Yan, D., Kong, Y., Ye, B., Shi, Y. and Zeng, X. (2019) Spatial variation of energy efficiency based on a Super-Slack-Based Measure: Evidence from 104 resource-based cities. *Journal of Cleaner Production*, 240, 117669. (doi:10.1016/j.jclepro.2019.117669)

Spatial variation of energy efficiency under different scenarios based on a s Super-Slack-Based Measure: Evidence from 104 resource-based cities

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Abstract:

Energy efficiency is tied to energy activities and environmental effects and serves as a useful tool for sustainability analysis. Few insights have been acquired for sustainability development from resource-based cities in developed or developing countries. A Super-Slack-Based Measure (Super-SBM) with undesirable outputs is established to account for the total-factor energy efficiency from an energy-economy-environment perspective. Using China as a case study, the spatial variation in energy efficiency from 104 resource-based cities is analysed, furthermore, the results are compared with a scenario that does not consider environmental constraints. Finally, resource-based cities are classified into three categories through K-means clustering technology: high-efficiency region, medium-efficiency region and low-efficiency region. The investigation results show the following: (1) Efficiency disparities exist in resource-based cities under different scenarios, as a whole, the energy efficiency in the scenario two considering by-products of energy activities is obviously lower, which can more truly represent the sustainability of resource-based cities. (2) Most resource-based cities are in low-efficiency zones with substantial room for improvement. Spatial agglomeration effect or spatial spillover effect appears in a few cities. (3) Urban development in developing countries may follow the full life cycle process of local resources. A total of 262 resource-based cities could be roughly categorized into four types. The energy efficiency of growing type is the highest, followed by grow-up type, recessionary type, and regenerative type. (4) The ordering of efficiency in resource-based city is as follows: oil and gas-based > multiple minerals-based > non-metallic-based > nonferrous metal-based > coal-based > forestry-based > ferrous metal-based. The discussion offered in this study for various types of resource-based cities could provide a reference for other cities or developing countries which are in similar industrialization phases and hope for sustainable development.

Keywords: Resource-based city; Energy efficiency; Sustainable development; Super-SBM model; K-means cluster.

1. Introduction

Energy activities and the associated environmental emissions are attracting substantial worldwide attention (Zeng et al., 2017; Sun et al., 2018). Among the important emissions sources, the carbon emissions generated by cities accounted for 69%, 80% and 85% of EU, USA and China, respectively (Li et al., 2018). Thus, the vital role of cities in circular economy and resource conservation is obvious. China consumes one fifth of the global energy and is the world's largest energy consumer. Besides, about 60% of China’s energy coms from imports, which is enough to make this country play a pivotal role in the global transition to sustainable development (Zeng et al., 2018). According to policy impacts assessment of the non-ferrous metal industry made by Li et al. (2018b), the energy efficiency of five metal productions performed better than the latest national standards. This indicates that current policy in China may be outdated, and it is necessary to update it for sustainable energy. In this context, exploring the link between energy consumption, economic output and negative environmental impacts, and to promote the transformation of urban patterns towards a sustainable one is a necessity (Kan et al., 2019).

There is no consensus on the identification criteria of resource-based cities, and the adopted identification methods are different. Early researchers mostly classified mining cities by the proportion of workers in the mining industry, with the threshold values ranging from 10% to 15% (Harris, 1943). Resource-based cities are regarded as regions that have risen or developed mainly depend on the exploitation of some kind of local resources, such as minerals or forests. These cities provide material reserves for the steady development of the national economy. According to the National Plan for the Sustainable Development of Resource-based Cities (2013-2020), an action programme for the comprehensive sustainable development of resource-based cities promulgated by China’s State Council in 2013, a city could be confirmed as a resource-based city as long as it meets one of the three indicators—the extractive industry performance, the resource output scale coefficient and the resource contribution degree. The plan uses a combination of qualitative and quantitative methods to define 262 resource-based cities, of which 126 are prefecture-level administrative regions (The State Council, 2013). These cities are the areas where resources are produced and consumed most, and inevitably the areas with the most serious environmental deterioration (Li et al., 2019). The expansion of resource products has led to long-term dominance of industry in most resource-based cities.

The level of development of finance, logistics, accommodation and catering industries is far behind the needs of cities, and it is difficult to maintain sustainable development.

Since the second half of the 19th century, resource-based towns or communities, such as those in the United States, Canada, and Australia, have been developed worldwide for the purpose of extracting and processing various resources. With large-scale industrial production, mineral resources have become an important production factor, and the economies of these regions have developed rapidly. After the 1960s, new energy sources emerged. These regions faced problems such as decreasing coal prices and substantially declining production. Some resource-based regions began to transform, such as those in Ruhr, Germany; Lorraine, France; and Kitakyushu, Japan. The rise and decline of these resource-based cities has led to research on the development and transformation of single-industry regions. Specifically, the economist Innis believes resource-based cities has experienced rapid development with a massive expansion of resources and a rapid decline after the exhaustion of those resources (Innis, 1930). Lucas (1971) proposed four development stages of resource-based regions: construction, recruitment, transition and maturity. Since that time, Bradbury (1979) extended the life-cycle theory of resource-based urban development proposed by Lucas, adding two new stages of development, the recession phase and the closure phase. After the 1980s, the resource economy gradually showed characteristics of becoming technology-intensive and resource-intensive, and the transformation path of resource-dependent areas has been given attention (Sharpe, 1988). Since the 21st century, the sustainability issues of a resource economy have gained considerable attention (Lockie et al., 2009; Li et al., 2016).

When an industry is dominant in a city and can promote the growth of other industries, then it is the leading industry of the city. The leading industries have some commonalities, such as strong industrial diffusion effect, high innovation rate and large potential in development. As a general rule, leading industries will be constrained by local resources and policies. The leading industries of countries or the same country at different development stages are different. Undoubtedly, resource enterprises are the leading industries of resource-based cities. Most arise in the early or middle stages of industrialization, which are large in scale and have obvious aggregation effects. These companies are generally regarded as high-input, high-consumption, low-technology and low-output. In fact, the simplistic and rigid industrial structure has affected the healthy development of other industries in resource-based cities to some extent. Resource exploitation has led to serious ecological damage, such as ecological collapse, landslides, air pollution, and water pollution, which has forced resource-based cities to seek economic development transformation, and improving energy efficiency has become an inevitable choice for urban transformation (Li et al., 2018). Many resource-based cities exist in China, and their resource exploitation levels, city scales and economic-social development levels are different. The problems in these cities are, therefore, also different. Thus, the government needs to build a differentiated policy system to guide the transformation and development of resource-based cities in different stages.

The main hypothesis of this study is that the development trajectory of resource-based cities may follow a specific life cycle process. There exist significant differences in efficiencies among different types of resource-based cities. The efficiency values of growing cities maybe relatively higher, the efficiency values of oil and gas-based and forestry-based cities maybe relatively higher, and the leading industries may exist spatial spillover effects. The structure of this research is as follows. The second section explains the various interpretations of energy efficiency and attention to urban efficiency from academic circles. The associated models and data sources are presented in the third section, followed by the energy efficiency results under different scenarios in the fourth section. The fifth section summarizes the conclusions and corresponding policy recommendations.

