ORIGINAL ARTICLE

Evolution and policy effect assessment for the spatial heterogeneity pattern of regional energy efficiency in China

Jinpeng Liu · Delin Wei · Yu Tian · Qiaochu Li

Abstract Energy security and environmental pollution have become key issues affecting the sustainable development of China's economy and society. Therefore, it is particularly important for China to adopt effective policies and measures to control the excessive growth of energy consumption and improve energy efficiency. This paper uses data envelopment analysis (DEA) to measure the total-factor energy efficiencies (TFEEs) of 30 provincial-level administrative regions in China from 2008 to 2017 and analyses the evolution of the spatial heterogeneity pattern of regional energy efficiency. Then, a spatial autocorrelation approach is applied to explore the spatial agglomeration characteristics of regional energy efficiency in China, and GeoDetector is used to assess the direct and cross-driving effects of five policy types on spatial heterogeneity and agglomeration characteristics. The results show that the spatial heterogeneity pattern of regional energy efficiency in China is significantly higher in the eastern area than in the central and western areas, with strong spatial agglomeration characteristics overall, but especially significant agglomeration in areas with low energy efficiency. Urbanisation is the leading policy driving spatial heterogeneity, and the interaction factors, especially those including urbanisation, form the most significant multiple spatial overlapping interaction effects. To improve regional energy efficiency, the government should consider overall national goals and the characteristics driving the spatial heterogeneity of energy efficiency and implement differentiated policies.

Keywords Energy efficiency · Spatial heterogeneity · Spatial agglomeration · GeoDetector · Policy effects

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Introduction

As the world's largest energy consumer, producer and net importer, China's primary energy consumption

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reached 32.735 million tonnes of oil equivalent in 2018, accounting for 23.61% of the global primary energy consumption and contributing 34.46% of the net increase in global energy consumption. The trend in China's primary energy consumption from 2009 to 2018 is shown in Fig. 1. Despite the slowdown of China's economic growth rate and the adjustment of its industrial structure, China's energy consumption still grew at a rate of 4.3% in 2018, well higher than the world average of 2.9%. The rapid growth of China's economy has been supported by a very high demand for energy over the past three decades, and energy consumption has become a lifeline for the survival and development of China's economy and society. Correspondingly, there is a relative shortage in the energy supply in China. The Chinese Academy of Social Sciences pointed out in its 'World Energy China Outlook 2018–2019' that the apparent gap between energy supply and demand will reach 846 million tonnes of standard coal by 2030. China's future development will thus face increasing energy constraints.

Since it first proposed building a resource-conserving and environmentally friendly society in 2006, China has actively explored ways to adjust its energy consumption structure and optimise production technologies. However, simultaneously, China still faces many challenges in energy development. In recent years, China's environmental problems have become increasingly prominent, as frequent hazy weather has greatly affected social production and residents' lives. The trend in carbon dioxide emissions in China from 2009 to 2018 is shown in Fig. 2.

The global political and economic landscape is undergoing major adjustments, and the relationship between energy supply and demand is experiencing major changes. China's energy security is highly uncertain. Energy security and environmental pollution have become key issues affecting the sustainable development of China's economy and society. In this context, it is particularly important to control excessive growth in energy consumption and improve energy efficiency. China has a vast territory, with the economically developed provinces being concentrated in eastern, southern and central China, while coal, natural gas and other resources are mainly distributed in western regions such as Nei Mongol, Shanxi and Xinjiang. Economic development and energy endowment are generally inversely distributed, with strong spatial heterogeneity. Balanced improvement to the energy efficiency across China will require more attention to be given to the economic development level and energy utilisation of different regions so that policies and measures can be selected that fit the

