs to satisfy the assumption: if $n \rightarrow \infty$, $h(n) \rightarrow \infty$.

2.3.3 Efficiency decomposition

The SBM-UN model described in Section 2.3.1 assumes that the return to scale remains unchanged. The efficiency result represents the comprehensive efficiency, which is TE. Under variable returns to scale (VRS), the condition $\sum_{i=1}^{i=n} \lambda_i = 1$ should be added to the constraints. At this point, the efficiency result represents the PTE. The SE can then be defined as follows (Yu et al., 2019):

$$SE = \frac{TE}{PTE} \quad (6)$$

The PTE of DMU is used to represent the intensity of ULUE, reflecting the production technology level, resource utilization, allocation level, and sustainable performance of a city. SE is the benefit of the unit input during land use for urban extension and the change trend of ULUE, which reflects the population scale effect, industrial agglomeration, market capacity etc. (Zhu et al., 2019). TE represents the performance of current and future land use scales (González et al., 2015). Therefore, the DEA model based on VRS can identify the causes of low ULUE, including inefficient production and adverse conditions. When $SE = 1$, the DMU has an effective land use scale (Zhao et al., 2018a).

2.4 Data sources and analysis

In this study, 26 prefecture-level cities were used as the decision-making units (DMUs) to examine ULUE. The

data were mainly obtained from public information sources, including the China Urban Construction Statistical Yearbook (MHURC, 2001–2019), China Urban Statistical Yearbook (NBSC, 2001–2019), and the statistical yearbooks of the individual cities in the Yangtze River Delta. To eliminate the effects of price factors, indicators of the annual average balance of net fixed assets and gross industrial output value above a designated value were converted to constant prices based on the year 2000 using the index of investment in fixed assets and ex-factory price indices of industrial products, respectively. When processing foreign direct investment (FDI) data, we first converted the amount into RMB according to the exchange rate of USD/RMB in 2000. The moving average method was used to account for missing data in individual years. Thus, we obtained city-level data of the Yangtze River Delta from 2000 to 2018.

This study used established models to analyze the data according to the following steps. First, we used the SBM model to measure the TE of the original data. The SBM model was also used to measure ULUE without undesirable outputs to determine the impact of adding undesirable outputs to the model. Second, spatial distribution diagrams were mapped using ArcGIS 10.2 (Environmental Systems Research Institute, United States). The kernel densities of ULUE in 2000, 2005, 2010, 2015, and 2018 were estimated using the Graph function in Eviews 10.0 (Quality Management System, United States). Finally, the SBM-UN model was used to determine the improvement potential of each ULUE variable in 2018 using the original input-output data (Yang et al., 2014; Liu et al., 2020). The SBM-UN model allowed the production of a dataset, which not only contained the ULUE of each city, but also included the proportion data of input redundancy, insufficient desirable output and excess undesirable output.

3 Results and Discussion

3.1 Overall changes in ULUE

Fig. 2 shows the average ULUE in the Yangtze River Delta from 2000 to 2018. The results from the SBM-UN model were significantly lower than those from the SBM model, owing to the negative impact of undesirable outputs and the fact that the input-output slack was overestimated in the SBM model. Without considering

the undesirable outputs, the input-output slack in the SBM model was overestimated, which distorted the evaluation results. This suggests that SBM-UN model results reflect the actual ULUE more accurately. The SBM-UN model results showed an overall decrease in ULUE of 19.06%, and the average value of ULUE from 2000 to 2018 was 0.681. The highest value on ULUE was 0.746 in 2018. The lowest value (0.605) was observed in 2009. Overall, ULUE from 2000 to 2018 exhibited a U-shaped trend.

To account for the interannual variation in ULUE, we divided the results into two stages. In the first stage (2001–2009), ULUE in the Yangtze River Delta was low. During this time, China joined the World Trade Organization and experienced rapid development. The Yangtze River Delta attracted considerable foreign investment and developed an export-oriented economy. Many cities, villages, and towns expanded, and industrial and university districts were established. For example, in Jiangsu Province, nine national and 71 provincial development zones were established, covering a total approved area of 830 km². However, the actual developed area was larger (Chen et al., 2019). This economic development led to a rapid reduction in the cultivated land area. Owing to the low level of industrial development and disorderly spread of construction land, ULUE was low. Combined with the actual situation of urban development in the Yangtze River Delta, the rapid economic development consumed a lot of resources. Therefore, increasing land supply has not been the best way to improve ULUE.

