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How technological innovations affect urban eco-efficiency in China: A prefecture-level panel data analysis

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ABSTRACT

This paper utilizes SBM-undesirable model and Malmquist index to examine the urban eco-efficiency in China and analyzes the regional heterogeneity. Through the panel data of 273 prefecture-level cities during 2007–2017 in China, the spatial Durbin model is used to examine the influencing factors of urban eco-efficiency associated with technological innovations. The results show that the average values of urban eco-efficiency of the East, Central, and West regions are 0.93, 0.88, and 0.90, respectively. The Moran's I of eco-efficiency is around 0.8, which shows a strong spatial heterogeneity. It is found that higher innovative ability can increase urban eco-efficiency. Education investment and innovation talents have a U-shape relationship with urban eco-efficiency, while capital investment and innovation performance have an inverted U-shape relationship with it. This research outlines the relationship between technological innovations and urban eco-efficiency, offering policy implications for China's eco-construction and sustainable urban development.

1. Introduction

With the pace of urbanization accelerating dramatically, China's economy has incurred extreme environmental costs, and several urban problems such as a sharp decline in biodiversity, resource shortage, and air pollution have emerged. The economic growth pattern characterized by "high input, high consumption, and high emissions" has contributed significantly to the increase in pollution of the regional eco-environment (Eugenia and Ming, 2003). Therefore, how to balance economic growth and ecological protection becomes an essential topic in China's policy agenda.

Under such background, the index of eco-efficiency as the ratio of economic growth and environmental resource consumption is frequently applied (Schaltegger and Sturm, 1990; WBCSD, 1996; OECD, 1998), which reflects not only the coordination of resources, economy, and environment but also the sustainable ability of a region to achieve economic prosperity with scarce resources. The technological innovations play a crucial role in realizing economic growth in an eco-friendly way (Klewitz and Hansen, 2014), but climate change in recent years indicates that technological innovation also has limitations in the balance of economic environment (Bertinelli et al., 2012). On the one hand, technological innovation improves the production efficiency as well as the economic performance of enterprises (Jaffe and Palmer, 1997). On the other hand, technological innovation in various industries doesn't all have the dual nature of economic growth and energy-saving. For example, chemical fertilizers and pesticides have also caused water pollution and eutrophication while increasing agricultural production. Improving eco-efficiency through technological innovations is one of China's goals to become an innovative country. However, whether technological innovation can stimulate economic growth and pollution reduction simultaneously is an important question to be answered (Qiao, 2015).

Regional heterogeneity and spatial interconnection are essential features affecting the effect of technological innovation on eco-efficiency. Owing to the existence of spatial interaction, the eco-efficiency of a city will have specific effects on the surrounding regions through diffusion or polarization (Pan et al., 2015). Therefore, the eco-efficiency of different cities are both interconnected and distinct. Because of the spatial dependence and spatial correlation of regional variables, ignoring the spatial spillover effect leads to errors in model estimation. Therefore, combining the spatial variation relationship with the quantitative relationship is important for comprehensively explaining technological innovation and urban eco-efficiency development.

Analyzing the characteristics of eco-efficiency of different urban regions and identifying the crucial factors that affect urban eco-efficiency

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in technological innovations can significantly help in formulating long-term urban eco-construction policies in different cities. It is also vital to promote the regional coordinated development of eco-efficiency among the cities dominated by different industrial structures. Based on the existing research, this paper integrates theoretical models with empirical data to answer the following four questions. (1) What is the spatial pattern of urban eco-efficiency in China at the prefecture-level cities? (2) What is the difference between the eco-efficiency patterns of cities in different regions? (3) Considering spatial contribution, which technological innovations factor is the main reason for the change in urban eco-efficiency? (4) To what extent does the spatial contribution brought by various technological innovation factors account for variations in urban eco-efficiency?

The rest of this research is organized as follows. Section 2 reviews the literature. Section 3 constructs an evaluation model of China's urban eco-efficiency and calculates the eco-efficiency of 273 prefecture-level cities during 2007–2017. Section 4 analyses the spatial correlation of China's urban eco-efficiency. Section 5 applies the spatial econometric model to analyze the relationship between eco-efficiency and technological innovations further. Finally, section 6 offers conclusions and policy suggestions.

2. Literature review

As an effective tool for examining the degree of harmony among "natural-economic-society", the relationship between eco-efficiency and its influencing factors is the focus of the current research. Most scholars mainly research on eco-efficiency on the economy (Pauleit et al., 2005; Wang et al., 2016), urbanization (Bai et al., 2018), and energy (Saling et al., 2005). There has been a prolonged discussion on whether technological innovations can effectively improve urban eco-efficiency. From an economic perspective, technological innovation is one of the core driving forces of economic development (Schumpeter, 1934). With the development of society, the model of economic growth will change from factor-driven to innovation-driven (Iyigun, 2006). From an environmental perspective, some green technological innovations have achieved material recycling (Brännlund et al., 2007), while some technological innovations have also offer eco-unfriendly technologies and products (Chang et al., 2014). But scholars have different views on the comprehensive role of economy and environment. Some believe that technological innovations improve the efficiency of resource utilization, and its positive effect on the environment is greater (Ghisetti and Quatraro, 2017). Others believe that environmental problems caused by economic progress can also be directly explained by technological progress (Ayres, 1996). The challenge of the low conversion rate of innovation is that technological innovation does not necessarily improve the economy (Brookes, 1990). From the aspect of coordinated development of the economic and environment, technological innovation may be an obstacle to eco-efficiency (Chang et al., 2015). Generally, technological innovations have a significant impact on eco-efficiency, but the effect is still uncertain. The ultimate result depends on the massive role of the two sides. Therefore, it is crucial to examine the impact of technological innovation on eco-efficiency.

There are three main methods of determining eco-efficiency, including the indicator system method (Meng et al., 2008), life-cycle assessment (Beames et al., 2015) and data envelopment analysis (DEA) (Fan et al., 2017), among which DEA is the most frequently applied. DEA was first proposed by Charnes (1979), and Färe et al. (1992) integrated the DEA method with the Malmquist index to examine the effects of dynamic changes and resource utilization efficiency. Tone (2001) further proposed a non-radial SBM model based on relaxation measurements, incorporating undesired outputs into the evaluation of the relative effectiveness of DEA (Tone, 2003). This model corrects the defect that all inputs of the original model are reduced in the same proportion and solves the measurement problem of green economy efficiency under the constraints of resources and environment (Tao et al., 2016). Additionally, considering the regional differences, many scholars have begun to incorporate spatial factors into the research process in recent years (Zhang et al., 2018; Agovino et al., 2018).