2. Literature review

The concept of energy efficiency concerns the contribution of the amount of energy consumed to maintaining and promoting the sustainable development of the entire economic, social and environmental system. Energy efficiency includes the macro-efficiency, physical efficiency, value efficiency, etc. The macro-efficiency measures the overall energy efficiency level of a country, region or industry. The most common measurement is the energy consumption per unit GDP, also known as the energy intensity. Physical efficiency reflects the technical equipment and management level of micro-economic organizations and is more suitable for comparisons among enterprises with the same production structure. Energy efficiency in this study refers to the production of the same amount of service or useful output with less energy (Patterson, 1996). In light of the number of inputs and outputs, energy efficiency can be divided into a single factor framework and a total factor framework. Energy efficiency under the single factor framework is usually measured by the energy intensity, but the influences of other factors on output are neglected, which produces certain limitations. Energy efficiency under the total factor framework takes into account the substitution effect between various input factors and is gradually becoming widely accepted (Hu and Wang, 2006).

Global consciousness of energy security and climate change has caused increased research interest in energy efficiency at the economic scale, beginning with Färe et al. (1983), who used the data envelopment analysis (DEA) model to study energy efficiency issues in power plants. According to the research scale, a large number of energy efficiency studies under the total factor framework can be divided into the national level (Guo et al., 2017), industrial level (Feng and Wang, 2018; Yan et al., 2017), provincial level (Zou et al., 2013; Wang et al., 2017), and enterprise level (Zhang et al., 2016; Hasanbeigi et al., 2010). Among these levels, the industry level receives the greatest amount of attention. For example, based on panel data from provincial industrial enterprises, Wang et al. (2012) assessed the energy consumption status of China's industrial sector. He found that the energy input in western provinces was excessive and that energy efficiency remains in need of promotion in most areas. Inadequate technology input and failure to achieve optimal production scale were the two major factors restricting efficiency improvement. Similarly, within the framework of the DEA model, China's provincial industrial energy efficiency was evaluated by Wu et al. (2012) through static and dynamic performance indexes, in which the dynamic indexes could be decomposed into two contributing parts to discriminate the endogenous power of efficiency changes. The research results validate the driving effect of technological progress on the energy efficiency. Li and Shi (2014) proposed a super-slack-based measure (SBM) model for addressing undesirable outputs under an assumption of weak disposition and carried out empirical research using this model. The results confirmed that the energy efficiency of China's light industry is higher than that of heavy industry, but the growing rate of the latter is faster, and the gap between these two is narrowing, which may be a premonition of economic structural change. In summary, DEA technology and its derivative models have been intensively applied in energy efficiency assessments (Hu and Wang, 2006) and investigations of other similar indications, such as environmental efficiency (Chang et al., 2013; Song et al., 2013) and eco-efficiency (Zhang et al., 2017; Fan et al., 2017).

Cities can be regarded as complex integrated systems that convert multiple inputs into multiple outputs, and improving the conversion efficiency of urban systems can enable limited resources to produce higher levels of output. Efficiency research at the city level is based on this idea. Scholars have conducted extensive explorations of rational measurements (Li et al., 2017; Zhou et al., 2016), regional differences (Yu et al., 2018a), and impact factors (Yu et al., 2018b) in terms of urban efficiency. However, few studies have focused on the energy efficiency of resource-based cities, let alone on discussions of different scenarios for resource-based cities. Although Li and Dewan (2017) measured the efficiency and main determinants of China's 116 resource-based cities, they only used cross-sectional data for 2012. Yu et al. (2015) studied the resource utilization efficiency of Chengde, but this investigation only involved one resource-based city and did not cover all of them. Related similar studies include those by Wei et al. (2012) and Lu et al. (2016).

In summary, there are two main dimensions in the study of energy efficiency. First, a considerable number of studies have focused on the differences and influencing factors of energy efficiency in different regions from different levels. Second, some scholars have analysed the energy utilization of high-energy consumption sectors, especially the industrial sector, from the perspective of organizational structure. However, few studies have been conducted at a more detailed level. As a complete spatial unit and a component of provinces, cities have different operational mechanisms and development laws than do provinces. To date, studies on the energy efficiency of urban units are lacking, let alone those on resource-based cities. The biggest difference between a resource-based city and an ordinary city lies in the existence of specific life cycle development laws. On one hand, resource-based cities show the universal law of urban development, and on the other hand, most cities will eventually fall into the cycle set by the “resource curse” as resources are exhausted.

The primary objective of this study is to assess the sustainable development capabilities of resource-based cities in China and to guide cities in exploring different transformation modes according to local conditions. Compared with previous studies, this research may provide the following contributions. First, previous energy efficiency studies focused on the national, provincial and industrial levels, while sustainability assessments of resource-based cities are very scarce. Taking resource-based cities as samples, this research conducts efficiency evaluation from a more microscopic scale. Second, the Super-SBM model can distinguish multiple decision-making units and put slack variables into the objective function. The model makes up for the deficiency of the traditional DEA model. Third, two different scenarios are innovatively set up to compare the energy efficiencies of resource-based cities. This is a useful attempt to analyse the effects of environmental pollutants on energy efficiency and has reference significance for similar research.

3. Methodology and data

3.1 Input-output indicators and data sources

A city is a function of capital, land, labour, technology, etc. This paper examines the energy efficiency of resource-based cities, and the energy element must be included. This type of efficiency reflects the energy utilization scenario of resource-based cities. The higher the energy efficiency, the more economic benefits can be obtained from less resource consumption. Following Wei et al. (2012), we select the total investment in fixed assets as the capital input and the number of employees in urban units at year-end as the labour input. But what different from him is that the annual electricity consumption is regarded as an energy input, this is due to that electricity is the main form of energy consumption in China and the estimated GDP elasticity of electricity demand is very close to the that of energy demand (Lin, 2003). Desirable output is expressed by the GDP of each city, and undesirable output is expressed by the industrial soot emissions, industrial sulfur dioxide emissions and industrial waste water discharges of each city. Among these indexes, the total investments in fixed assets and GDP are reduced by the total investments in fixed-asset indexes and GDP indexes of the provinces in which the cities are located, and the base period is the year 2010.

The time interval of this study is from 2010 to 2016. All data are from the *China Urban Statistical Yearbook* and the Statistical Bulletins of National Economic and Social Development of Cities. Due to the missing data in input or output indicators, 12 cities, including Linyi, Jinzhong, Panjin, Shuangyashan, Huludao, Mudanjiang, Baise, Liupanshui, Bijie, Pu'er, Jinchang and Longnan, were not included. Therefore, 104 prefecture-level cities in China were selected as research objects, and the input-output indicators required for the efficiency measurements of the resource-based cities are summarized in Table 1. Table 2 shows the statistical features of the input-output indicators.

Table 1 Input-output indicators of total-factor energy efficiency in resource-based cities

Input indicator	Output indicator	
	Desirable output	Undesirable output
Energy input: annual electricity consumption of the whole city	Gross regional product	Industrial soot emissions Industrial sulfur dioxide emissions Industrial waste water discharge
Capital input: total investment in fixed assets		
Labour input: number of employees in urban units at year-end		

Table 2 Descriptive statistics of input and output indicators

Variable	Input indicators			Output indicators			
	Total investment in fixed assets (10^4 Yuan)	Employees in urban units (10^4 persons)	Electricity consumption （10^8 kwh）	GDP (10^8 Yuan)	Industrial soot emissions (10^3 tons)	Industrial sulfur dioxide emissions (10^3 tons)	Industrial waste water discharge (10^3 tons)
Mean	721.46	32.93	60.96	1281.83	46.57	61.02	5.12
Median	597.23	27.47	39.20	954.04	24.44	46.83	4.04
Max	2928.08	448.44	565.08	8039.57	3257.26	331.86	23.88
Min	111.34	7.1	1.11	143.59	0.88	1.46	0.13
Std. dev.	513.94	0.93	70.97	1094.96	136.95	52.54	4.13

Note: Each sample contains 728 observations, and 7 indicators were included for the panel data from 2010 to 2016.