The second stage lasted from 2010 to 2018, a period during which ULUE increased significantly. This was mainly due to a shortage in the supply of construction land. Additionally, policies restricting economic development zones and protecting farmland were formulated

by all levels of government, which enhanced land use intensity. Moreover, the significant impact of the global economic crisis made the export-oriented and extensive economy of the Yangtze River Delta unsustainable.

3.2 Spatio-temporal patterns of ULUE

Spatial disparities in ULUE were notable across the Yangtze River Delta (Fig. 3). In 2000, Shanghai, Hangzhou, and Ningbo, the three main cities in the Yangtze River Delta, exhibited the highest land use efficiency and intensity level, likely due to good economic and land management policies. However, the average ULUE for Yancheng, Nantong, Tongling, and Taizhou together was only 0.526, far below the average value for the Yangtze River Delta. The ULUE of Maanshan and Chuzhou decreased significantly over the study period, with an annual decrease of 18.8% and 13.5%, respectively. In 2010, low-ULUE cities were unevenly distributed across the Yangtze River Delta. In 2015 and 2018, Shanghai, Suzhou, Nanjing, Hangzhou, Ningbo, and other regional central cities exhibited higher land use efficiency. These cities were mainly located in the ‘Z’ development axis along the Shanghai–Nanjing, Shanghai–Hangzhou, and Hangzhou–Ningbo railway in the Yangtze River Delta and showed a clear hierarchical distribution.

The local governments of high-ULUE cities paid more attention to environmental protection, had reasonable resource allocation, and set higher industrial introduction thresholds than cities with low development levels (such as Taizhou, Yancheng, and Tongling). For example, Nanjing adaptively reused the waste land of an industrial park, thereby increasing ULUE (Gao and Yuan, 2017). Conversely, marginal cities in the Yangtze River Delta, such as Anqing, Chuzhou, and Yancheng, were in the initial stage of economic expansion and exhibited low industrial levels. Owing to incomplete sustainable land use policies, these cities followed a traditional development model that relied exclusively on increasing land supply to drive economic growth, resulting in low ULUE. The cities with different levels of ULUE showed significant differentiation along the characteristics of ‘large agglomeration’ and ‘small dispersion’ (most of the cities are concentrated, and the rest are scattered in space). The imbalance in spatio-temporal patterns in ULUE was more prominent, similarly to the findings in developed urban areas in the European

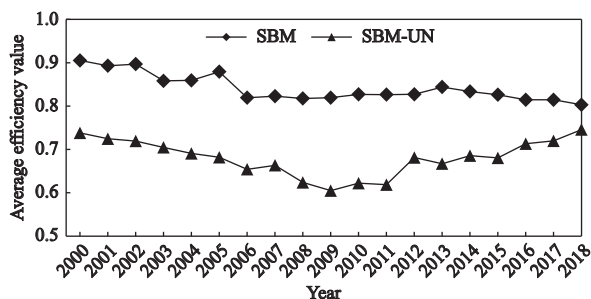


Fig. 2 Urban land use efficiency in the Yangtze River Delta of China from 2000 to 2018