Currently, most research on urban eco-efficiency focuses on urban agglomerations (Tao et al., 2017; Huang et al., 2018b) or provincial-level (Wang et al., 2011; Chang et al., 2013), and the research from prefecture-level cities perspective is scarce. Due to the differences in eco-efficiency between cities, ignoring the differences between cities will affect the applicability of research results. There are applicability challenges in the research conclusion. Most of the urban eco-efficiencies are analyzed from the perspectives of economy, environment, and energy. As a crucial factor affecting eco-efficiency, the relationship between technological innovations and eco-efficiency is still controversial (Xu and Qu, 2001). Most of the above research points on the influencing factors of eco-efficiency focus on quantitative relations, neglecting the spatial spillover effect between regions, and failing to reflect the spatial development of eco-efficiency (Liu et al., 2017).

Based on a systematic review of relevant literature and theories, this research integrates theoretical models with empirical evidence. First, this paper constructs a measurement model of China's urban eco-efficiency and analyzes the eco-efficiency development trends of different types of cities from 2007 to 2017. Second, this paper analyses the heterogeneity and spatial effects of China's urban eco-efficiency from both temporal and spatial dimensions. Third, this study applies the spatial econometric model to study the influencing factors of urban eco-efficiency in terms of the technological innovation. Finally, this research offers policy recommendations for China's future urban eco-construction development and environmental policy formulation of different urban types.

3. Evaluation of urban eco-efficiency

3.1. Model settings

This research utilizes the SBM-Undesirable model to examine urban eco-efficiency. Assuming that a system has n decision-making units, an input index value x_i, output index value y_i, and an undesired output indicator value b_i. Then the decision unit set (T_{DMU}) can be expressed as equation (1) (Tone, 2003):

$$T_{DMU} = \left\{ \left(x_1, y_1, b_1\right), \left(x_2, y_2, b_2\right), \cdots \left(x_n, y_n, b_n\right) \right\} \tag{1}$$

Based on Tone's SBM-Undesirable model, each unit has m inputs, n_1 expected outputs and n_2 undesired outputs. With X, Y, B as inputs, expected outputs, and undesired output matrices, the model can be constructed as follows:

$$\min_{\lambda, s^+, s^-} \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{ik}}}{1 + \frac{1}{n_1+n_2}\left(\sum_{r=1}^{n_1} \frac{s_r^+}{y_{rk}} + \sum_{t=1}^{n_2} \frac{s_t^{b-}}{b_{rk}}\right)} \tag{2}$$

$$st \begin{cases} X\lambda + S^- = x_k \\ Y\lambda - S^+ = y_k \\ B\lambda + S^{b-} = b_k \\ \lambda \geq 0, S^- \geq 0, S^+ \geq 0, S^{b-} \geq 0 \end{cases}$$

Where x_k, y_k, b_k are inputs, expected outputs, and undesired output indicators respectively; s^-, s^+, s^{b-} represent the amount of relaxation of each indicator; S^-, S^+, S^{b-} represent the relaxation matrix of each indicator; λ is the weight of each input element; ρ is the efficiency value, and when $\rho = 1$ the decision unit is located at the optimal production frontier.

This research uses the RD-Malmquist model (Ray and Desli, 1997) to analyze the dynamic urban eco-efficiency from 2007 to 2017.

$$M\left(x^t,y^t,x^{t+1},y^{t+1}\right)=\left(M_t\cdot M_{t+1}\right)^{\frac{1}{2}}=\left[\frac{D^t(x^{t+1},y^{t+1})}{D^t(x^t,y^t)}\frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}}$$
$$=\left[\frac{D_V^t(x^t,y^t)}{D_V^{t+1}(x^t,y^t)}\frac{D_V^t(x^{t+1},y^{t+1})}{D_V^{t+1}(x^{t+1},y^{t+1})}\right]^{\frac{1}{2}}\times\frac{D_V^{t+1}(x^{t+1},y^{t+1})}{D_V^t(x^t,y^t)}\times \tag{3}$$
$$\left[\frac{D_C^t(x^{t+1},y^{t+1})/D_V^t(x^{t+1},y^{t+1})}{D_C^t(x^t,y^t)/D_V^t(x^t,y^t)}\frac{D_C^{t+1}(x^{t+1},y^{t+1})/D_V^{t+1}(x^{t+1},y^{t+1})}{D_C^{t+1}(x^t,y^t)/D_V^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}}$$

Where x and y represent the input and output, $D^t\left(x^t,y^t\right)$ represents the distance function of decision-making unit (DMU) in t period, D_V and D_C respectively indicate the distance function in the case of variable returns to scale and constant returns to scale. The first term represents the technology progress index (TECH), the second term represents pure technical efficiency (PECH), the third term represents scale efficiency (SECH), and the product of the second term and the third term is technical efficiency (EFFCH). Equation (2) can simplify the total factor productivity index (TFP) as equation (4):

$$\begin{aligned}M\left(x^t,y^t,x^{t+1},y^{t+1}\right)&=TFP\\&=TECH\times EFFCH\\&=TECH\times PECH\times SECH\end{aligned} \tag{4}$$

Any index that is greater than 1 indicates that the factor promotes efficiency. Any index less than 1 shows a declining efficiency.

3.2. Index selection and data sources

The evaluation index of urban eco-efficiency includes three parts: the economy, resources, and environment. The World Business Council for Sustainable Development (WBCSD) offers varieties of input-output indicators as alternative indicators, of which labor, land, material resources, and capital are the primary indicators of input. This research uses land, capital, energy and labor as input indicators. (1) Land: As one of the three major production factors, it's a crucial input for urban development. Most researches have included land input into the eco-efficiency evaluation system (Huang et al., 2018a). This research uses urban construction land as the input of land resources. (2) Capital: Capital investment is the economic basis of urban development. This research reflects the capital investment in a certain period with public capital investment (Xu, 2010). (3) Energy: Since energy consumption data at the city level has not been published, the total annual electricity consumption of cities is used to represent energy input by referring to the references (Li and Lin, 2016; Zhang et al., 2017). (4) Labor: The number of employees at the end of every year is used as the labor input indicator and reflects the actual labor input in a certain period (Richards et al., 2017).

The expected output should reflect urban economic development and eco-environment improvement. The commonly used indicators include GDP, per capita disposable income, green area, and so on. Economic development is also accompanied by energy and environmental pollution. According to literature, industrial sulfur dioxide and soot emissions are often used as undesired outputs (Li and Lin, 2016; Li and Wu, 2017). According to data availability, this research utilizes comparable GDP as the economic expected output, per capita green space and green coverage area as the environmental expected output index (Ma et al., 2019). The soot, waste water and SO_2 missions are used as undesired output (Bai et al., 2018; Huang et al., 2018b). The input index and output index should meet a positive correlation (Tone, 2003). The pearson correlation coefficient (PCC) test results are shown in Table 1.

