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Study of spatial patterns and spatial effects of energy eco-efficiency in China

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Abstract: Energy eco-efficiency is a concept integrating ecological and economic benefits arising from energy utilization and serves as a measure of efficiency in the energy–environment–economy system. Using the slacks-based measure (SBM) model considering undesirable output, this study first measures the energy eco-efficiency of provinces in China from 1997 to 2012. It then analyzes the spatial distribution and evolution of energy eco-efficiency from three aspects: scale, intensity, and grain of spatial patterns. Finally, it examines the spatial spillover effects and influencing factors of energy eco-efficiency in different provinces by means of a spatial econometric model. The following conclusions are drawn: (1) The overall energy eco-efficiency is relatively low in China, with energy-inefficient regions accounting for about 40%. Guangdong, Hainan and Fujian provinces enjoy the highest energy eco-efficiency, while Ningxia, Gansu, Qinghai, and Xinjiang are representative regions with low efficiency. Thus, the pattern of evolution of China's overall energy eco-efficiency is U-shaped. Among local regions, four main patterns of evolution are found: increasing, fluctuating, mutating, and leveling. (2) At the provincial level, China's energy eco-efficiency features significant spatial agglomeration both globally and locally. High–high agglomeration occurs mainly in the eastern and southern coastal regions and low–low agglomeration in the northwestern region and the middle reaches of the Yellow River. Changes in spatial patterns have occurred mainly in areas with high–low and low–high agglomeration, with the most remarkable change taking place in the Beijing–Tianjin–Hebei region. (3) There exist significant spatial effects of energy eco-efficiency among provinces in China. For the energy eco-efficiency of a given region, spatial spillovers from adjacent regions outweigh the influence of errors in adjacent regions. Industrial structure has the greatest influence on energy eco-efficiency.

Keywords: energy eco-efficiency; SBM model; spatial pattern; spatial econometric model

1 Introduction

Energy is a global and strategic aspect of the development of human society, connected with issues of climate change and environmental pollution and with implications for international

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politics and economics. The regional distribution of energy resources in China is unbalanced. Coal is widely distributed in 1458 cities and counties (out of more than 2300 in China), with 90% in the northern area north of the Qinling–Huaihe line and 85% in the midwestern area. Petroleum and natural gas resources are concentrated in the northeast, north, and northwest. The natural gas concentrations are higher than the coal resources, with Heilongjiang Province and the provinces along the Bohai Sea sharing the largest reserve. Hydro-energy resources are mainly distributed in the southwest and strongly complement the local spatial insufficiency of fossil fuel energy. The features of China's energy resources can be summarized as follows: (a) total energy production and sales are large, while per capita values are small; (b) the volumes of coal and hydropower resources are large, with coal consumption dominating those of other energy resources; (c) oil and natural gas resources are relatively poor; (d) energy resources and economic layout are not coordinated; (e) there is both poor energy supply and considerable waste of energy. According to the *2015 BP World Energy Statistics Yearbook*, China's energy consumption accounts for 23% of global energy consumption and its energy supply for 19% of the global figure. Worldwide, China currently ranks first in energy production, consumption, and carbon dioxide emission. The major goal of China's energy development strategy is reduction of energy consumption and carbon emission.

Improving energy efficiency is key to solving the energy issue, which is essentially that of energy utilization, namely, how energy consumption can contribute to maintaining and promoting the sustainable development of human society. Eco-efficiency, which considers both ecological and economic benefits, is concerned with sustainable development, taking account of constraints imposed by environmental effects as well as the need for efficient utilization of available resources, and is currently the subject of studies at many levels, including enterprise, industrial, regional, and national (WBCSD, 2000; Yin *et al*., 2012). The core aim of energy efficiency and eco-efficiency is to create greater social value with less resource consumption and less environmental impact. Studies of energy eco-efficiency have considered its evolution with an emphasis on energy, and that of energy efficiency based on environmental factors. Improving energy eco-efficiency is a basic requirement for the development of a low-carbon economy and is key to shifting the economy from one involving high energy consumption, high carbon, and high pollution to one with low energy consumption, low carbon, and low pollution.