3.2 Super-SBM model within undesirable outputs

DEA is a nonparametric evaluation method that is widely used to evaluate the relative effectiveness of similar departments or organizations (Sueyoshi et al., 2017). Its basic principles are to determine the relatively effective production frontier by mathematical programming, keep the input or output of each decision-making unit unchanged, project each DMU (decision making unit) onto the production frontier surface, and then estimate the relative effectiveness of the DMUs according to the degree of their deviation from the production frontier. The greatest advantage of this technology is that it does not need to consider the functional relationship between input and output and does not need preset estimation parameters and weight hypotheses, thus avoiding subjective judgement. The DEA model usually assumes that producing more output while using less input is the criterion for optimal efficiency; however, when undesirable output exists, it is considered efficient to produce more good output and less bad output while using less input resources.

Efficiency is evaluated from two aspects: angle and radial. The angle aspect is divided into input-oriented or output-oriented, and the radial aspect evaluates input and output changes proportionally. In the actual production process, there are cases of input redundancy and insufficient output, and if relaxation is not considered, the obtained efficiency value is inaccurate. Based on this principle, Tone (2001) proposed a new measure of efficiency (SBM) based on input excesses and output shortfalls. This new measure is a derivative of DEA that adds slack variables to the objective function. Subsequently, Tone (2003) proposed an SBM model capable of dealing with undesirable outputs, dividing output factors into desirable and undesirable outputs.

Suppose that there are *n* DMUs in the production system, and each DMU has the three vectors of input, desired output and undesirable output. Every DMU uses *m* inputs to produce s_1 desired outputs and s_2 undesirable outputs. The three vectors are represented as:

$$X = [x_1, x_2, \dots, x_n] \in R^{m\times n}, Y^g = [y_1^g, y_2^g, \dots, y_n^g] \in R^{s_1\times n},$$

$$Y^b = [y_1^b, y_2^b, \dots, y_n^b] \in R^{s_2\times n}$$

Among them, $X > 0$， $Y^g > 0, Y^b > 0$, and accordingly, two hypotheses about the production probability set (PPS) were proposed:

Assumption one: weak disposability of output, which occurs when $(x, y^g, y^b) \in T$ and $0 \leq \theta \leq 1$, then $(x, \theta y^g, \theta y^b) \in T$.

Assumption two: empty connection between desired output and undesirable output, which occurs when $(x, y^g, y^b) \in T$, if $y^g = 0$, then $y^b = 0$.

Based on the above assumptions, PPS can be defined as

$$\mathrm{P} = \left\{ (x, y^g, y^b) \mid x \geq X\lambda,\ \ y^g \leq Y^g\lambda,\ \ y^b \geq Y^b\lambda,\ \ \lambda \geq 0 \right\} \tag{1}$$

Where λ is a constant vector representing the weight of each DMU. The SBM formula within the undesirable output used for measuring each DMU$\left(x_0, y_0^g, y_0^b\right)$ is shown as follows:

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

$$s.t.\quad x_0 = X\lambda + s^-;$$

$$y_0^g = Y^g\lambda - s^g;$$

$$y_0^b = Y^b\lambda + s^b;$$

$$\lambda \geq 0, s^- \geq 0, s^g \geq 0,\ s^b \geq 0 \tag{2}$$

In the above formula, S^-, S^g, S^b represent slacks in inputs, desirable outputs, and undesirable outputs, respectively. The objective function ρ represents the efficiency value of the DMU$\left(x_0, y_0^g, y_0^b\right)$, which indicates that s^-, s^g, and s^b are strictly decreasing, and $0 \leq p \leq 1$. Estimation of the DMU$\left(x_0, y_0^g, y_0^b\right)$ is efficient only when $\rho = 1$, *i.e.*, when $S^- = 0, S^g = 0, S^b = 0$, the estimation is inefficient only when $0 \leq \rho \leq 1$, meaning that at least one of the three variables, s^-, s^g, or s^b, is not equal to 0. The above model 2 is non-linear programming and can be transformed into an equivalent form.

$$\tau = \min t - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}$$

$$s.t.\quad 1 = t + \frac{1}{(s_1 + s_2)}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)$$

$$x_0 t = X\mu + s^-,\ \ y_0^g t = Y^g\mu - s^g,\ \ y_0^b t = Y^b\mu + s^b$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \mu \geq 0, t > 0 \tag{3}$$

In the DEA efficiency evaluation, the efficiency value of the optimal unit is 1, and when there are multiple efficient DMUs, the efficiency value cannot be further discriminated. The super-efficiency DEA model is improved for this case, allowing the efficiency value to be greater than 1. To provide more reasonable efficiency evaluation results, this study will adopt the Super-SBM model combined with the studies of Tone (2002) and Li. et al. (2013). The Super-SBM model is as follows:

$$p^{*} = min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x_{\iota}}}{x_{i0}}}{\frac{1}{s_1+s_2}(\sum_{r=1}^{s_1}\frac{y_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{y_r^b}{y_{r0}^b})}$$

$$s.t.\ \ \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j\, x_j,$$

$$\bar{y}^g \leq \sum_{j=1,\neq 0}^{n} \lambda_j\, y_j^g,$$

$$\bar{y}^b \geq \sum_{j=1,\neq 0}^{n} \theta_j\, y_j^b,$$

$$\bar{x} \geq x_0\ and\ \bar{y}^g \leq\ y_0^g,\ \bar{y}^b \leq\ y_0^b, \bar{y}^g \geq 0, \lambda \geq 0. \tag{4}$$

Various models can be derived by setting various restrictions on the traditional DEA, and the difference between the super-efficiency model and the standard-efficiency model is that the DMU to be evaluated is removed from the reference set. This can distinguish multiple efficient DMUs. The Super-SBM model is a combination of the super-efficiency DEA model and the SBM model, which not only properly handles undesirable outputs but also distinguishes efficient DMUs. Therefore, it has superiority over the traditional DEA model. Based on this, this research employs formula (4) to calculate the energy efficiency of China's 104 resource-based cities and compare the impacts of environmental pollutants on urban energy efficiency under different scenarios to provide useful policy recommendations for improving energy efficiency at the city level.

4. Results and discussion

The energy efficiencies of resource-based cities in both scenarios are demonstrated, and their differences are analysed in this section. Specifically, resource-based cities can be classified according to their development stage and dominant resources, and a discussion addressing different types of cities could provide a glimpse of the life cycle and industrial characteristics of resource-based cities.