It can be found from Table 1 that there is a weak negative correlation between Labor and SO_2 emissions. As the SO_2 emissions is an unexpected output index, the relationship between them is reasonable in a practical sense. Labor has a weak positive correlation with other indicators. The reason may be that the conversion relationship between labor input and outputs weakens the direct correlation between them (Prinz and Pegels, 2018). The correlation between the other variables is strong, and all of them show a significant positive correlation. Therefore, the index selection is reasonable. Based on the input-output relationship, this research constructs an evaluation index system of urban eco-efficiency, as shown in Table 2.

During selection, we applied the 80% rule to preclude cities in which the missing values exceeded 20% (Sabina et al., 2006). Finally, a total of 273 cities were selected from 2007 to 2017 based on data availability and effectiveness. *SPSS* software supplements the missing data with the EM algorithm.

3.3. Trends in China's urban eco-efficiency

Different regions have shown rapid growth in economic development. Some central and western regions have had increased economic development than the eastern regions. Although the eco-efficiency of the West and Central show an overall upward trend, it also lags behind the East. The eco-efficiency has experienced a short-term decline in the past 11 years, but it has maintained an overall upward trend. The main reason for the drastic decline of eco-efficiency in 2008 could be the economic crisis that slowed the growth of investments in China and reduced urban eco-construction. In 2017, the eco-efficiency of the three regions declined, which was consistent with the current situation that China's regional differentiation converged for the first time this year. Analyzing the reasons, China proposed environmental protection and production restriction policies in 2017 to achieve high-quality economic development, which impacted the economy of all three regions. Although the quality of the environment has improved, the efficiency of inputs and outputs has been limited. The regional gap has gradually minimized. From the research data in Fig. 1, the eco-efficiency of the three areas shows a consistent development trend. The urban eco-efficiency of the eastern region has always dominated. The West has developed rapidly and gradually overtook the Central. However, the development of the Central is insufficient, and its eco-efficiency is lower than the national average.

Fig. 2 shows that the TFP fluctuated thrice in 11 years. The causes of thermal fluctuations were explored through factor decomposition. Results show that the contribution of TECH and EFFCH varies across time. Notably, TFP and TECH exhibit similar trends indicating TECH is the main driving force for TFPCH growth.

Table 1
PCC test results.

	Comparable price GDP	Per capita green space	Green coverage area	Soot emissions	Waste water emissions	SO_2 emissions
Land	0.7597***	0.0496***	0.9033***	0.3729***	0.0325*	0.2681***
Capital	0.7916***	0.0167	0.7503***	0.3119***	0.0282	0.2333***
Energy	0.8764***	0.0899***	0.7384***	0.4669***	0.0519***	0.2801***
Labor	0.0128	0.0383**	0.0114	0.0032	0.0074	−0.0063

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 2
Evaluation index system of urban eco-efficiency in China.

Type	Indicator	Sources
Inputs	Built-up area (square kilometers)	China Urban Statistics Yearbook
	Urban capital Statistics (10,000 yuan)	China Urban Statistics Yearbook
	Urban electricity consumption (10,000 kWh)	China Urban Construction Statistics Yearbook
	Number of employees at the end of the year(person)	China Urban Statistics Yearbook
Desirable outputs	Comparable price GDP (10,000 yuan)	China Urban Statistics Yearbook
	Per capita public green area (m^2)	China Urban Construction Statistics Yearbook
	Green area of the built-up area (hectare)	
Undesirale outputs	Soot emissions (tons)	China Urban Statistics Yearbook
	Waste water emissions(10,000 tons)	China Urban Statistics Yearbook
	SO_2 emissions (tons)	China Urban Statistics Yearbook

(1) The economic crisis of 2008 affected the development of technology, which caused significant fluctuations in TECH and EFFCH. PECH and SECH were both greater than 1, indicating that the development of urban institutions and management levels increased the use of element resources in DMU. The gap between the actual-scale of cities and the optimal-scale of production is reducing. The change in the level of EFFCH makes up for the loss of TECH and makes the overall TFP development stable.
(2) The decline in TECH majorly caused a sharp decline in TFP in 2013–2014. The technological progress of this period couldn't balance economy and environment. The severe haze weather that hit the country for the first time in 2013 also confirmed this. Although both PECH and SECH are greater than 1, the change in the level of EFFCH cannot make up for the loss of TECH, eventually leading to a decline in TFP.
(3) China issued ten environmental protection policies in 2016–2017 to promote eco-protection vigorously. The decline in TFP indicates that despite the environmental protection policies, the development of eco-efficiency is limited. TECH, PECH and SECH are all slightly less than 1. It shows that at the beginning of the implementation of the policy, the economy is temporarily influenced while the environment is improved. The decline of SECH indicates that there could be reasons such as unfair competition and financial constraints between cities, which inhibits the DMU from operating at the appropriate level.

Various factors frequently fluctuate around 1, indicating that although China's eco-construction has attained particular results, its development is not stable. TECH is the primary influencer of TFP, and choosing the indicators that can reflect technological innovation to examine its specific relationship with urban eco-efficiency has particular practical significance for the government to formulate relevant policies.

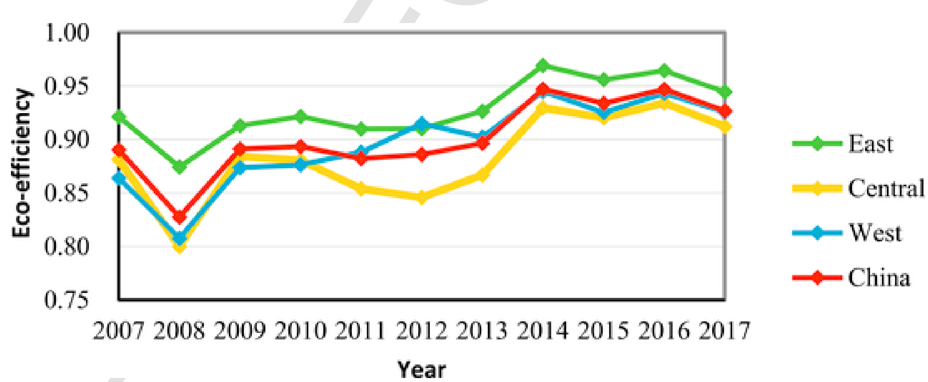


Fig. 1. Trends in annual average eco-efficiency of the whole nation and three regions.