There has been much research on energy efficiency. The Chinese domestic literature, giving priority to provincial and industrial levels, has focused mainly on the following aspects: evaluation index; methods and models of energy efficiency; the relationship of energy efficiency to economic development and other factors; and temporal changes and spatial differences in energy efficiency, together with their mutual interactions and the factors influencing them (Shi *et al*., 2006; Wei *et al*., 2007; Wang *et al*., 2010; Chen *et al*., 2014). Applications and analyses from different perspectives have given rise to different definitions of energy efficiency, with consequent differences in measurement indices (Patterson *et al*., 2009; Wei *et al*., 2009; APERC, 2000). Based on systematic consideration of energy utilization, energy efficiency has been evaluated in the context of total factor production theory (Hu *et al*., 2006). The principal evaluation methods used for total factor energy efficiency have been data envelopment analysis (DEA) and stochastic frontier analysis (SFA), with the former being given priority. Models used have included variable returns to scale (VRS), constant returns to scale (CRS), three-stage DEA, the Malmquist index, and super-efficiency DEA, among others. The slacks-based measure (SBM) model based on undesirable output has become widely used in the study of total factor energy efficiency evolution as research has increasingly focused on environmental pollution and ecological damage in the process of energy consumption (Lin *et al*., 2012; Hu *et al*., 2014; Lu *et al*., 2014; He *et al*., 2002; Li *et al*., 2012; Guo *et al*., 2013; Zhou *et al*., 2012; Zuo *et al*., 2011; Qian *et al*., 2013). However, the selection of indices and the methods for handling undesirable output vary among different researchers. Zhang *et al*. (2011) selected industrial waste gas discharge as an index for measuring pollutant emissions, taking the pollution caused in the process of energy utilization to be primarily air pollution and assuming that 70% of carbon dioxide emission, 90% of sulfur dioxide emission, and 67% of nitrogen dioxide emission in the atmosphere are caused by fossil fuel use. Yuan *et al*. (2009), using the entropy method, took as their index of undesirable output pollutant emission comprising the volume of industrial waste water discharge and the volume of industrial waste gas discharge. Wang *et al*. (2014) suggested a comprehensive output index combining GDP as desirable output and CO_2 emission as undesirable output. The present paper, using the entropy method, adopts as an undesirable output index to measure energy eco-efficiency a combination of CO_2 emission, volume of SO_2 discharged, volume of industrial dusts and fumes discharged, volume of industrial waste water discharged, volume of industrial waste gas discharged, and volume of industrial solid wastes discharged. It then analyzes the spatial pattern and spatial effects of provincial energy eco-efficiency in China according to the efficiency values thereby obtained.

The spatial distributions of all kinds of geographical phenomena can be reflected by spatial patterns in size, shape, number, type, and combination (Fu *et al*., 2014). According to Zhang Jintun's research, these spatial patterns can be depicted from three aspects: scale, intensity, and grain (Zhang *et al*., 2004). The present paper, using the pattern of scale, intensity, and grain, investigates the spatial pattern of China's energy eco-efficiency and analyzes its regional distribution, regional differences, and agglomeration. The stress here is on the function of spillover effects resulting from external effects in space and how these alter spatial patterns by means of spatial heterogeneity, spatial dependence, and spatial clustering mechanism, through a process of diffusion. This study of spatial effects on China energy eco-efficiency is concerned with efficiency in the energy–environmental–economic system from two aspects: the spatial interaction mechanism and economic interaction. In recent years, academic research on the spatial pattern of energy efficiency has mainly used the spatial autocorrelation method, while research on its influencing factors has been based on the ordinary least squares (OLS) regression model, the vector error correction (VEC) model, the Tobit model, and spatial econometric models (Zeng *et al*., 2010; Wu *et al*., 2012; Li *et al*., 2008; Yang *et al*., 2011). Among the related literature, Cheng *et al*. (2013), adopting the spatial autocorrelation method and a spatial econometric model, analyzed the temporal and spatial pattern evolution of carbon emission intensity in China's energy utilization, Pan *et al*. (2012), using the spatial autocorrelation method, analyzed overall and local spatial differences in provincial energy efficiency, and Xu *et al*. (2011), using the super-efficiency DEA and a spatial econometric model, measured China's provincial energy efficiency in 1991–2012 and analyzed its spatial effects.

This paper first measures China's provincial energy eco-efficiency using the SBM model based on the consideration of undesirable output, then analyzes its spatial pattern from the three aspects of scale, intensity, and grain, and finally examines the spatial effects and influencing factors by applying the spatial lag model (SLM) and the spatial error model (SEM).

2 Research methods and data processing

2.1 SBM model

The SBM model, proposed and developed by Tone (2001), is a nonradial and nonangular measurement belonging to the class of DEA models. The traditional DEA model is a radial and angular measurement lacking consideration of input–output relaxation, whereas the SBM model puts the slack variable into the objective function and can evaluate efficiency based on undesirable output more effectively (Tu *et al.*, 2011). This study estimates China's provincial energy eco-efficiency using the SBM model based on consideration of undesirable output, input–output types, and returns to fixed scale (Zhao *et al.*, 2014). The model is given by

$$\rho = \min \frac{1 - \frac{1}{N}\sum_{n=1}^{N} s_n^x / x_{k'n}^{t'}}{1 + \frac{1}{M+I}\left(\sum_{m=1}^{M} s_m^y / y_{k'm}^{t'} + \sum_{i=1}^{I} s_i^b / b_{k'i}^{t'} \right)}$$

$$\begin{aligned} \text{s.t.}\quad & \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^{t'},\ n = 1,\ldots,N \\ & \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y = y_{k'm}^{t'},\ m = 1,\ldots,M \\ & \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b = b_{k'i}^{t'},\ i = 1,\ldots,I \\ & z_k^t \geqslant 0,\ s_n^x \geqslant 0,\ s_m^y \geqslant 0,\ s_i^b \geqslant 0,\ k = 1,\ldots,K \end{aligned} \tag{1}$$

where ρ is the efficiency value, N, M, and I represent the numbers of inputs, desirable outputs, and undesirable outputs, (s_n^x, s_m^y, s_i^b) is the relaxation vector for inputs, desirable outputs, and undesirable outputs, $(x_{k'n}^{t'}, y_{k'm}^{t'}, b_{k'i}^{t'})$ represents the input–output value at time t' for the k'th design-making unit, and z_k^t is the weight of the design-making unit. The objective function ρ decreases strictly monotonically with s_n^x, s_m^y, s_i^b. It takes values in the range $0<\rho\leqslant 1$; when $\rho=1$, the design-making unit is at the efficiency front edge, while when $\rho<1$, the design-making unit shows an efficiency loss.