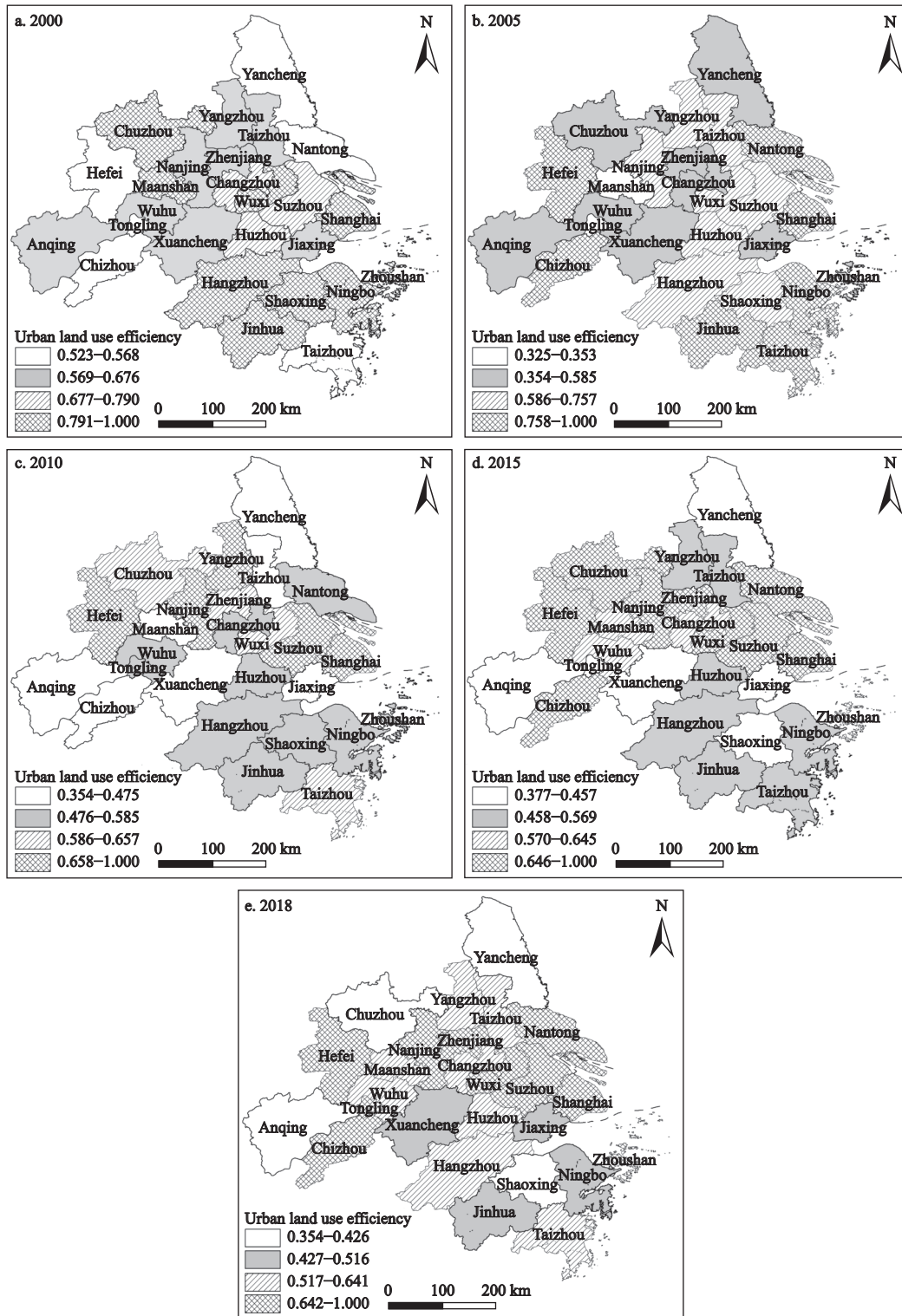


Fig. 3 Regional patterns of urban land use efficiency in the Yangtze River Delta of China in 2000, 2005, 2010, 2015 and 2018

Union and North America (Williams et al., 2002; Muscat et al., 2022).

The kernel density of ULUE for 2000–2018 is shown

in Fig. 4. During the study period, the center of the density curve first moved to the left and then to the right, the number of peaks remained at two, and the

peak width decreased significantly. This indicates that the ULUE of the Yangtze River Delta gradually increased, and the difference between cities decreased. From 2000 to 2018, the kernel density followed a bimodal distribution, with most cities falling into two ULUE categories (Lu et al., 2018). Some cities in the Yangtze River Delta had a relatively low ULUE due to insufficient implementation of land use policies (Tan et al., 2005; Guo et al., 2014; Jin et al., 2019). However, other cities paid attention to environmental protection and rational resource allocation. The threshold of industry introduction was higher than that of poorly-developed cities, which led to the relatively intensive utilization of construction land. This will inevitably result in the polarization of ULUE in the Yangtze River Delta (Lu et al., 2018).