4.1 Efficiency comparison results

To accurately analyse the impact of atmospheric pollutants on urban efficiency, this research uses the Super-SBM model to calculate the energy efficiency values of China's 104 resource-based cities under different scenarios during 2010-2016. Scenario one does not consider environmental constraints, that is, it includes no undesirable output. Scenario two takes environmental constraints into account, that is, industrial soot emissions, industrial waste water discharges, and industrial sulfur dioxide emissions are regarded as undesirable outputs. Tables 3 and 4 are the energy efficiency calculation results for resource-based cities under the two different scenarios. Table 3 shows the resource-based cities under scenario one. The 10 cities with the highest energy efficiencies are Ordos, Karamay, Lvliang, Daqing, Yulin, Zigong, Hengyang, Hechi, Dongying, and Jining. The 10 cities with the lowest energy efficiencies are Chizhou, Ya'an, Yichun^2, Xuancheng, Fuxin, Pingxiang, Hezhou, Pingliang, Lijiang, and Guangyuan. Similarly, the values of the resource-based cities under scenario two are shown in Table 4. The 10 cities with the highest energy efficiencies are Ordos, Dongying, Daqing, Karamay, Lvliang, Yan'an, Qingyang, Songyuan, Nanchong and Tai'an, while the 10 cities with the lowest energy efficiencies are Baiyin, Ezhou, Xinzhou, Hegang, Yichun^1, Datong, Pingliang, Pingxiang, Fuxin and Shizuishan.

Under both scenarios, the energy efficiencies of the five cities of Erdos, Karamay, Lvliang, Daqing and Dongying are at a high level, indicating that these cities use resources more fully and effectively than do other cities. The energy efficiencies of the four cities of Yichun^2, Pingliang, Pingxiang and Fuxin are at a low level, indicating that the energy utilization of these cities is not efficient enough, and much room for improvement exists.

In scenario one, the efficiency values of five cities are greater than 1, and in scenario two, the efficiency values of 10 cities are greater than 1, which indicates that environmental constraints will result in more cities being effective in their efficiency estimations. For example, Dongying, Qingyang, Yan'an, etc. are efficient in scenario two but not in scenario one. On one hand, these cities may emit less atmospheric pollutants, and the impact of pollutants on their energy efficiency is limited. On the other hand, the economic development of these cities is not growing. When the GDP is regarded as a single output indicator, the method is not the most efficient.

In scenario one, the average energy efficiency is 0.5383, which reaches only 54% of the optimal level. In scenario two, the average energy efficiency is 0.5131, which reaches only 51% of the optimal level. These results suggest that the energy efficiencies of resource-based cities in the above two scenarios are not high. Figure 1 shows the energy efficiency changes and the growth rates of resource-based cities under the two scenarios. Except for those in 2012, the efficiency values under scenario one are higher than those under scenario two, indicating that the produced industrial pollutants caused a reduction in energy efficiency. The annual growth rates of the efficiency values in scenario one range from -8.95% to -4.12%, and in scenario two, these rates range from -12.95% to -8.89%. Scenario two has a larger magnitude of change than does scenario one. In summary, significant differences exist in the efficiency values of resource-based cities under different scenarios. The energy efficiency may be overestimated without considering the environmental pollutants; therefore, the sustainable development of China’s resource-based cities can be more accurately reflected in scenario two than in scenario one.

Table 3 The average efficiency values of resource-based cities under scenario one (2010-2016)

Rank	City	Energy Efficiency	Rank	City	Energy Efficiency	Rank	City	Energy Efficiency
1	Ordos	1.5839	36	Zhangye	0.5520	71	Panzhihua	0.4479
2	Karamay	1.1716	37	Luzhou	0.5516	72	Baoshan	0.4461
3	Lvliang	1.1121	38	Yichun[1]	0.5514	73	Xinyu	0.4351
4	Daqing	1.0270	39	Chenzhou	0.5500	74	Heihe	0.4350
5	Yulin	1.0089	40	Suzhou	0.5487	75	Jiaozuo	0.4340
6	Zigong	0.8713	41	Handan	0.5484	76	Fushun	0.4330
7	Hengyang	0.7824	42	Benxi	0.5360	77	Maanshan	0.4310
8	Hechi	0.7823	43	Sanmenxia	0.5331	78	Suqian	0.4223
9	Dongying	0.7149	44	Xuzhou	0.5317	79	Wuwei	0.4216
10	Jilin	0.7120	45	Dazhou	0.5290	80	Zhangjiakou	0.4176
11	Tangshan	0.7010	46	Sanming	0.5131	80	Jingdezhen	0.4176
12	Zaozhuang	0.6990	47	Wuhai	0.5030	82	Liaoyuan	0.4166
13	Zibo	0.6947	48	Jilin	0.5019	83	Huaibei	0.4147
14	Tai’an	0.6941	49	Shaoyang	0.5017	84	Xinzhou	0.4100
15	Songyuan	0.6916	50	Laiwu	0.4963	85	Zhaotong	0.4093
16	Hulunbuir	0.6797	51	Chifeng	0.4921	86	Tonghua	0.4076
17	Longyan	0.6754	52	Nanyang	0.4913	87	Hegang	0.4036
18	Jincheng	0.6431	53	Nanchong	0.4909	88	Ezhou	0.4003
19	Qingyang	0.6360	54	Chengde	0.4904	89	Hebi	0.3947
20	Guang’an	0.6351	55	Qitaihe	0.4853	90	Baiyin	0.3907
21	Loudi	0.6254	56	Xingtai	0.4737	91	Yangquan	0.3834
22	Anshan	0.6171	57	Puyang	0.4701	92	Tongchuan	0.3814
23	Pingdingshan	0.6170	58	Luoyang	0.4693	93	Shizuishan	0.3779
24	Weinan	0.6054	59	Yuncheng	0.4673	94	Datong	0.3770
25	Shuozhou	0.6053	60	Anshun	0.4659	95	Chizhou	0.3731
26	Bozhou	0.6050	61	Chuzhou	0.4637	96	Ya’an	0.3700
27	Jixi	0.5889	62	Huainan	0.4614	97	Yichun[2]	0.3603
28	Huzhou	0.5883	63	Baoji	0.4603	98	Xuancheng	0.3594
29	Baotou	0.5861	64	Tongling	0.4591	99	Fuxin	0.3403
30	Linyi	0.5860	65	Shaoguan	0.4559	100	Pingxiang	0.3384
31	Yan’an	0.5853	66	Lincang	0.4531	101	Hezhou	0.3301
32	Qujing	0.5737	67	Huangshi	0.4513	102	Pingliang	0.3297
33	Xianyang	0.5676	68	Yunfu	0.4503	103	Lijiang	0.3141
34	Changzhi	0.5597	69	Baishan	0.4493	104	Guangyuan	0.2706
35	Ganzhou	0.5596	70	Nanping	0.4489			

Note: Yichun[1] is part of Jiangxi Province, and Yichun[2] is part of Heilongjiang Province.

Table 4 The average efficiency values of resource-based cities under scenario two (2010-2016)