2.2 Spatial autocorrelation index

Spatial autocorrelation measures the agglomeration of spatial unit attribute values (Getis *et al.*, 1992). Global spatial correlation is concerned with the total correlation of the spatial distribution pattern and its significance for all spatial objects in the region. The global

Moran's I index is a measure of spatial autocorrelation and is given by

$$I = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sigma^2 \sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{2}$$

where x_i is the observed value for region i, n is the number of observed values,

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

and

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

The spatial weight matrix w_{ij} is the binary adjacency matrix. The Z test statistic is given by

$$Z = \frac{I - E(I)}{\sqrt{\mathrm{Var}(I)}} \tag{3}$$

where $E(I)$ is the expectation and Var(I) is the variance. If the value of I is significantly positive, indicating a positive spatial correlation, then higher- and lower-energy-efficiency regions each exhibit a clustering trend in space. Global spatial autocorrelation, which assumes spatial homogeneity, cannot reflect local clustering features, and therefore a local spatial autocorrelation analysis is required. Local spatial autocorrelation reflects the spatial correlation degree for each province and its adjacent provinces. As a measure of this, the local Moran's I index is given by

$$I_i = z_i \sum_{i\neq j}^{n} w_{ij} z_j \tag{4}$$

where I_i is the local Moran's I index of region i, Z_i is the energy eco-efficiency of region i after standardization of Z, and w_{ij} is the spatial weight matrix. A positive (respectively negative) Moran's I index indicates factor adjacency of similar (respectively different) types and attribute values. The larger the absolute value, the higher the adjacency. A Moran scatter diagram takes the observed value Z as the X-axis, and the corresponding spatial lag factor Wz as the Y-axis, giving four agglomerations: high–high (HH), low–low (LL), low–high (LH), and high–low (HL).

2.3 Spatial econometric model

Spatial econometrics analyzes the spatial distribution of variables and disturbances in the context of spatial heterogeneity. In spatial econometrics, the SLM and the SEM are often used to measure spatial effects due to spatial correlation.

The SLM is given by

$$y = \rho W y + X\beta + \varepsilon \tag{5}$$

where y is the dependent variable vector, X is the explanatory variable matrix, W is the spatial weight matrix, Wy is the space-lagged dependent variable, and ρ is the spatial regression coefficient reflecting the diffusion and spillover between adjacent spatial units. The parameter β represents the influence of X on Y, Wy reflects the effect of spatial distance on spatial behavior, and ε is a random error term vector.

The SEM mainly deals with the spillover effect of dependent variables on a given region and the effect of factors influencing the dependent variable through a spatial conduction mechanism. In contrast to the SLM, the SEM takes account of the spatial dependence in the destabilization error term and the influence on a given local area of errors in adjacent areas. The SEM is given by

$$\begin{aligned} y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + \mu \end{aligned} \tag{6}$$

where y is the dependent variable vector, X is the explanatory variable matrix, W is the spatial weight matrix, ε is a random error term vector, λ is the spatial error coefficient of the dependent variable, and μ is a random error vector with a Gaussian distribution. The parameter β reflects the influence of independent variables on dependent variables, and the parameter λ measures the effect on a given local area of errors in adjacent areas.

A Hausman test was applied to both the SLM and SEM models before estimation to determine whether to adopt a fixed-effect-coefficient or random-effect-coefficient estimation method and to measure the significance of the SLM model LM-Lag value and the SEM model LM-Err value (Sun *et al*., 2014).

2.4 Unit research, variable selection, and data sources

This study of spatial differences in energy eco-efficiency in China is based on the eight continental economic regions: the northeastern region consisting of Heilongjiang, Jilin, and Liaoning; the northern coastal region consisting of Shandong, Hebei, Beijing, and Tianjin; the eastern coastal region including Shanghai, Jiangsu, and Zhejiang; the southern coastal region including Guangdong, Fujian, and Hainan; the middle reaches of the Yangtze River comprising Hunan, Hubei, Jiangxi, and Anhui; the middle reaches of the Yellow River comprising Shaanxi, Henan, Shanxi, and inner Mongolia; the southwestern region including Guangxi, Yunnan, Guizhou, Sichuan, and Chongqing; and the northwestern region including Gansu, Qinghai, Ningxia, and Xinjiang. These comprise 30 provincial administrative regions in total, not including Tibet, Hong Kong, Macau, and Taiwan.