As shown in Fig. 4, the density curve in 2000 has a main peak and a secondary peak, corresponding to cities with the high and sub-high ULUE, respectively. The density of the secondary peak was significantly lower than that of the main peak. From 2000 to 2010, the right end of the density curve gradually moved to the right, whereas the left end moved to the left, indicating a reduction in the gap between the high and low-ULUE cities in the Yangtze River Delta. Compared with 2000, the height of the main peak increased and that of the secondary peak decreased in 2005, resulting in a bimodal distribution. The width and height of the kernel density distribution continued to decline in 2010, again indicating a decrease in the difference in ULUE in the Yangtze River Delta. Only one peak was observed in 2015. However, similar to 2000 and 2005, the kernel density curve in 2018 also followed a bimodal distribution. In addition, the density value of the main peak was far lower than that of the secondary peak, which contrasted with the distribution pattern in 2005 and 2015. Over time, it is expected that cities would gradually move from the high-ULUE group into the low-ULUE group at the varying speeds, with the disparities in ULUE showing the ‘club convergence’ feature.

3.3 Impact factors of ULUE patterns

According to the results of efficiency decomposition, we can explore the main contributors to the dynamic evolution of ULUE. Thus, we calculated the TE, PTE, and SE of the 26 cities in the Yangtze River Delta from 2000 to 2018 (Fig. 5). The average PTE and SE values

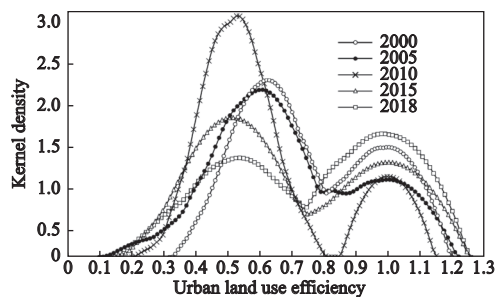


Fig. 4 Kernel density distribution of urban land use efficiency in the Yangtze River Delta of China

were 0.766 and 0.889, respectively. The correlation coefficient between PTE and TE was 0.823 and that between SE and TE was 0.917.

Through the above analysis, we found that the values of PTE and SE helped to explain the contributors of TE. The plots indicate the inner cities in the Yangtze River Delta. Fig. 6 shows the relationships between TE and both PTE and SE. According to the scatter plots, the points vary considerably in distance from the 45° line, indicating that TE is affected by both PTE and SE (Yang et al., 2013; Yu et al., 2019). Fig. 6a indicates that PTE shows more similarity to TE than SE and the low level of TE in the Yangtze River Delta is mainly caused by PTE. However, more points in Figure 6b lie in the upper part of the scatter plot, indicating that SE contributes more to TE than PTE.

Shanghai, Hefei, Nanjing, Suzhou, and Wuxi had the highest TE in 2000–2018 (Table 2). These cities are located in the core economic and social development area of the Yangtze River Delta and show intensive land use. Conversely, the TEs of Anqing and Yancheng were only 0.463 and 0.472, respectively. In these cities, urban land use is extensive, and investment in pollution treatment and environmental protection technologies is insufficient. Thus, land use in these cities should be altered,

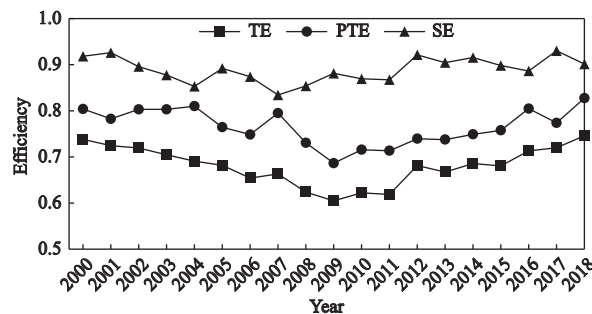


Fig. 5 Technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) of urban land use efficiency in the Yangtze River Delta from 2000 to 2018

and environmental pollution should be controlled to increase ULUE. Shanghai, Nanjing, and Suzhou had an average PTE of 0.967, which was almost 46.98% higher than that of Xuancheng, Yancheng, and Anqing. In contrast, Zhoushan, Chizhou, and Tongling, which are located in marginal social and economic development areas of the Yangtze River Delta with a sufficient supply of construction land, had the highest SE. Cities such as Huzhou, Shaoxing and Jiaxing have underwent rapid development of industrialization and urbanization, resulting in high land development intensity and a limited supply of construction land, which made their average SE low, only 0.822. In contrast to previous studies (Lu et al., 2018; Yu et al., 2019), we observed no significant linear relationship between efficiency and scale in

the Yangtze River Delta. This could be due to the high integration and low input-output gap between the unit area and unit labor force. Therefore, the disparities among cities in the Yangtze River Delta should be given more attention. The most suitable strategy was to improve the ULUE of cities located in marginal areas.