Rank	City	Energy Efficiency	Rank	City	Energy Efficiency	Rank	City	Energy Efficiency
1	Ordos	1.1764	36	Xuzhou	0.5120	71	Qitaihe	0.3710
2	Dongying	1.1391	37	Huzhou	0.5107	72	Shaoguan	0.3690
3	Daqing	1.0974	38	Suzhou	0.4999	73	Guangyuan	0.3666
4	Karamay	1.0937	38	Linyi	0.4999	74	Xinyu	0.3626
5	Lvliang	1.0571	40	Jilin	0.4994	75	Benxi	0.3607
6	Yan’an	1.0464	41	Sanming	0.4993	76	Zhangjiakou	0.3547
7	Qingyang	1.0450	42	Liaoyuan	0.4987	77	Tongling	0.3509
8	Songyuan	1.0391	43	Anshan	0.4914	78	Jiaozuo	0.3501
9	Nanchong	1.0236	44	Zibo	0.4897	79	Maanshan	0.3459
10	Tai’an	1.0179	45	Handan	0.4876	80	Fushun	0.3441
11	Zigong	0.9367	46	Suqian	0.4843	80	Chizhou	0.3441
12	Weinan	0.8091	47	Heihe	0.4790	82	Huainan	0.3326
13	Xianyang	0.8014	48	Chengde	0.4783	83	Laiwu	0.3319
14	Yulin	0.7823	49	Jincheng	0.4774	84	Huangshi	0.3311
15	Bozhou	0.7471	50	Nanping	0.4766	85	Yuncheng	0.3294
16	Hechi	0.7160	51	Sanmenxia	0.4704	86	Hebi	0.3283
17	Nanyang	0.6929	52	Shuozhou	0.4687	87	Lijiang	0.3249
18	Jining	0.6817	53	Baishan	0.4680	88	Huaibei	0.3246
19	Baotou	0.6624	54	Pingdingshan	0.4634	89	Wuhai	0.3200
20	Longyan	0.6473	55	Lincang	0.4531	90	Anshun	0.3134
21	Hulunbuir	0.6389	56	Qujing	0.4526	91	Yangquan	0.2971
22	Hengyang	0.6296	57	Yichun1	0.4489	92	Hezhou	0.2969
23	Dazhou	0.6274	58	Chifeng	0.4477	93	Panzhihua	0.2884
24	Shaoyang	0.6031	59	Ya’an	0.4346	94	Tongchuan	0.2874
25	Loudi	0.5947	60	Yunfu	0.4320	95	Baiyin	0.2833
26	Chenzhou	0.5861	61	Luoyang	0.4301	96	Ezhou	0.2786
27	Zaozhuang	0.5856	62	Zhangye	0.4264	97	Xinzhou	0.2767
28	Guang’an	0.5760	63	Jixi	0.4247	98	Hegang	0.2681
29	Wuwei	0.5540	64	Baoshan	0.4054	99	Yichun^{2}	0.2637
30	Baoji	0.5493	65	Zhaotong	0.3976	100	Datong	0.2619
31	Chuzhou	0.5434	66	Xuancheng	0.3930	101	Pingliang	0.2491
32	Ganzhou	0.5357	67	Xingtai	0.3824	102	Pingxiang	0.2461
33	Puyang	0.5356	68	Jingdezhen	0.3810	103	Fuxin	0.2434
34	Luzhou	0.5286	69	Changzhi	0.3790	104	Shizuishan	0.2337
35	Tangshan	0.5146	70	Tonghua	0.3721			

Note: Yichun^{1} is part of Jiangxi Province, and Yichun^{2} is part of Heilongjiang Province.

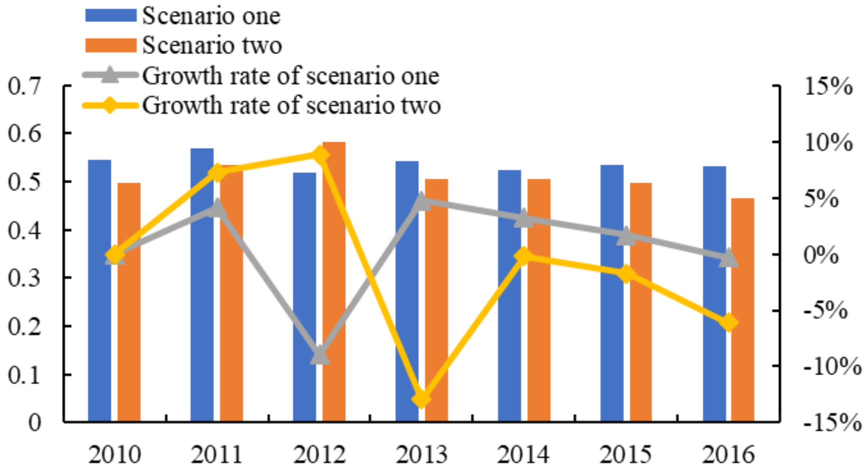

Fig. 1 Energy efficiencies and growth rates of resource-based cities under the two scenarios (2010-2016)

4.2 Efficiency disparity analysis

The energy efficiency in scenario two is much closer to the degree of urban sustainable development in the actual situation; thus, the efficiencies in scenario two were adopted to analyse the disparity from two aspects, the urban development stage and urban-dominant resources.

4.2.1 In terms of the urban development stage

In the National Plan for the Sustainable Development of Resource-based Cities (2013-2020) promulgated by the Chinese Government, a total of 262 resource-based cities are categorized into growing type, grow-up type, recessionary type, and regenerative type. As shown in Table 5, these cities are classified according to the synthetic relation of the degree of resource support capability and existing problems.

Table 5 Definition of four types of resource-based city in China

Classification	Characteristics	Problems to be faced
Growing city	Large reserves of resources, large-scale development of resources and rapid economic growth	Extensive resource exploitation and unbalanced economic development
Grow-up city	High intensity and stability of resource exploitation and a mature system of resource transportation and deep processing	Ecological environment is seriously damaged and contradictions exist in the interest reallocation
Recessionary city	Resources are almost exhausted, weak endogenous power in urban development	Miners' living conditions deteriorated, social security was in arrears, and geological hazards were serious

Regenerative city	Majority of mining activities stopped and cities basically got rid of resource dependence	Innovation capacity is not high and the function matching is imperfect

This paper covers 12 cities in the growing period, 57 cities in the grow-up period, 22 cities in the recession period and 13 cities in the regeneration period. Figure 2 shows the energy efficiency changes in resource-based cities at different developmental stages. The growing cities have the highest energy efficiencies (the average value is 0.7725), followed by the grow-up cities (the average value is 0.5245) and the recessionary cities (the average value is 0.4805), and the regenerative cities have the lowest energy efficiencies (the average value is 0.3612). The development of resource-based cities presents a cyclical feature, that is, the energy efficiency first increases, then decreases, and finally rebounds. This process occurs mainly because resource-based cities usually rely on the exploitation of mineral resources. The energy efficiency of cities at different stages is correlated to the degree of resource utilization. Growing cities and grow-up cities have great potential for resource security and strong sustainable development capacity. As mining difficulty and production costs increase in a city, production at the same level of GDP will consume more energy, and the city will gradually enter recession period. The exhaustion of resources will affect the city's sustainable development capabilities, and the city will begin to explore a transformation path.

The urban efficiencies of 24 resource-based cities in China were estimated by Wei et al. (2012). The results show that only a few reached the optimum level. This is consistent with the findings of this study. The drivers of efficiency changes were also explored by Wei et al. (2012) and the scale efficiency is the most significant factor. Similarly, the efficiency differences among 116 resource-based cities were analyzed by Li and Dewan (2017). Unlike our study, they use cross-sectional data, while we use panel data. According to Li and Dewan (2017), the efficiencies of most resource-based cities are low. Industrialization level, service industry and built-up area can positively promote this kind of efficiency.

The developmental trajectory of resource-based cities follows specific life-cycle characteristics. Initially, the resource industry of growing cities enables the rapid development of the urban economy. At the same time, the cities receive sufficient investment in technology and the most efficient energy utilization. The resource industry of grow-up cities is in a stable stage, with abundant resources, and the energy efficiency is between that of growing cities and regenerative cities. The resources of recessionary cities tend to be exhausted, and economic development is lagging, so their sustainable development degree is the lowest. Regenerative cities have essentially eliminated resource dependence and developed alternative industries, and high-tech and clean energy have been promoted; thus, the energy efficiency is higher in these cities than in recessionary cities.