This paper constructs an input–output index for energy eco-efficiency evaluation on the base of total factor production theory, taking the total energy consumption in various regions over the years as energy input, the employment population at the end of the year as labor input, the transaction value in technical markets as technical input, the real GDP per capita in 1990 as a constant-value desirable output index, and the comprehensive value comprising CO_2 emission, volume of SO_2 discharged, volume of industrial dusts and fumes discharged, volume of industrial waste water discharged, volume of industrial waste gas discharged, and volume of industrial solid wastes discharged calculated by the entropy method as the undesirable output. The capital stock is calculated using the perpetual inventory method. The initial capital stock is measured by applying the results of research by Zhang *et al*. (2004) and Shan *et al.* (2013). In the present paper, the capital stock is replaced by the constant base 1990 fixed assets investment. The CO_2 emission is estimated using the IPCC method (IPCC, 2006):

$$CO_2 = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times COF_i \times (44/12) \tag{7}$$

where i indicates the type of fossil fuel, E_i is the fossil fuel energy consumption, NCV_i is the average low calorific value of the fuel, CEF_i is the carbon emission coefficient of unit calorific value, and COF_i is the carbon oxidation factor. The total CO_2 emission is calculated for n = 8 types of fossil fuel: coal, coke, crude oil, gasoline, fuel oil, kerosene, diesel oil, and natural gas.

This paper determines the spatial effect of China's energy eco-efficiency using the SLM and SEM and its influencing factors. The value of energy eco-efficiency in various regions over the years is taken as the dependent vector, and the economic development level, industrial structure, foreign direct investment, urbanization level, foreign trade openness, population, government energy investment, and transportation infrastructure are taken as the explanatory variables, while the indicators are the logarithm of per capita GDP, the GDP ratio of secondary industry total output, the total investment of foreign enterprise, the proportion of urban population, the total population, the total input and output at the end of the year, the fixed-assets investment of state-owned energy industry, and the highway traffic mileage (the sum of highways, railways, and inland waterways) per unit area.

The study period is from 1997 to 2012 (because, before 1996, Sichuan Province included Chongqing) and the data were collected from the *China Environmental Statistical Yearbook*, the *China Energy Statistical Yearbook*, and the *China Statistical Yearbook* from 1997 to 2013.

3 Analysis of spatial pattern of China's energy eco-efficiency

3.1 Spatial pattern scale of energy eco-efficiency

The spatial pattern scale of energy eco-efficiency is measured by the regional energy eco-efficiency value, and these have a positive correlation. The spatial pattern is relative because of the relative energy eco-efficiency calculated on the base of the SBM model. The energy eco-efficiency has the following features in terms of scale and evolution.

The value of China's regional energy eco-efficiency is low and is mainly on a small scale. Energy-inefficient areas account for about 40%, moderate-efficiency areas for 30%, mid- to high-efficiency areas for 20%, and high-efficiency areas for 10%. The overall energy eco-efficiency of China is at a medium level, with the average value of energy eco-efficiency in various regions ranging from 0.400 to 0.600 over the years and the average value over the research period 1997–2012 being 0.544.

The pattern of evolution of China's energy eco-efficiency is U-shaped. The average value of energy eco-efficiency in various regions changed irregularly in 1997–2000, fell rapidly, then rose in a wave-like manner in 2001–2012, with 2005 being the turning point, as shown in Figure 1. The patterns of evolution at regional and national scales differed. At a regional scale, the trajectory of energy eco-efficiency exhibits four trends in different regions: increasing, fluctuating, mutating, and leveling, as shown in Figure 2. In the increasing region (mainly Shanghai, Beijing, Tianjin, and Zhejiang), the efficiency value increased continually; in the fluctuating region (mainly Guangdong, Fujian, Jiangsu, and Shandong), it undulated, especially in mid- to high-efficiency areas; in the mutating region (mainly Inner Mongolia, Shanxi, Liaoning, and Xinjiang), it exhibited large fluctuations, with outliers; and in the leveling region (mainly Qinghai, Gansu, Ningxia, and Yunnan), it changed insignificantly during the research period.