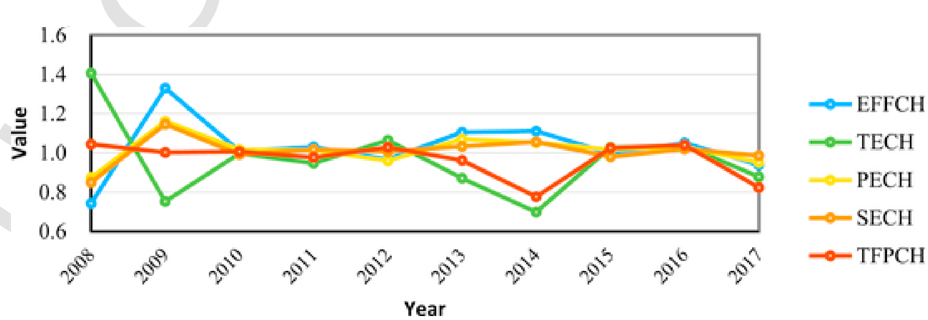


Fig. 2. Total factor productivity decomposition.

3.4. Spatial distribution of urban eco-efficiency in China

The spatial and temporal distribution maps of urban eco-efficiency in 2007, 2011 and 2017 drawn by *QGIS* are shown in Fig. 3. The deeper the color, the higher the urban eco-efficiency.

Generally, China's urban eco-efficiency has various limitations. The eastern coastal areas have become an efficient gathering area for urban eco-efficiency development, while the West such as Gansu, Guangxi, and Guizhou have become inefficient gathering areas. This observation reflects the typical features of spatial agglomeration. The high-efficiency growth zone has grown from 155 cities in 2007 to 190 cities in 2017. The level of urban eco-efficiency has increased gradually. These cities are majorly found in the southeast coast, northeast and other regions, and gradually transferred to the inland. The input-output efficiency of urban eco-construction in these regions is relatively high. The medium and high growth rate of cities is mainly found in the central part, while the number of cities in inefficient and medium-inefficient areas has reduced from 67 to 16. The low eco-efficiency level has improved significantly. These cities are zonal distributions, most of which are marginalized areas.

4. Spatial correlation analysis of urban eco-efficiency

4.1. Global Moran's I

Before using the econometric model for spatial correlation analysis, it is imperative to determine spatial autocorrelation and spatial heterogeneity in the data(Cheng et al., 2017). Highlighting the spatial features of China's urban eco-efficiency, this research uses *Moran's I* to evaluate the similarity in adjacent cities and examine whether there is spatial agglomeration in urban eco-efficiency.

The calculation formula of *Global Moran's I* is as follows:

$$Moran's\,I = \frac{n\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\left(y_i-\bar{y}\right)\left(y_j-\bar{y}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2} \tag{5}$$

$$W_{ij} = \begin{pmatrix} W_{11} & \cdots & W_{1n} \\ \vdots & \ddots & \vdots \\ W_{n1} & \cdots & a_{nn} \end{pmatrix} \tag{6}$$

where *n* refers to the total amount of spatial regions; y refers to urban eco-efficiency; $\bar{y}$ is the average of eco-efficiency; W_{ij} refers to Spatial Weight Matrix. In this paper, the binary 0–1 spatial neighboring weight matrix is chosen. When the regions *i* and *j* are adjacent, they are 1 and not adjacent to 0. *Moran's I* > 0 indicates that eco-efficiency has a positive spatial correlation, and cities with similar efficiency have spatial aggregation situation. Alternatively, when *Moran's I* < 0, it shows a spatial exclusion phenomenon. When *Moran's I* $= 0$, the values of different regions appear spatially as independent or random distributions.

The statistics *Z* value is applied to determine spatial autocorrelation in different regions. *E(I)* represents the expectation value, and *VAR(I)* represents the variance. Then the *Z* value formula can be expressed as follows:

$$Z = \frac{Moran's\,I - E(I)}{\sqrt{VAR(I)}} \tag{7}$$

Using *GeoDa* software to analyze the spatial correlation features of urban eco-efficiency from 2007 to 2017. The results are shown in Table 3.

Table 3 shows that the spatial aggregation effect of urban eco-efficiency is usual from 2007 to 2017, and all show significant positive spatial autocorrelation. Within the 11 years, the *Global Moran's I* with

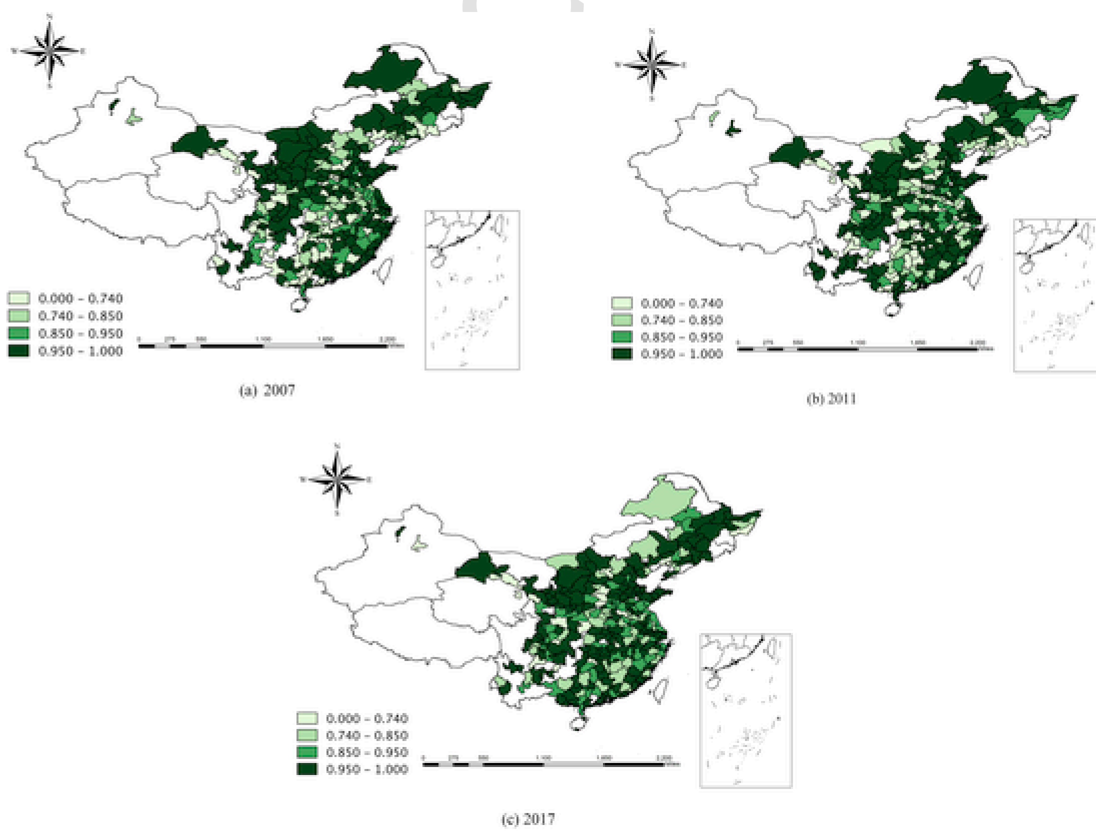


Fig. 3. Equal intervals maps of China's urban eco-efficiency in 2007, 2011, and 2017.