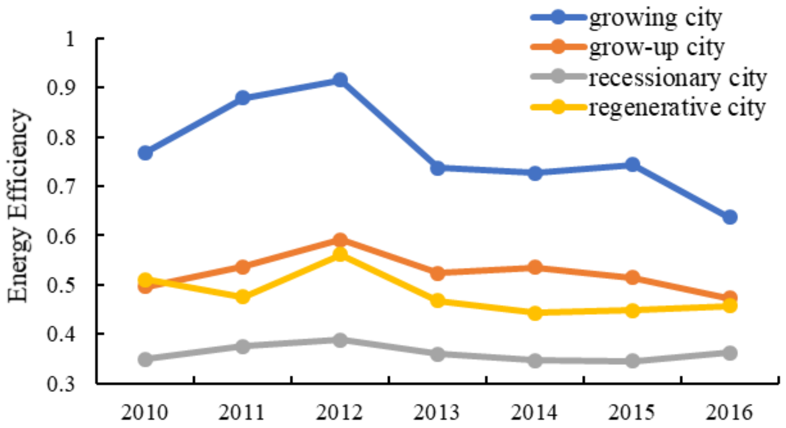

Fig. 2 Energy efficiencies of resource-based cities at different development stages

4.2.2 In terms of urban-dependent industry

According to different dominant industries, resource-based cities can be divided into forestry-based, oil and gas-based, nonferrous metal-based, non-metallic-based, coal-based, ferrous metal-based and multiple minerals-based industries. Among these categories, the multiple minerals-based category refers to the use of two or more resources in the dominant industry. It can be seen from Figure 3 that the energy efficiencies of different resource-based cities show marked differences, and there is no significant fluctuation during the period 2010-2016. Overall, the order of energy efficiency is oil and gas-based > multiple minerals-based > non-metallic-based > nonferrous metal-based > coal-based > forestry-based > ferrous metal-based. Energy efficiencies can generally be divided into four categories. This is partly different from Sun et al. (2012), the results obtained by their study is nonferrous metal-based > forestry-based > coal-based > oil and gas-based > steel-based > industrial mineral-based.

The first category is oil and gas-based cities, which have the highest efficiencies (the average value is 0.9014), with values much higher than the efficiencies of other types of cities. This high level is mainly because oil and natural gas are cleaner than other energy sources and have high investment and high return characteristics. Oil and gas-based cities usually suffer less ecological damage and have high total economic output. For example, Karamay's dominant industries are oil and gas exploration and petroleum refineries. Its reserves of oil and gas resources account for nearly 80% of the world’s reserves, and Karamay was once ranked first in China's per capita GDP.

The second category is multiple minerals-based cities (the average value is 0.531), non-metallic-based cities (the average value is 0.4971) and nonferrous metal-based cities (the average value is 0.4834), and the efficiency values of this category are at a moderate level. The low energy efficiency of non-metallic-based cities is related to the characteristics of the non-metallic mining industry. On one hand, the technical level of the entire industry is not high enough. Most enterprises lie at the front end of the industrial chain and are mainly engaged in raw ore and primary processing products. Fewer large-scale types of equipment are required for deep processing, and the energy consumption per unit of product is high. On the other hand, the scale of the enterprise is small and scattered, and resource recycling needs to be improved. Resources are wasted when non-metallic mineral products are exported, resulting in a low comprehensive resource utilization rate. The third category comprises coal-based cities (the average value is 0.4547), forestry-based cities (the average value is 0.407), and ferrous metal-based cities (the average value is 0.3787), with the lowest efficiency levels. Compared with those in other cities, industrial pollution in coal-based and ferrous metal-based cities is more serious, and a large number of labour-intensive industries are clustered. Furthermore, the technical requirements for industrial equipment and educational backgrounds of the workers are very low, which is not conducive to taking advantage of labour productivity. To explore the urban sustainable transformation, some efforts seem to be beneficial, such as biogas promotion and reuse of waste resources (Marousek et al., 2018; Hašková, 2017).

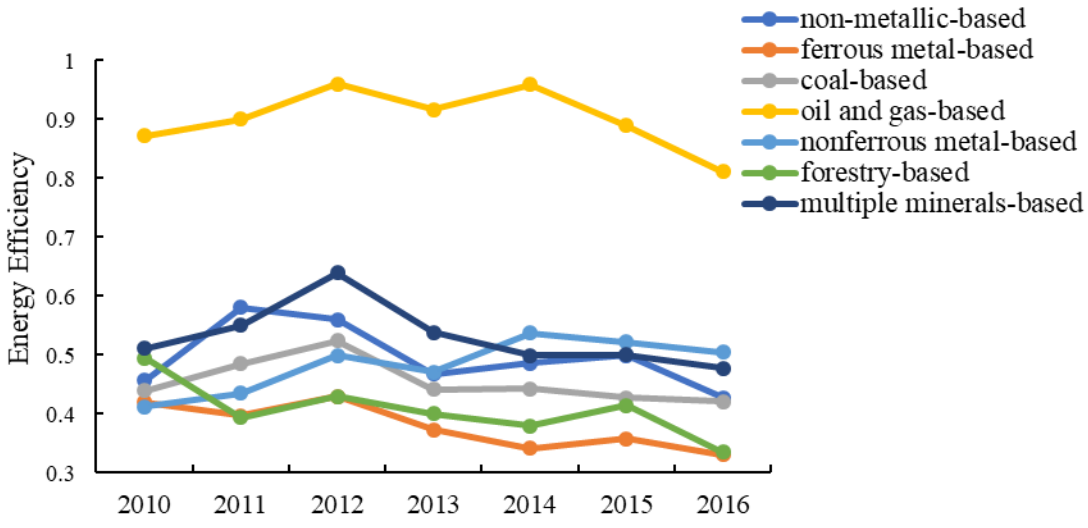

Fig. 3 Energy efficiencies of resource-based cities with different dominant resource types

5. Cluster analysis

Clustering technology can be used to study the logical or physical relationship between data by grouping and categorizing unordered objects for better analysis and processing. This multivariate statistical analysis classifies individuals or samples according to their characteristics, with the aim of making individuals in the same category as homogenous as possible, while the categories are as heterogeneous as possible. Clustering results can not only reveal intrinsic relationships in data but can also provide an important basis for mining deep-seated laws. The K-means clustering algorithm is widely used. This method uses distance as the evaluation index of similarity (Kanungo et al.，2004). For a given data set X containing n d-dimensional data points and the category K to be separated, the Euclidean distance is selected as the similarity index, and the objective is to minimize the sum of the squares of each cluster. When the least squares method and the Lagrangian principle are used in combination, the cluster centre is the average value of the data in the corresponding categories. To converge the algorithm, the final cluster centre should be kept as constant as possible during the iterative process.

$$J = \sum_{k=1}^{k} \sum_{i=1}^{n} \left| \left| x_i - u_k \right| \right|^2 \tag{5}$$

Thus, the above K-means clustering method was adopted to classify the energy efficiency of China's resource-based cities from 2010 to 2016 under different scenarios. Areas with similar characteristics were classified into one category, and all cities were divided into high-energy efficiency zones, medium-energy efficiency zones and low-energy efficiency zones. As shown in Table 5, five cities belong to the high-efficiency zone, 40 cities belong to the medium-efficiency zone, and 59 cities belong to the low-efficiency zone in scenario one. In scenario two, 11 cities belong to the high-efficiency zone, 43 cities belong to the medium-efficiency zone and 50 cities belong to the low-efficiency zone. There are some differences between the city classifications produced by the two scenarios. In scenario two, the number of cities in to the high-efficiency zone is larger, and the number of cities in the low-efficiency zone is smaller.