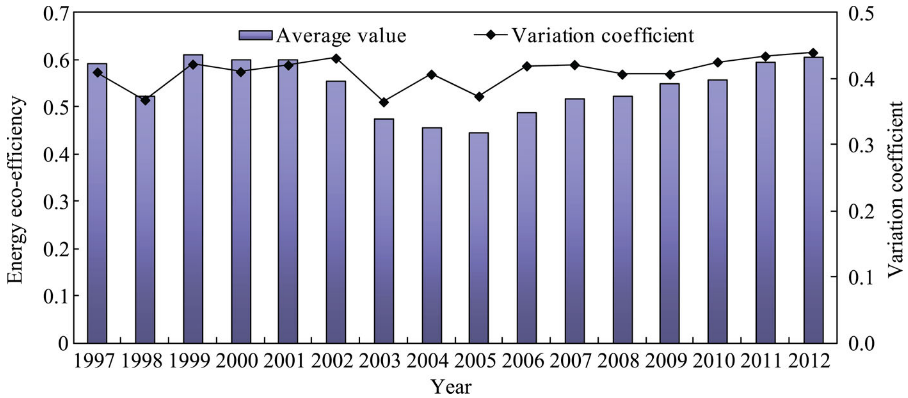

Figure 1 Average value and variation coefficient of energy eco-efficiency

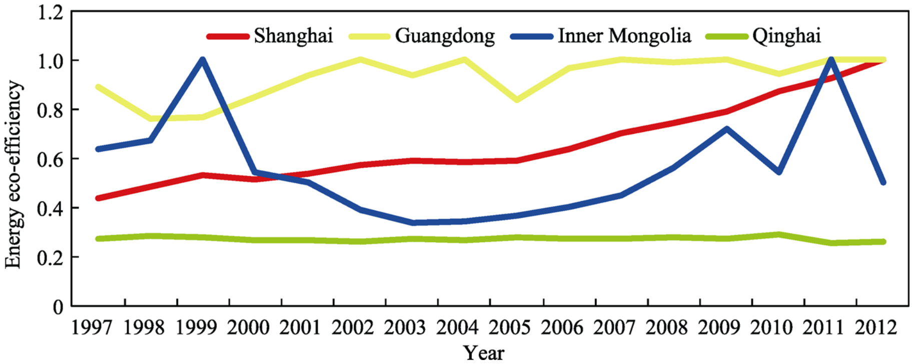

Figure 2 Evolutionary trends of energy eco-efficiency

3.2 Spatial pattern intensity of energy eco-efficiency

The spatial pattern intensity of energy eco-efficiency is represented by the value of the regional energy eco-efficiency. The research period in this paper includes four five-year plans for China's national social and economic development: the Ninth (1996–2000), Tenth (2001–2005), Eleventh (2006–2010), and Twelfth (2011–2015) Five-Year Plans. This paper takes development conditions in 2000, 2004, 2008, and 2012 to represent regional development conditions in different periods determined by the intersections between the study period and the periods of the Ninth (1996–2000), Tenth (2001–2005), Eleventh (2006–2010), and Twelfth (2011–2015) Five-Year Plans.

The following conclusions can be drawn from the analysis of the spatial pattern intensity of energy eco-efficiency. China's energy eco-efficiency exhibits an overall disproportion. The coefficient of variation of the energy eco-efficiency in various regions in 1997–2012 ranges from 0.3 to 0.5, and its fluctuation range is relatively small. It experienced a V-shaped fluctuation in 1997–1999 and a W-shaped fluctuation in 2002–2006. The overall differences in China's energy eco-efficiency changed in an orderly manner, with expansion and reduction, while the overall pattern of differences changed insignificantly in the long term, with the overall spatial pattern intensity remaining relatively stable.

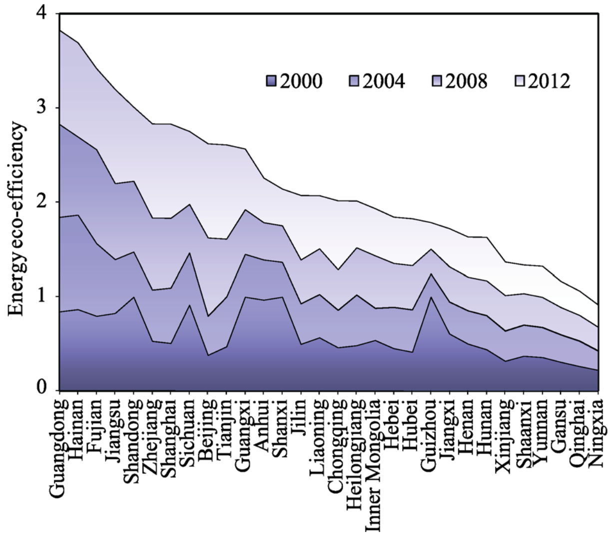

Figure 3 Spatial heterogeneity of energy eco-efficiency in China

The regional differences in energy eco-efficiency are remarkable. As can be seen from Figure 3, Xinjiang, Shaanxi, Yunnan, Gansu, Qinghai, and Ningxia remained inefficient throughout the study period, whereas Guangdong, Hainan, Fujian, Jiangsu, Shandong, Zhejiang, Shanghai, and Sichuan showed increasingly high energy eco-efficiency, with Guangdong, Hainan, and Fujian being at the forefront. In particular, Beijing and Tianjin showed dramatic increases in efficiency during the early stages of the 12th Five-Year Plan.

China’s energy eco-efficiency exhibits regional agglomerations. The value of energy eco-efficiency of each province in China is similar to that of adjacent areas, showing a definite characteristic of spatial agglomeration. Low efficiency is found mainly in the northwestern region and the middle reaches of the Yellow and Yangtze Rivers, moderate efficiency is found mainly in the northern coastal, northeastern, and southwestern regions, and high efficiency is found mainly in the southern coastal and eastern coastal regions (Figure 4).