Table 3
Global Moran's I of urban eco-efficiency in China from 2007 to 2017.

Year	Moran's I	E(I)	SD(I)	Z-value	P-value
2007	0.748149	−0.0038	0.0385	19.5636	0.001
2008	0.646522	−0.0038	0.0392	16.5897	0.001
2009	0.790292	−0.0038	0.0396	20.0826	0.001
2010	0.791453	−0.0038	0.0397	20.0742	0.001
2011	0.772527	−0.0038	0.0396	19.6107	0.001
2012	0.762752	−0.0038	0.0398	19.2668	0.001
2013	0.876856	−0.0038	0.0417	21.1166	0.001
2014	0.838096	−0.0038	0.0408	20.6464	0.001
2015	0.847621	−0.0038	0.0411	20.7493	0.001
2016	0.830288	−0.0038	0.0415	20.1159	0.001
2017	0.823128	−0.0038	0.0412	20.1140	0.001

Empirical Bayes (EB) rate fluctuated while the spatial agglomeration effect of urban eco-efficiency increased slightly.

4.2. Local Moran's I

When analyzing the regional spatial autocorrelation embodied by the *Global Moran's I*, the positive correlations of some regions and the negative correlations of adjacent areas cancels each other out. Therefore, *Local Moran's I* is introduced to further analyze the spatial correlation of a specific observation with its surrounding observations on a particular indicator. The calculation formula of local indicator of spatial association (LISA) is as follows:

$$I_i(d) = \frac{(y_i - \bar{y})}{S^2} \sum_{j=1}^{n} W_{ij} (y_i - \bar{y}) (y_j - \bar{y}) \tag{8}$$

Where $S^2 = \frac{1}{n}\sum_{i=1}^{n} (y_i - \bar{y})^2$ represents the variance of urban eco-efficiency.

Fig. 4 shows the *Local Moran's I* scatter plots of China's urban eco-efficiency and the *LISA* spatial aggregation map of 5% horizontal. The horizontal and vertical axes in *Moran's I* scatter plot represent eco-efficiency and spatial lag eco-efficiency, respectively. From the distribution of scatter points, 273 cities are distributed in four quadrants: the first and third quadrant's *Ii(d)* > 0, which respectively represent the high-high association and low-low association; the second and fourth quadrant's *Ii(d)* < 0, which respectively represent the low-high association and high-low association.

In Fig. 4, the *HH* regions mainly concentrated in East and West, and have a trend to gradually shift to inland. The *LL* areas are primarily found in Hunan, Guangxi, Henan, Liaoning, and Shaanxi. The number of cities decreased from 14 in 2007 to 9 in 2017, and the urban distribution has shifted from decentralized to concentrated. The results show that the cities with inefficient growth restrain the improvement of neighboring cities and have adverse spillover effects. *HL* clusters and *LH* clusters are scattered in Henan, Hubei, Inner Mongolia, and other areas. Generally, after 11 years of development, the urban eco-efficiency of most cities has improved, showing a strong spatial dependence. The local correlation effect is relatively usual.

The regional differences can be attributed to China's introduction to a series of environmental protection policies in 1992. Policy privilege accelerated the construction of urban ecology in the eastern coastal areas. Additionally, the eastern coastal economic region was opened earlier, and the development of the regional economy made the eastern coastal area concentrate on the environmental impact. The eco-efficiency of these cities has been relatively high. With different economic situations and technical levels, the central region over-emphasizes on economy and neglect environmental problems in development, resulting in relatively low eco-efficiency. From a regional point of view, the *HL* region mostly focuses on the central region, and the average efficiency of the central region shows a trend of decreasing first and then increasing. In the course of development, the central region has improved its eco-efficiency by introducing the experience and technology of the east and is still in the process of development. As a result of its conditions, the western region has low eco-efficiency. With the implementation of policies such as the Western Development, the western region seizes the opportunity of development and transforms its development model, and began to centralize on the green development. Initial success has been achieved in the development of eco-cities in the West. The *LL* region has significantly been reduced, gradually developing towards *LH*.

From the development trend aspect, the eastern region will maintain an effective regional radiation effect in the future, *HL* regions will gradually develop to *HH* regions, and *LL* regions will develop progressively to *LH* regions. Ultimately, *H* regions will drive *L* regions, which will have a pull effect on the eco-efficiency of adjacent cities.

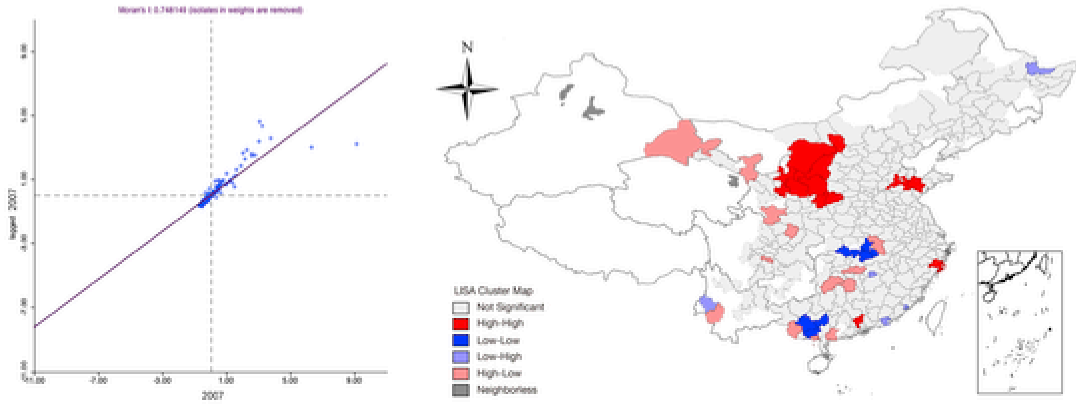
5. Relationship between innovation and urban eco-efficiency

Section 4 shows that eco-efficiency between different cities has strong spatial dependence. Therefore, this research further analyzes the factors of the technological innovation affecting the eco-efficiency through spatial econometric models.