Table 5 Clustering analysis of resource-based cities under the two scenarios

Zone division	Scenario one	Scenario two
High-energy efficiency zone	Lvliang, Erdos, Daqing, Yulin, Karamay	Lvliang, Erdos, Songyuan, Daqing, Dongying, Tai'an, Nanchong, Zigong, Yan'an, Qingyang, Karamay
Medium-energy efficiency zone	Tangshan, Handan, Shuozhou, Changzhi, Jincheng, Baotou, Hulunbuir, Benxi, Anshan, Songyuan, Xuzhou, Jixi, Huzhou, Suzhou, Bozhou, Longyan, Ganzhou, Yichun^2, Dongying, Zibo, Linyi, Zaozhuang, Jining, Tai'an, Sanmenxia, Pingdingshan, Hengyang, Chenzhou, Loudi, Hechi, Guang'an, Zigong, Luzhou, Dazhou, Qujing, Yan'an, Weinan, Xianyang, Zhangye, Qingyang	Chengde, Tangshan, Handan, Shuozhou, Jincheng, Baotou, Hulubuir, Anshan, Liaoyuan, Baishan, Heihe, Xuzhou, Suqian, Huzhou, Suzhou, Bozhou, Chuzhou, Nanping, Sanming, Longyan, Ganzhou, Zibo, Linyi, Zaozhuang, Jining, Jilin, Sanmenxia, Puyang, Pingdingshan, Nanyang, Hengyang, Chenzhou, Shaoyang, Loudi, Hechi, Guang'an, Luzhou, Dazhou, Weinan, Xianyang, Baoji, Yulin, Wuwei
Low-energy	Zhangjiakou, Chengde, Xingtai, Datong,	Zhangjiakou, Xingtai, Datong, Yangquan,

efficiency zone	Yangquan, Xinzhou, Yuncheng, Wuhai, Chifeng, Fuxin, Fushun, Jilin, Liaoyuan, Tonghua, Baishan, Heihe, Yichun^{1}, Hegang, Qitaihe, Suqian, Huaibei, Huainan, Chuzhou, Maanshan, Tongling, Chizhou, Xuancheng, Nanping, Sanming, Jingdezhen, Xinyu, Pingxiang, Laiwu, Luoyang, Jiaozuo, Hebi, Puyang, Nanyang, Ezhou, Huangshi, Shaoyang, Shaoguan, Yunfu, Hezhou, Guangyuan, Nanchong, Panzhihua, Ya'an, Anshun, Baoshan, Zhaotong, Lijiang, LincangTongchuan, Baoji, Baiyin, Wuwei, Pingxiang, Shizuishan	Changzhi, Xinzhou, Yuncheng, Wuhai, Chifeng, Fuxin, Fushun, Benxi, Tonghua, Yichun^{2}, Hegang, Qitaihe, Jixi, Huaibei, Huainan, Maanshan, Tongling, Chizhou, Xuancheng, Jingdezhen, Xinyu, Pingxiang, Yichun^{1}, Laiwu, Luoyang, Jiaozuo, Hebi, Ezhou, Huangshi, Shaoguan, Yunfu, Hezhou, Guangyuan, Panzhihua, Ya'an, Anshun, Qujing, Baoshan, Zhaotong, Lijiang, Lincang, Tongchuan, Baiyin, Zhangye, Pingliang, Shizuishan

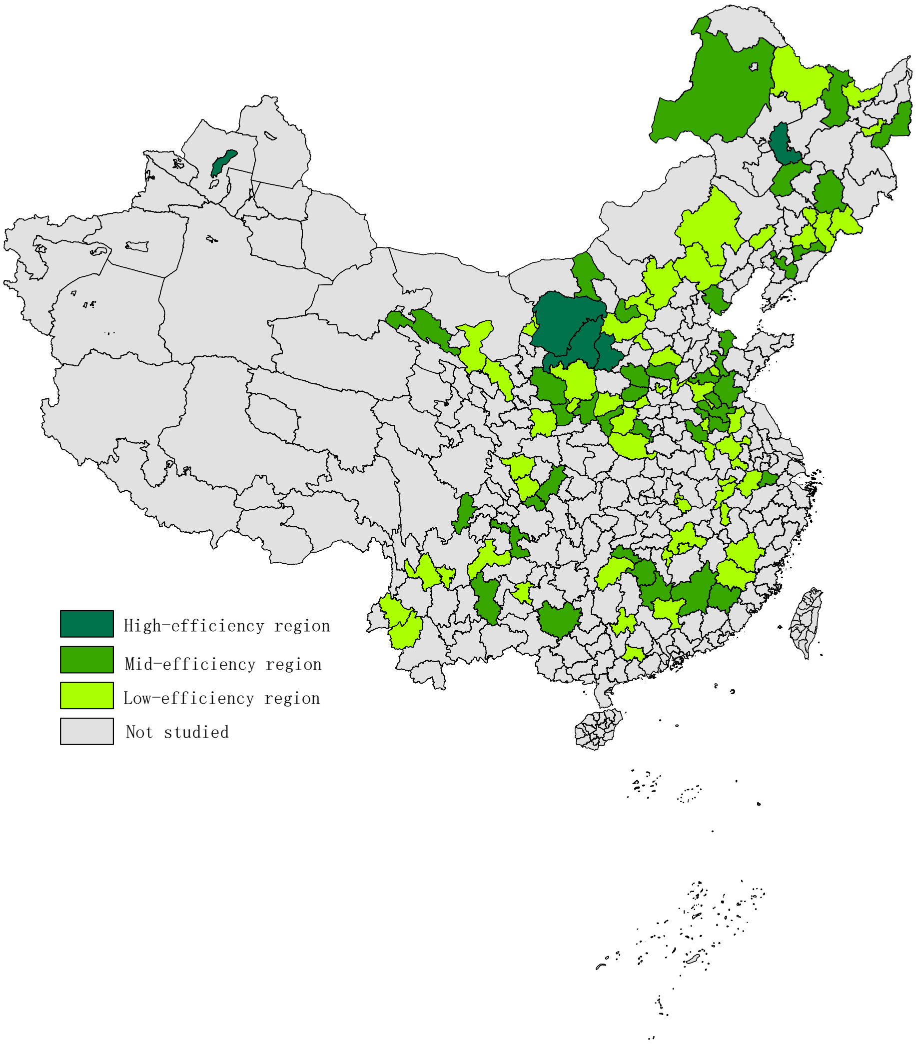

Fig. 4 Energy efficiency divisions in China's resource-based cities under scenario one