The development of energy eco-efficiency in the eight regions differs among the four five-year plan periods, with the Ninth Five-Year Plan period in particular showing marked differences from the other periods. The southwestern region and the middle reaches of the Yangtze and Yellow Rivers enjoyed high values in the 9th Five-Year Plan period, but increased only slightly or even gradually decreased in the following periods. The eco-efficiency in the eastern and southern coastal regions increased continually during the study periods, notably in the eastern coastal region during the 11th and 12th Five-Year Plans

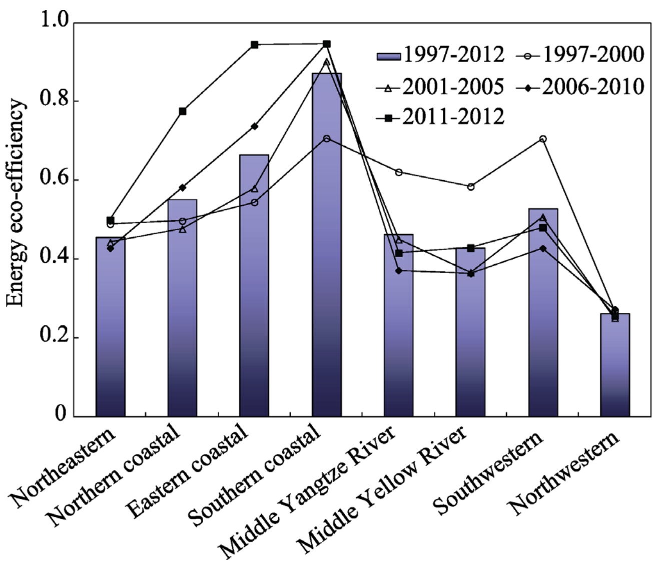

Figure 4 Energy eco-efficiency in eight major regions

and in the southern coastal region during the 10th Five-Year Plan. The eco-efficiency in the northern coastal region increased greatly during the 11th Five-Year Plan and the early stages of the 12th Five-Year Plan, but decreased during the 10th Five-Year Plan compared with the 9th Five-Year Plan. The eco-efficiency of the northeastern region rose again during the early stages of the 12th Five-Year Plan after a fall during the 10th Five-Year Plan. The eco-efficiency of the northwestern region remained low throughout the study period.

3.3 Spatial pattern grain of energy eco-efficiency

The spatial pattern grain is measured by the agglomeration of the value of energy eco-efficiency in each spatial unit. The pattern of distribution of the value of the energy eco-efficiency is its spatial pattern grain. The global Moran's I index of energy eco-efficiency of various regions in China from 1997 to 2012 (Table 1) shows a positive spatial correlation of energy efficiency among the regions, passing the test at 5% significance level in 2001–2012. In general, China's energy eco-efficiency exhibits fluctuations, but there is convergence toward a significant overall agglomeration.

Table 1 Global Moran's I index of energy eco-efficiency

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
I	0.144	0.154	0.016	0.201	0.314	0.238	0.343	0.384	0.384	0.467	0.480	0.404	0.353	0.415	0.259	0.421
Z	1.412	1.494	0.404	1.870	2.767	2.159	2.996	3.330	3.330	3.984	4.087	3.477	3.074	3.570	2.332	3.610
P	0.079	0.068	0.343	0.031	0.003	0.015	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.010	0.000

The regional agglomeration distribution reflects the spatial pattern grain. Study of local agglomeration is necessary because the global Moran's I index cannot demonstrate the spatial agglomeration features of a given region. From the local indicators of spatial association (LISA) clustering map of China's energy eco-efficiency in Figure 5, it can be seen that the local spatial correlation of energy eco-efficiency has the following features.

The overall energy eco-efficiency shows a notable spatial club phenomenon, with HH-, LL-, and LH-agglomeration regions exceeding HL-agglomeration regions. Among various regions, the LL-agglomeration region is the largest, accounting for 43%, followed by the HH-agglomeration region, accounting for about 27%, and then the HL- and LH-agglomeration regions, accounting for just 13% and 17%, respectively.

HH agglomeration occurs mainly in the eastern and southern coastal regions, LL agglomeration mainly in the northwestern region and the middle reaches of the Yellow River, HL agglomeration mainly in Sichuan Province in the southwestern region, and LH agglomeration mainly in the middle reaches of the Yangtze River. The agglomeration type of energy eco-efficiency in the northern coastal and northeastern regions is unstable.

Changes in agglomeration pattern of energy eco-efficiency occurred basically in areas of HL and LH agglomeration. At the time points 2000, 2004, 2008, and 2012, the agglomeration type transformed notably in the Beijing–Tianjin–Hebei region, evolving from LL to HL-agglomeration and finally to HH agglomeration. The agglomeration types of energy eco-efficiency of Shanxi, Heilongjiang, Inner Mongolia, and Chongqing also changed considerably in certain periods.