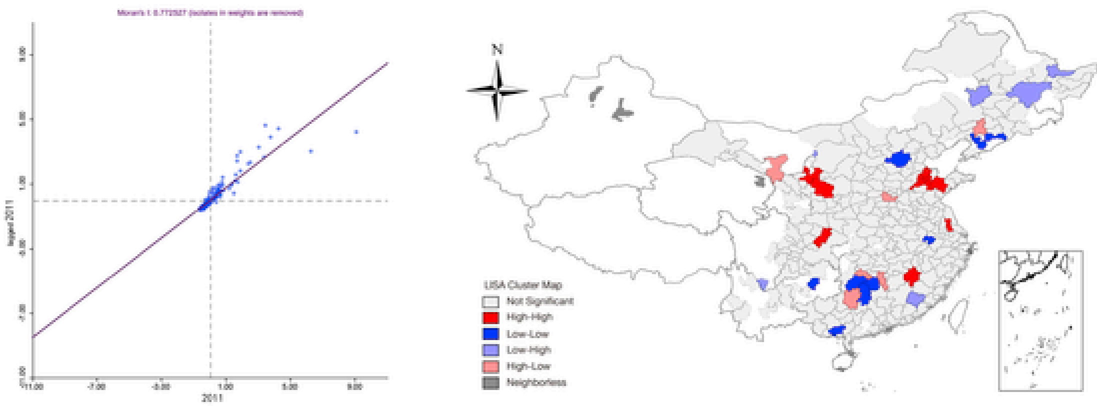
5.1. Indicator selection

Eco-efficiency reflects on the coordinated development of the economy and environment. Therefore, it should be explored whether the technological innovation can serve eco-efficiency as a whole rather than from one aspect (Brännlund et al., 2007). Currently, research shows that capital investment, innovative talents, innovation capabilities, and green technology output are often selected as variables to measure the relationship between innovation and the green economy (Jordaan et al., 2017). This research picks indicators based on technological innovation:

(1) Capital investment: Investment in science is one of the essential indicators to promote technology innovation. Because of the existing relationship between technology investment and pollution discharge, the ratio of science and technology expenditure to GDP is used to assess innovation capital investment (Borghesi et al., 2015).
(2) Education investment: Innovation is a way of transforming education investment into regional output (Jaffe et al., 1993). Therefore, education investment dramatically affects the development of urban innovation and the sustainability of technological improvement in eco-construction. This research uses the ratio of education expenditure to GDP to assess the role of education investment in the process of eco-efficiency.
(3) Innovative talents: Human capital is a crucial factor in determining the quality of innovation output and also an ideal link in transforming input into innovation output. The improvement of human capital can further influence urban eco-efficiency through the creation and dissemination of the latest scientific achievements. This research determines the proportion of scientific research practitioners per 10,000 people (Anzola-Román et al., 2018).
(4) Innovative ability: The technological innovation ability can influence the development of urban eco-efficiency by changing its industrial growth model. The energy-saving technology is the main driving force for promoting sustainable urban development. The number of patent grants is a direct reflection of innovation capability. This research uses the year-end patent grants for every 10,000



(a) Local scatter plot of eco-efficiency and LISA agglomeration maps(2007).



(b) Local scatter plot of eco-efficiency and LISA agglomeration maps(2011).

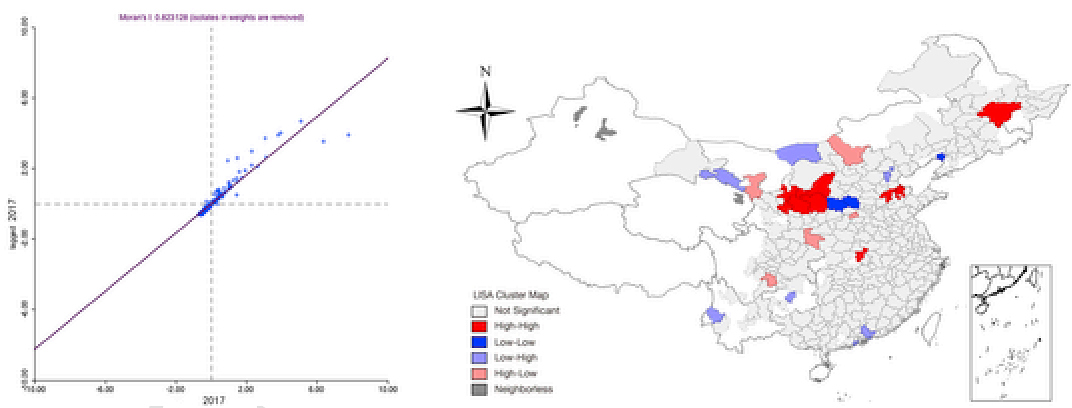


Fig. 4. LISA agglomeration maps of urban eco-efficiency in 2007, 2011 and 2017.

employees to measure regional technological innovation capabilities (Yuan and Xiang, 2018).

(5) Innovation performance: The practical application effect of innovation should be determined by the actual benefits brought by innovation (Rauter et al., 2019). Utility model patents are new technical solutions based on practicality. Compared with invention patents and design patents, utility model patents significantly improve the productivity of the economy. The technological transformations derived from utility model patents can also be easily applied to the market (Prud'homme, 2017). This research uses the "proportion of utility model patents" to determine innovation performance.

Currently, research has shown that the relationship between technological innovation and eco-efficiency is not linear (Yi and An, 2018). Based on scholars' theoretical framework, this research further constructs a square term for each explanatory variable to examine the relationship between technological innovation and urban eco-efficiency better. The patent-related data are derived from the *Chinese Research Data Services (CNDRS)*, and other indicators are all from *China Urban Statistics Year*book. LLC test results show that variables are all stable at 5% level, which will not cause false regression (shown in Table S1).

5.2. Model

5.2.1. Model selection

The Hausman statistic is commonly used in model selection. Analyzed by Stata14.0, the data tests show that *chi2 (17)* = 9197.01, *Prob* ≥ *chi2* = 0.0000. *Wald* test and *Lratio* test are used to determine the adaptation model. The test results show that the *Wald* test results are *chi2(8)* = 1141.26, *Prob* > *chi2* = 0.0000, *Lratio* test results are *chi2(8)* = 291.03, *Prob* > *chi2* = 0.0000. According to the test results, the *Wald* and *Lratio* test rejected the hypotheses of $\theta = 0$ and $\theta = -\beta\rho$ respectively. The test indicating that the model passed the test at 5% level, and compared with the *SAR* and *SEM* models, the *SDM* model has a better fit than this research.

In summary, we used the spatial effect *SDM* model to examine the spatial relationship between technological innovation and eco-efficiency.