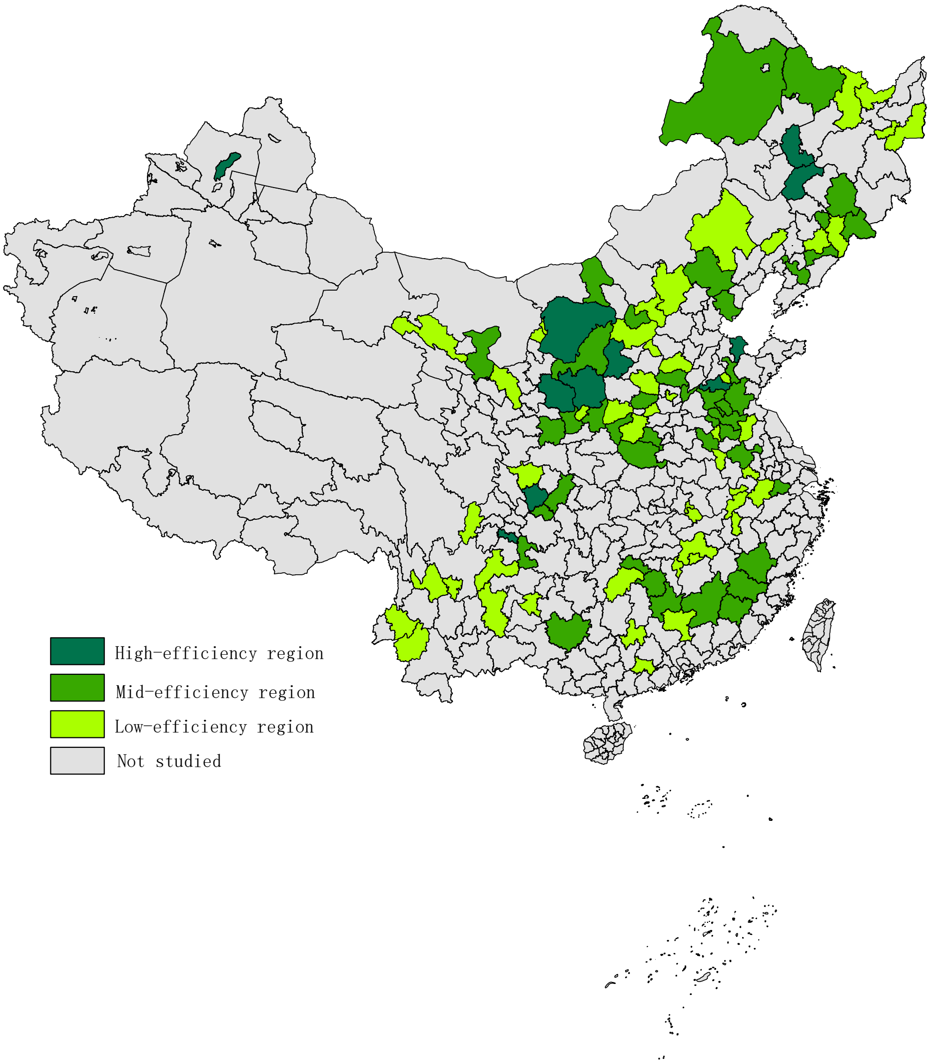

Fig. 5 Energy efficiency divisions in China's resource-based cities under scenario two

6. Conclusions and policy implications

6.1 Conclusion

Resource-based cities are extremely dependent on resources; however, after experiencing large-scale resource exploitation, resources will be exhausted. At this time, the comparative advantages of these areas are no longer in existence, and industrial clusters are difficult to form, which is detrimental to the local economy. Generally, resource depletion is a challenge that every resource-based city faces or will face. To date, nearly half of Chinese resource-based cities have been confronted with severe economic structural transformation problems, and the growing demand for sustainable development is a fuelled topic. The inevitable choice for extracting resource-based cities in China from non-sustainable predicaments is industrial transformation. Industrial transformation is characterized by changes in energy efficiency, and this work sheds new light on the energy efficiency of resource-based cities and provides broad enlightenment for policymakers.

Using the Super-SBM model including undesirable outputs, as well as the K-means clustering technique, this study measured the energy efficiency of China's resource-based cities from 2010 to 2016. The 104 resource-based cities are classified into high-efficiency regions, medium-efficiency regions and low-efficiency regions in line with the efficiency values. On the basis of the findings offered by this study, efficiency disparities exist in resource-based cities under different scenarios, as a whole, the energy efficiency in the scenario considering by-products of energy activities is obviously lower, which can more truly represent the sustainability of resource-based cities. The great part of the research hypotheses is confirmed. Firstly, the development of resource-based cities follows specific life-cycle characteristics. The ordering of cities from highest- efficiency to lowest-efficiency is growing cities, grow-up cities, recessionary cities, and regenerative cities. Secondly, most resource-based cities are categorized as low-efficiency regions, indicating great potential to upgrade. The efficiency differences between various types of cities are manifested, and these differences did not change significantly as time elapsed. Thirdly, the energy efficiency assessment of various resource-based cities can provide inspiration for other cities or developing countries which are in similar industrialization phases, to formulate urban sustainable development policies.

6.2 Policy recommendations for efficiency promotion

In view of the fact that the economic transformation of resource-based cities is an important and strategic measure, developing countries can draw lessons from foreign experience and give preferential support to the economic transformation of cities in terms of industrial policies and infrastructure through legislation. Such as the

Czech Republic (Mardoyan and Braun, 2015).

(1) Formulate urban development plans according to local conditions

According to the results of this study, the efficiency differences between different types of resource-based cities are obvious, so the gap between cities needs to be narrowed to alleviate the imbalance of regional development. Resource-based cities can be divided into growth-period, maturity-period, recession-period and regeneration-period cities or into forestry-based, oil and gas-based, nonferrous metal-based, non-metallic-based, coal-based, ferrous metal-based and multiple minerals-based cities. The efficiencies of recession-period cities and ferrous metal-based cities are the lowest in each group. Therefore, the government should formulate different development strategies for different types of resource-based cities. For example, for growing cities, the relationship between resource exploitation and urban development should be rationally planned to avoid excessive dependence on resource industries. For regenerative cities, emphasis should be placed on supporting alternative industries and promoting the reemployment of unemployed workers. For ferrous metal-based cities, environmental protection should be put first.

(2) Adjusting the input-output structure

Long-term urban sustainable development strategies, rather than short-term higher GDP growth rate goals, need to be designed by the central government. More attention needs to be paid to paid to inefficient cities, especially the recessionary cities and ferrous metal-based cities with the lowest efficiencies. Specifically, the local government could play a more active role in putting more public expenditure on promoting the training of mining workers and the green consumption concept. For resource-based cities with relatively low energy inefficiencies, efforts should be made to adjust the input-output structure to improve the resource allocation level, and at the same time, investment in science and technology should be increased to enable efficient and clean production technologies to be developed and, finally, to control pollution emissions from economic operations.

(3) From a single industry to a diversified industry

The economic transformation of resource-based cities does not mean that traditional industries should be abandoned altogether. Specifically, this not only requires technological upgradation for traditional industries that still have competitive advantages, but also give consideration to financial support for emerging industries. In addition, the comprehensive utilization of associated resources, symbiotic resources and waste should also be carried out to improve the overall urban efficiency. Under such circumstances, the government needs to shift economic production activities from industries with low added value to those with high added value. For example, the vast majority of rare earth elements in the world come from Baotou City, China. In the past, raw materials for rare earth elements were produced in Baotou via processes which were subcontracted by foreign enterprises, including Japan and Korea, and then sold back to China. However, new material processing of rare earths with high value added and high technology levels can create huge sustainable wealth. With the gradual combination of high-tech and rare earth industries in China, rare earth products are given higher added value, which is also making Baotou's industry shift from resource-intensive to knowledge-intensive.

Acknowledgments

This work is supported by Shenzhen Municipal Development and Reform Commission, Shenzhen Environmental Science and New Energy Technology Engineering Laboratory (No. SDRC [2016]172). The authors gratefully acknowledge financial support from National Natural Science Foundation of China (No.71803182 and No.21808119), China Postdoctoral Science Foundation (No. 2019M650733 No. 2018M641379).

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