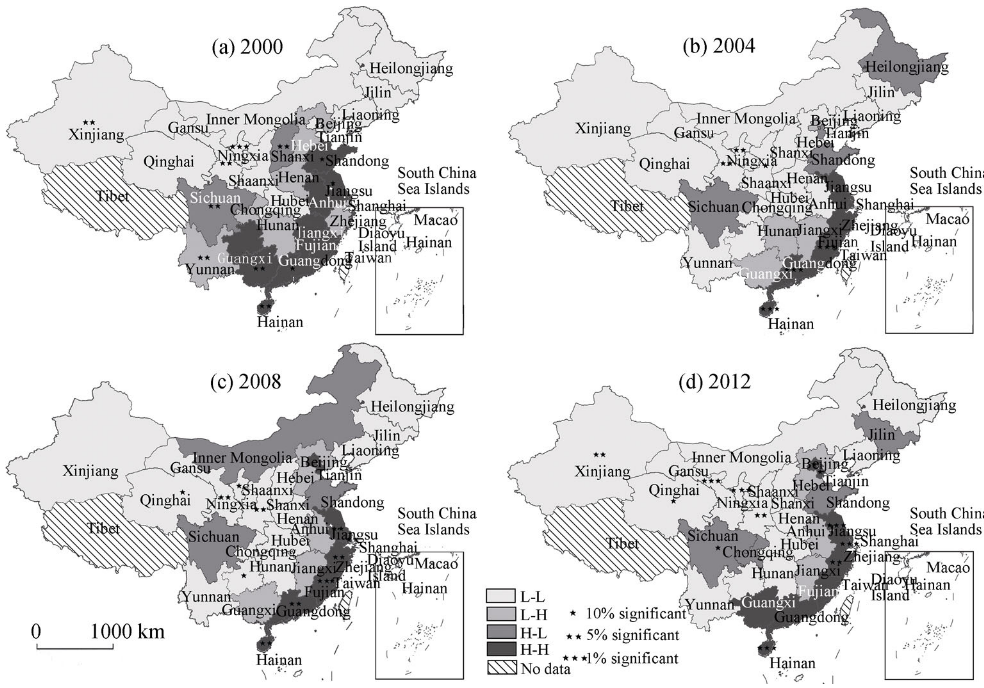

Figure 5 Evolution of local spatial association patterns of energy eco-efficiency

4 Analysis of the spatial effect of China's energy eco-efficiency

4.1 Measurement of spatial effects of energy eco-efficiency

From studies of the spatial pattern of China's energy eco-efficiency, it is clear that it exhibits a distinct spatial agglomeration. The formation and evolution of the spatial pattern of energy eco-efficiency are influenced by the disequilibrium of regional economic development, industrial structure, resources, population, and spatial interactions between adjacent areas. The question arises as to whether China's energy eco-efficiency has a spatial effect, and, if so, what the mechanism of this effect is. This study has measured and analyzed the spatial effect using the SLM and SEM models based on the above considerations.

The two predicted spatial mechanisms function simultaneously according to the validated test results of the SLM and SEM models (Table 2). According to the SLM model, the regional energy eco-efficiency is affected not only by local influencing factors, but also by the adjacent energy eco-efficiency and related factors. According to the SEM model, it is affected by adjacent influencing factors and by random effects. The spatial regression coefficient is 0.328 and the spatial error coefficient is 0.285, reflecting the fact that the spatial spillover effect of adjacent areas exceeds the impact of errors in adjacent areas on the regional energy eco-efficiency. The results of the SLM and SEM models are similar to those of the two spatial econometric models.

4.2 Analysis of the factors influencing the spatial effect of energy eco-efficiency

Table 2 shows that the impacts of urbanization rate and volume of foreign trade on energy eco-efficiency are insignificant. The impact of urbanization on economic efficiency is more complicated, with the decline in rural surplus labor and difficulty of urbanization, although urbanization is key to realizing transformation of the mode of economic development (Liu *et al.*, 2014). The influence of international trade on energy efficiency changes constantly along with the adjustment of foreign trade policy and structure. The industrial structure, economic development, population size, traffic base, foreign investment, and energy investment have significant influences on energy eco-efficiency. The influencing coefficients of industrial structure, energy investment, and traffic base are negative, while those of economic development, population size and foreign investment are positive.

Table 2 Model regression results

Variable	SAR	SEM
X_1	0.074***	0.113***
X_2	–0.311***	–0.302***
X_3	0.081***	0.083***
X_4	–0.039	–0.041
X_5	0.082***	0.090***
X_6	0.008	–0.004
X_7	–0.047***	–0.063***
X_8	–0.083***	–0.074***
ρ	0.328***	
λ		0.285***
R^2	0.490	0.654
Log-likelihood	174.376	236.070
H	27.750***	256.572***
LM	39.906***	39.906***
R-LM	11.658***	11.658***

*** significance at 1% level

(1) The influence of industrial structure on energy eco-efficiency is the greatest. The negative coefficient of industrial structure explains why the increase in secondary industry leads to a decrease in energy eco-efficiency, because the energy consumption intensity of each industry is different and the industries with high energy consumption and heavy pollution are mainly secondary industries. Thus, optimization of industrial structure is key to improving energy eco-efficiency, and the cities in the northeastern and central regions are key points in the adjustment of industrial structure (Guan *et al.*, 2014).