3.4 Potential for ULUE improvement

We selected the urban land use data in 2018 for the improvement potential analysis of each variable (Table 3).

Across the region, the average proportion of redundant investment in fixed assets was 8.53%, whereas the output of average wage of employees was less than 24%. Moreover, the industrial SO₂ emissions exceeded 45.42% of the national standard. Our results showed

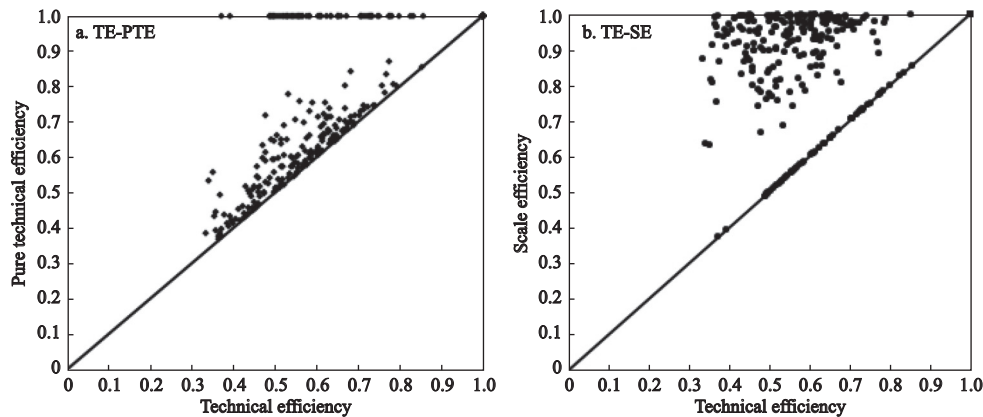


Fig. 6 Decomposition analysis showing the relative contributions of pure technical efficiency (PTE) and scale efficiency (SE) to the technical efficiency (TE)

Table 2 Average technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) of urban land use efficiency of cities in the Yangtze River Delta of China from 2000 to 2018

Ctiy	TE	PTE	SE	Ctiy	TE	PTE	SE
Shanghai	1.000	1.000	1.000	Huzhou	0.621	0.784	0.792
Nanjing	0.885	0.969	0.913	Shaoxing	0.612	0.738	0.829
Wuxi	0.862	0.866	0.995	Jinhua	0.727	0.729	0.998
Changzhou	0.711	0.757	0.939	Zhoushan	0.819	0.819	1.000
Suzhou	0.871	0.931	0.935	Taizhou	0.744	0.824	0.903
Nantong	0.717	0.834	0.859	Hefei	0.913	0.917	0.996
Yancheng	0.472	0.510	0.924	Chuzhou	0.703	0.762	0.922
Yangzhou	0.761	0.837	0.910	Maanshan	0.604	0.652	0.927
Zhenjiang	0.732	0.785	0.932	Wuhu	0.602	0.622	0.968
Taizhou	0.658	0.730	0.902	Xuancheng	0.498	0.509	0.979
Hangzhou	0.681	0.793	0.859	Tongling	0.566	0.566	1.000
Ningbo	0.806	0.840	0.959	Chizhou	0.804	0.804	1.000
Jiaxing	0.510	0.604	0.844	Anqing	0.463	0.518	0.894

Table 3 Input-output adjustment and improvement potential of each urban land use efficiency index for various cities in the Yangtze River Delta in 2018