5.2.2. Model settings

The general spatial model formula with all interaction effects is as follows (Anselin, 1988):

$$y_{it} = \tau y_{i,t-1} + \rho W_1 y_t + \beta x_{it} + \delta W_2 X_t + u_i + \gamma_t \tag{9}$$

$$u_{it} = \lambda W_3 u + \varepsilon_{it} \tag{10}$$

Where W_1 is the spatial weight matrix of the dependent variable, $W_2$is the spatial weight matrix of the independent variable,$\rho W_1 y_t$ is the spatial lag term of the independent variable, W_3 is the spatial weight matrix of random perturbation terms, u_i is the spatial individual effect, γ_t is the time effect,ε is an arbitrary disturbance term ρ,θ,λ are the corresponding spatial regression coefficients. When$\lambda = 0$, the model can be reduced to the *SDM* model as formula 11.

$$y_{it} = \tau y_{i,t-1} + \rho W_1 y_t + \beta x_{it} + \delta W_2 X_t + \gamma_t + \varepsilon_{it} \tag{11}$$

To reduce the heteroscedasticity and collinearity of variables and make the data more stable, this paper normalizes the logarithm of all variables:

$$\begin{aligned} \ln\, eff_{it} = \rho W_1\ \ln\, eff_{it} + \beta_1\ \ln\, X \\ + \beta_2 (\ln\, X)^2 + \delta W_2\ \ln\, X_t + \gamma_t + \varepsilon_{it} \end{aligned} \tag{12}$$

Where *eff* is urban eco-efficiency, *X* refers to the factors affecting efficiency, namely capital investment (TECR), education investment (EDU), innovative talents (SCIP), innovation ability (Patent) and technology output (Umg), and uses the number 2 as the suffix to distinguish the square term.

PCC test is performed on the logarithmic index to test the correlation. All variables are weakly correlated at 1% level (shown in Table S2). The variance expansion factor (VIF) values of all variables are around 1 (shown in Table S3), which means that the multicollinearity problem between the variables is very weak, and the index selection is reasonable.

5.3. Analysis of spatial regression results

5.3.1. Evaluation of factors affecting urban eco-efficiency

The results of the spatial *SDM* model are estimated. The results are shown in Table 4.

Table 4
Estimation of results of spatial measurement models.

	Robust						
	eff	Coef.	Std.Err.	Z	P>|z|	[95%Conf.Interval]	
Main							
	LnTECR	-.6928161	.1161263	−5.97	0.000	-.9204195	-.4652127
	LnTECR2	-.0732999	.0178249	−4.11	0.000	-.1082361	-.0383637
	LnEDU	.2,602,541	.0634659	4.10	0.000	.1,358,632	.3,846,449
	LnEDU2	.1,346,299	.0473145	2.85	0.004	.0418951	.2,273,646
	LnSCIP	.0084443	.0962345	0.09	0.930	-.1,801,719	.1,970,605
	LnSCIP2	.0446693	.0375078	1.19	0.234	-.0288447	.1,181,833
	LnPatent	.2,275,872	.0675035	3.37	0.001	.0952828	.3,598,916
	LnPatent2	-.0068408	.0104437	−0.66	0.512	-.0273102	.0136286
	LnUmg	-.7,340,137	.2,417,063	−3.04	0.002	−1.207749	-.2,602,781
	LnUmg2	-.2,809,968	.1,288,042	−2.18	0.029	-.5,334,483	-.0285452
	_cons	−2.212639	.3,120,193	−7.09	0.000	−2.824186	−1.601093
Wx							
	LnTECR	.0771185	.0062212	12.40	0.000	.0649251	.0893118
	LnTECR2	.0127539	.0012375	10.31	0.000	.0103285	.0151793
	LnEDU	-.0406924	.0026792	−15.19	0.000	-.0459436	-.0354412
	LnEDU2	-.005853	.0025062	−2.34	0.020	-.0107651	-.0009409
	LnSCIP	.0675764	.0089109	7.58	0.000	.0501113	.0850414
	LnSCIP2	.0357487	.0054824	6.52	0.000	.0250034	.046494
	LnPatent	-.000948	.0025817	−0.37	0.713	-.006008	.0041121
	LnPatent2	.0002368	.0003857	0.61	0.539	-.0005192	.0009927
	LnUmg	.511565	.0211924	24.14	0.000	.4,700,286	.5,531,014
	LnUmg2	.3,240,256	.0140504	23.06	0.000	.2,964,872	.3,515,639
Spatial							
	rho	.2,964,742	2.36e-06	1.3e+05	0.000	.2,964,696	.2,964,788
Variance							
	lgt_theta	-.414674	.1,192,706	−3.48	0.001	-.6,484,402	-.1,809,079
	sigma2_e	1.292614	.0395403	32.69	0.000	1.215116	1.370112

The relationships between variable factors and eco-efficiency within the domain are plotted as shown in Fig. 5.

From the regression results and Fig. 5:

(1) There is an inverted U-shape relationship between urban eco-efficiency and capital investment. It shows that the capital investment in a reasonable range will ameliorate the eco-efficiency. But there is a threshold for the ability of capital investment to improve eco-efficiency. Firstly, too much investment in capital will lead to the reduction of direct investment in other elements such as environmental and ecological governance. Secondly, investment over a certain value will cause element investment redundancy. Generally, China's capital investment is in the scaling stage that can promote the progress of eco-efficiency.

(2) Both of ln EDUR and ln SCIP have a positive U-shape relationship with eco-efficiency. It shows that there is a lag in the education investment and the improvement of human capital. The increase of investment in education will not produce immediate effect. With the improvement of innovative human capital, the sustainable development of innovative achievements will promote the urban eco-efficiency. However, the talent input is not significant at the 5% level, which is inconsistent with the general cognitive results. Irrespective of China's large talent output, the rate of results conversion, and the contribution rate of science and technology are still low. There is a vacuum in the transformation of innovation ability for economic development and eco-construction.

(3) Fig. 5 shows a nonlinear monotonic increasing relationship between LnPatent and eco-efficiency. The improvement of innovation ability will promote the eco-efficiency. The coefficients of innovation performance are both positive and significant at 5% level. The inverted U-shape relationship means that with the application of utility model patents, the eco-efficiency has gradually improved. But when the proportion of utility model patents is too much, it will hinder the improvement of eco-efficiency by affecting the number of innovative invention patents.

5.3.2. Effect decomposing

As a result of the spatial spillover effect, the change of one factor will not only affect the research objective directly (direct effect) but also indirectly affect the neighboring cities (indirect effect). Based on this, the effects of the *SDM* model are decomposed into the following form (Anselin, 1988):

$$y_{it} = (I-\rho W)^{-1}\left(X_{it} + WX_{it}\theta\right) + (I-\rho W)^{-1}\alpha_i + (I-\rho W)^{-1}\lambda_i + (I-\rho W)^{-1}\varepsilon_{it} \tag{13}$$

Both direct and indirect effects can be derived from the dependent variable's partial derivative of the independent variable:

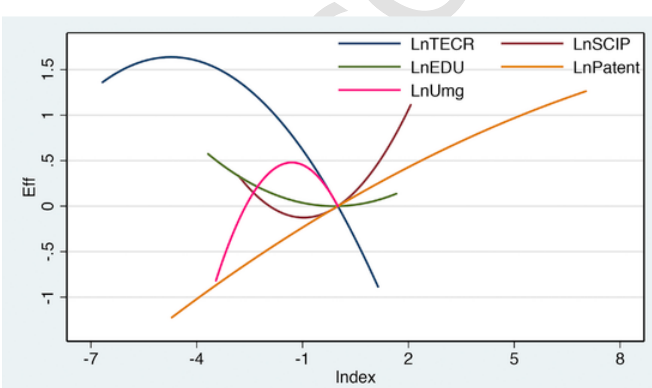


Fig. 5. The relationship between various factors and eco-efficiency.