(2) The regions with high energy consumption and high energy efficiency do not match the spatial distribution of energy resources and energy enterprises. Energy resources are mainly in northern and northwestern China, while the regions with high energy consumption and high energy efficiency are mainly in eastern and southern coastal areas. The negative coefficient of energy investment reflects the fact that the energy efficiency of certain areas cannot be improved by national investment in their energy enterprises. The negative coefficient of the traffic base indicates the higher transportation cost of energy utilization in China. The five comprehensive energy bases, namely, Shanxi, eastern Inner Mongolia, the Ordos Basin, southwestern China, and Xinjiang, have great energy production capacity and huge output, but their energy eco-efficiency is lower.

(3) The influences of economic development, population size, and foreign investment on energy eco-efficiency are through promotion and inhibition. On the one hand, economic development improves production efficiency, promotes technological progress and innovation, upgrades industrial structure, and increases energy eco-efficiency; on the other hand, it promotes industrialization and urbanization, multiplies energy consumption, causes an imbalance in energy supply and demand, leads to instabilities in energy price, and disrupts energy consumption structure, among other things. The influence of population growth on en-

ergy eco-efficiency is complex and nonlinear. Population growth mainly causes two economic effects. One is scale economy, promoting division of labor and technological progress; the other is pressure on economic resources and the environment. These two effects both have a significant influence on energy eco-efficiency. Foreign investment increases energy eco-efficiency through upgrading industrial structure and promoting technological progress, but decreases it by pursuing only economic interests and ignoring energy consumption and environmental pollution. The influencing coefficients of economic development, population size, and foreign investment are positive (Table 2), indicating that their effects on promoting energy eco-efficiency exceed their inhibitory effects. Economic development, population size and foreign investment also influence surrounding areas through spatial transfer of capital flow, technology flow, and labor flow. The population flow and capital flow caused by economic factors often exhibit some hysteresis (Xiao *et al*., 2013). There are many other factors, such as the policy system, innovation ability, marketization, education, and finance, that influence energy eco-efficiency and its spillover effects (Huang *et al*., 2014).

5 Conclusions and discussion

5.1 Conclusions

(1) China's energy eco-efficiency had a U-shaped evolution pattern overall from 1997 to 2012, and, in local regions, the pattern of evolution included four types: increasing, fluctuating, mutating, and leveling. The overall spatial distribution pattern of energy eco-efficiency varied slightly in different periods, while the energy eco-efficiency development in given regions changed greatly. Guangdong, Hainan, and Fujian are at the forefront of energy eco-efficiency, while Ningxia, Gansu, Qinghai, and Xinjiang fall far behind.

(2) China's energy eco-efficiency exhibits fluctuations, but there is convergence toward significant global spatial agglomeration on a provincial scale. HH agglomeration occurs mainly in the eastern and southern coastal regions, LL agglomeration mainly in the northwestern region and the middle reaches of the Yellow River, HL agglomeration mainly in Sichuan Province in the southwestern region, and LH agglomeration mainly in the middle reaches of the Yangtze River. The changes in agglomeration pattern of energy eco-efficiency occurred basically in the regions of HL and LH agglomeration (notably in Beijing–Tianjin–Hebei), while the distribution of HH- and LL-agglomeration regions remained stable.

(3) There are mutual effects of energy eco-efficiency and a spatial dependence among Chinese provinces, with the spatial effect being remarkable. The influence of the spatial spillover effect between adjacent areas exceeds the impact of errors in adjacent areas on regional energy eco-efficiency. Among the influencing factors, the influence of industrial structure on energy eco-efficiency is the greatest, those of energy investment and transportation infrastructure are negative, and those of economic, population, and foreign investment are positive, while the direct influences of urbanization rate and volume of foreign trade are insignificant.

5.2 Discussion

(1) The spatial pattern of China's energy eco-efficiency is the result of multiple factors

and is a concentrated reflection of social and economic development. It is necessary to consider the reality of China's economic development and respect the laws of social and economic development in pursuing comprehensive, coordinated, and sustainable development of economy, society, resources, and ecology. China's coal-power-centered energy structure will persist for a long time, the coal supply restricts the development of the power industry as well as other industries, and the large proportion of coal in terminal energy consumption is the root cause of low energy eco-efficiency. Deepening coal resource tax reform, improving the energy pricing mechanism, establishing and perfecting regional interest compensation mechanisms, and supporting the continued development of alternative industries in resource-depleted areas are good starting points for reducing the large proportion of coal in terminal energy consumption.

(2) In response to global climate change, the Chinese government committed at the United Nations Climate Conference in 2009 to reduce unit-GDP carbon dioxide emissions by 40%–45% by 2020 compared with 2005. To achieve these goals, it is necessary to increase technological progress and adjust the industrial and energy structure, as well as promoting urbanization and improving relevant system and policy measures. Much attention and joint efforts are also required from regions, industries, enterprises, and individuals. To optimize the ecological and economic benefits of energy utilization, it is necessary to implement increases in energy eco-efficiency at the macro, meso, micro, and personal levels.

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