DMU	Input redundancy				Output shortage				Output excess			
	Score	Urban construction land area	Investment in fixed assets	Number of employees in secondary and tertiary industries	Added value of secondary and tertiary industries	Average wage of employees	Green coverage of built-up areas	Wastewater discharge	Industrial SO ₂ emissions	Smoke discharge		
Shanghai	1	0	0	0	0	0	0	0	0	0		
Nanjing	1	0	0	0	0	0	0	0	0	0		
Wuxi	1	0	0	0	0	0	0	0	0	0		
Changzhou	0.641	598.10(54.47)	0	0	0	12686.98(14.97)	0	4256.53(31.97)	16453.83(58.42)	33253.27(60.55)		
Suzhou	1	0	0	0	0	0	0	0	0	0		
Nantong	1	0	0	0	0	0	0	0	0	0		
Yancheng	0.374	592.41(62.60)	992.74(33.63)	124.11(36.50)	0	51474.07(80.08)	7.26(17.21)	6181.88(56.18)	14921.47(77.80)	9304.11(63.98)		
Yangzhou	0.590	430.05(54.37)	631.30(24.80)	0	0	29902.10(41.73)	0	1599.14(23.58)	6977.23(62.31)	1662.98(21.47)		
Zhenjiang	1	0	0	0	0	0	0	0	0	0		
Taizhou	0.585	611.93(63.37)	576.12(23.12)	1.05(0.48)	0	32559.76(49.70)	0	0	6943.03(59.24)	1271.17(18.89)		
Hangzhou	0.588	521.22(38.76)	727.12(16.84)	64.68(10.52)	0	29050.36(30.05)	8.89(22.24)	11728.30(47.76)	19593.96(73.95)	3580.35(21.91)		
Ningbo	0.516	828.66(55.78)	680.92(18.44)	84.03(16.30)	0	30482.02(33.24)	9.21(23.12)	4434.92(30.74)	19569.51(76.64)	9626.74(48.81)		
Jiaxing	0.447	399.46(55.64)	553.30(24.94)	105.66(34.67)	0	6749.44(8.14)	0	15194.43(77.15)	18987.06(84.33)	6181.34(56.44)		
Huzhou	0.550	216.86(50.76)	0	37.39(22.27)	0	22092.02(30.54)	0	5971.13(70.50)	16000.27(72.34)	7746.85(51.51)		
Shaoxing	0.415	1504.08(80.60)	427.50(18.61)	75.45(24.90)	0	30897.68(45.78)	0	19899.69(79.42)	14944.61(79.15)	4098.40(42.97)		
Jimhua	0.512	383.61(57.04)	26.15(1.61)	104.15(37.08)	0	11617.08(14.13)	0	2454.57(38.33)	10250.95(74.74)	10776.87(71.55)		
Zhoushan	1	0	0	0	0	0	0	0	0	0		
Taizhou	0.614	246.85(40.05)	0	116.41(34.51)	0	38194.28(53.93)	0	632.02(12.33)	4339.26(42.94)	2230.18(25.39)		
Hefei	1	0	0	0	0	0	0	0	0	0		
Chuzhou	0.426	134.45(47.13)	235.34(17.21)	109.83(58.70)	0	26210.62(38.97)	0	802.53(34.01)	13485.68(83.12)	5779.70(73.77)		
Maanshan	0.614	21.99(11.51)	0	11.66(11.42)	0	26297.37(36.62)	0	6790.48(78.95)	34186.86(91.02)	65408.58(95.68)		
Wuhu	0.585	41.53(14.77)	403.40(21.78)	31.70(18.45)	0	29683.77(44.38)	0	515.53(14.42)	36051.05(91.70)	23614.89(87.18)		
Xuancheng	0.451	171.29(56.78)	77.84(6.95)	70.49(52.14)	0	22796.39(33.15)	0	405.58(25.04)	9858.37(76.56)	10440.01(81.75)		
Tongling	1	0	0	0	0	0	0	0	0	0		
Chizhou	1	0	0	0	0	0	0	0	0	0		
Anqing	0.354	443.34(73.17)	193.28(13.83)	140.71(62.59)	0	40021.81(68.64)	0	953.08(35.84)	9479.14(76.57)	5145.02(69.81)		

Note: Data in parentheses indicate the percentage (%) of the input-output adjustment and improvement potential of each index.