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdots \frac{\partial E(Y)}{\partial x_{Nk}}\right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix} = (I-\rho W)^{-1} \begin{bmatrix} \beta_k & \omega_{12}\theta_k & \cdots & \omega_{1N}\theta_k \\ \omega_{21}\theta_k & \beta_k & \cdots & \omega_{2N}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{N1}\theta_k & \omega_{N2}\theta_k & \cdots & \beta_k \end{bmatrix} \tag{14}$$

Where W_{ij} is the (i,j)$^{\text{th}}$ element of matrix W. It can be known from equation (14) that the direct effect is represented by the main diagonal element of the partial derivative matrix, the indirect effect is represented by the remaining elements, and the overall effect is the sum of the direct effect and the indirect effect. The spatial effect decomposition result is shown in Table 5.

Explain the influencing factors and their spatial effects as follows:

(1) Within the domain of definition, the direct effect of capital investment is inverted U-shape, and the indirect effects shows a non-linear monotonically increasing relationship. Capital investment in the appropriate scope can promote the eco-efficiency of local and neighboring cities. When the input value exceeds the peak value, the direct investment in other elements of local cities will be reduced. It will affect the eco-efficiency of local cities.

(2) The direct and indirect effects of talent input and innovation performance are inverted U-shape. When the input value exceeds the peak value, the eco-efficiency of local and neighboring cities is inhibited. The direct effect coefficient is greater than the indirect effect coefficient, indicating that the impact of these three factors on local eco-efficiency is higher than on the surrounding cities.

(3) Within the domain of definition, the direct and indirect effects of education investment show a non-linear monotonically increasing relationship, and its indirect effect is an inverted U-shape relationship. The direct effect of innovation ability is inverted U-shape, and the indirect effect is nonlinear monotonic decreasing relationship. Education investment and innovation ability can promote the eco-efficiency of local cities. The improvement of the innovation ability

Table 5
Decomposing of Spatial effect.

	Direct	Indirect	Total
LnTECR	-.2,610,767***	.0199321***	-.2,411,446***
	(.0221029)	(.0058425)	(.0249784)
LnTECR2	-.0432707***	.0013802	-.0418905***
	(.0044474)	(.0009087)	(.0049007)
LnEDU	.1,368,049***	-.0060082**	.1,307,966***
	(.0091124)	(.0028167)	(.0096708)
LnEDU2	.0198808**	-.005393**	.0144878
	(.0083187)	(.0022517)	(.0088993)
LnSCIP	-.2,320,865***	-.0112068**	-.2,432,933***
	(.0314423)	(.0044698)	(.0329851)
LnSCIP2	-.1,234,165***	-.0079084***	-.1,313,248***
	(.0196927)	(.002103)	(.0210591)
LnPatent	.0018926	-.0105131***	-.0086205
	(.0091017)	(.0032369)	(.0095344)
LnPatent2	-.0006692	.0002914	-.0003778
	(.0013523)	(.0004566)	(.0013754)
LnUmg	−1.725422***	-.0473046***	−1.772727***
	(.0700847)	(.011172)	(.0722995)
LnUmg2	−1.093438***	-.0385105***	−1.131948***
	(.0464574)	(.0062038)	(.0483523)

Note: ***p < 0.01, **p < 0.05, *p < 0.1, standard errors in parentheses.

of local cities attracts innovative talents from neighboring cities to transfer to regional areas, and restrains the construction of the neighboring cities. In the long-term development process, the direct effect promotes the urban eco-efficiency.

6. Conclusion and suggestions

Based on the panel data of 273 prefecture-level cities in China from 2007 to 2017, this research constructs urban eco-efficiency evaluation indicators that reflect environmental friendliness and economic growth. SBM-Undesirable model is used to analyze the trends from different region's perspective and determine urban eco-efficiency in China. The results show that urban eco-efficiency has strong spatial differentiation and spatial correlation with the largest value in the east, the second in the west, and the smallest in the middle. The development trend shows high efficient regions driving low-efficiency regions. The eco-efficiency gap between East and West is gradually decreasing. From the decomposition of the Malmquist index, technological progress is the main driving force of TFP.

The spatial measurement results highlight that capital investment and innovation performance both have an inverted U-shape relationship with eco-efficiency. The relationship between innovation capacity and eco-efficiency is a non-linear monotonically increasing relationship. Within a reasonable investment range, capital investment and utility model patents will promote urban eco-efficiency, but the excessive investment will affect the coordinated development of the economy and environment. Both education investment and innovative talents have a U-shape relationship with urban eco-efficiency. The application of innovation talents is time-delay, but with the transformation of talents and innovative technology, the sustainable development of innovation capacity will ultimately improve the urban eco-efficiency. All explanatory innovation variables show a strong spatial spillover effect. Capital investment, innovation ability, and innovation performance within the appropriate range all contribute to the improvement of the eco-efficiency of local and surrounding cities. Excessive investment in education and innovation capacity of local cities will inhibit the construction and development of surrounding cities.

Based on the research conclusions, the impact mechanism of technological innovation on urban eco-efficiency is discussed:

(1) The research results show that the mechanism of technological innovation's impact on eco-efficiency conforms to the growth pole theory. In the early stage of development, the large-scale growth of local technological innovation factors may produce a siphon effect, attracting the resources transfer from neighboring cities to regional areas, and restrains the eco-efficiency of the neighboring cities. After the growth pole has reached a certain stage, the technological innovation resources of local cities will have a positive impact on the eco-efficiency of surrounding cities through the diffusion effect.
(2) Due to the phenomenon of growth pole, urban eco-efficiency can't achieve a high steady-state level in the short-term. So regional heterogeneity needs to be highly valued, and take advantage of technological innovation and its spatial spillover effect. In this context, the government should build an evaluation system with eco-efficiency as the core to form competition pressure between cities, to promote cities to align with high eco-efficiency regions. Additionally, the spillover effect of high eco-efficient regions should better promote the steady development of eco-efficiency in other cities.

CRediT authorship contribution statement

Weidong Chen: Conceptualization, Writing - original draft, Resources, Funding acquisition, Supervision. **Wen Si:** Conceptualization, Methodology, Data curation, Investigation, Writing - original draft. **Zhan-Ming Chen:** Investigation, Formal analysis, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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