DMU: decision-making unit

that the cities with low ULUE generally experienced the phenomenon of redundant inputs, serious environmental pollution, and excessive undesired outputs, which made the utilization of land resource inefficient. Meanwhile, large variations were observed among cities. For example, the redundancy ratio of urban land in Shaoxing was 80.60%, whereas that in Maanshan was 11.51%. Thus, the scale and structure of the input elements in some cities were not reasonable, spatial allocation of land resource was inefficient, and the undesirable outputs were too high. Furthermore, the effective outputs of most cities were insufficient. Therefore, the results of the SBM-UN model can be used by each city to adjust their input–output factors to increase ULUE. In summary, the ULUE in most cities could be improved by increasing the intensity of capital investment, optimizing the spatial allocation of factors, reducing the negative external output, and increasing the effective output. To improve the overall ULUE in the Yangtze River Delta, it is necessary to increase the PTE, strengthen management and adjust the land use structure.

4 Conclusions

We investigated 26 cities in the Yangtze River Delta and developed a novel ULUE evaluation model (the SBM-UN model), which considers undesirable outputs to assess ULUE more accurately. We also determined the spatiotemporal patterns of ULUE in the Yangtze River Delta and the factors contributing to ULUE, as well as potential ways to improve ULUE. Our results showed that the proposed model is an effective planning tool for improving ULUE that can be used in other megacity regions across the world. The conclusions of this empirical study are summarized as follows: 1) ULUE in the Yangtze River Delta was relatively low from 2000 to 2018 and followed a U-shaped trend. Moreover, including undesirable outputs such as environmental pollution in the SBM-UN model had a negative impact on ULUE, reducing it by 19.06%. This finding indicated that neglecting the effect of undesirable outputs results in an overestimation of ULUE. 2) The spatial distribution pattern of ULUE revealed significant regional differences. The ULUE of central cities in the Yangtze River Delta (such as Shanghai, Hangzhou, and Ningbo) remained high throughout the study period, whereas those of Yancheng in Jiangsu, Taizhou in

Zhejiang, and Tongling in Anhui were low. According to kernel density estimation, ULUE in the Yangtze River Delta gradually declined and was accompanied by spatial polarization. The levels of economic development and ULUE were associated. 3) PTE contributed more to the evolution trend of TE, whereas SE contributed more to the change in ULUE. Overall, the contribution of SE was larger than that of PTE. Our findings also illustrated that, by strictly managing the scale of new construction land, we can effectively avoid land use waste and improve ULUE. 4) Cities with low ULUE generally had redundant inputs, insufficient outputs, and excessive negative environmental outputs.

Based on these results and previous empirical studies, we present several policy implications for promoting intensive land use and improving ULUE for cities in the Yangtze River Delta. For cities with low ULUE (such as Anqing, Tongling, and Yangzhou), in addition to developing urban economy, it is necessary to improve environmental quality, limit the scale of land expansion, revitalize the stock of construction land, and develop low-efficiency land. Additionally, further attention should be paid to realize land intensive development and green development based on regional natural resources and environmental capacity. Conversely, cities with high ULUE should focus on the optimal allocation of land resource and technological innovation. A change from capital-driven to innovation-driven development could further improve ULUE. Furthermore, measures such as industrial upgrading and structural optimization should be considered to improve ULUE. Finally, in view of the current regional differences in ULUE, urban authorities should employ big-data analysis and simulations to improve the planning of new urban spaces. Especially for regional integration planning in the Yangtze River Delta, it is necessary to clarify the function and orientation of each city in order to ensure that further development balances or reduces regional differences in ULUE. Nevertheless, we acknowledge some limitations to this study. Due to the unavailability of other relevant data, the negative environmental outputs in the SBM-UN model only included wastewater discharge, industrial SO₂ emissions, and smoke discharge. Such limitations in the statistical indicators may result in biased evaluation results. With the release of more detailed data, information on other negative indicators of urban land use, such as organic compounds and carbon dioxide,

could be collected. Incorporating these data into the model would improve the accuracy of the results in future studies. In addition, we examined ULUE at the city scale. Future studies should explore ULUE variation within cities to take into account the much larger city administrations found in China compared to other countries. Furthermore, the use of a smaller analytical unit, such as the county unit, could improve sample coverage and produce evaluation results that more accurately represent local conditions.

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