Fig. 1 Comparison of primary energy consumption trends in China and the world from 2009 to 2018. Source: BP Amoco (2019a)
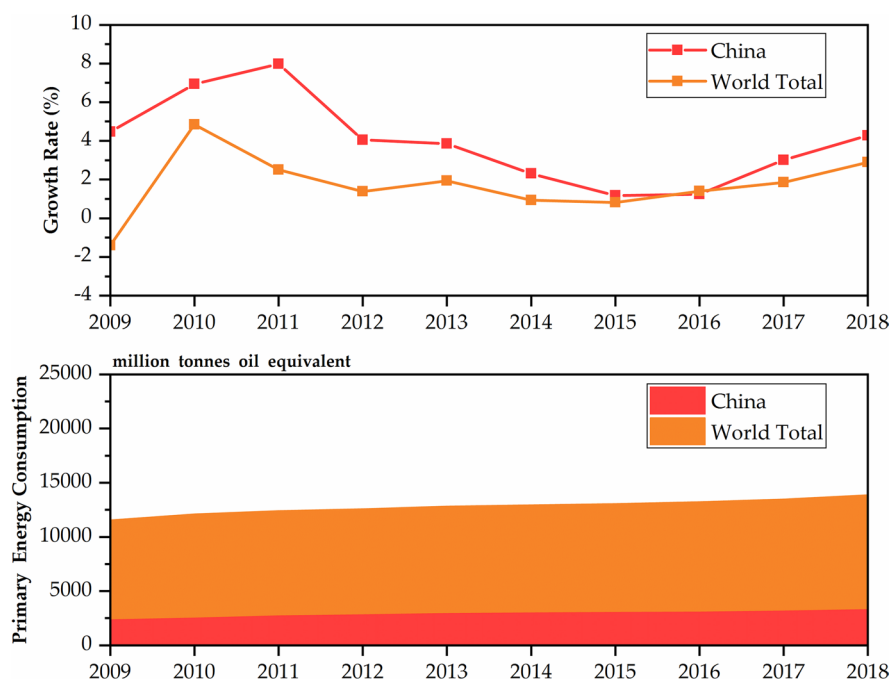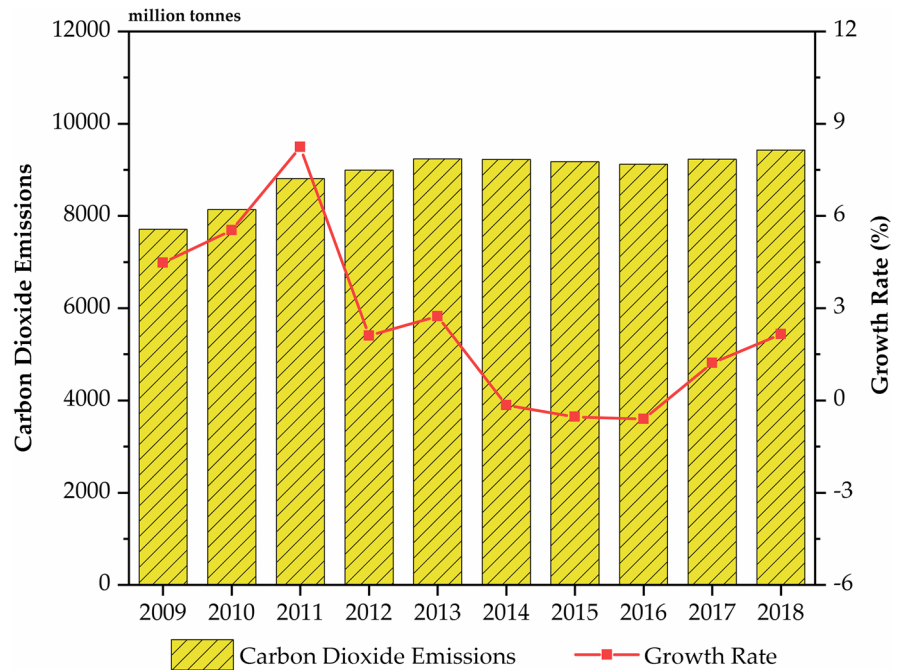
Fig. 2 Trend in carbon dioxide emissions in China from 2009 to 2018. Source: BP Amoco (2019b)

development reality according to local conditions. In this paper, the total-factor energy efficiencies (TFEEs) of 30 provincial administrative regions in China from 2008 to 2017 are measured, and the evolution of their spatial heterogeneity patterns is analysed. The results are then used to assess how the effects of different policy factors drive the characteristics of spatial agglomeration in regional energy efficiency in China. The research results can provide strong theoretical support to help the Chinese government to formulate differentiated regional energy conservation and emission reduction targets and energy efficiency improvement strategies. The main contributions of this paper can be summarised in the following five points.

Data envelopment analysis (DEA) and spatial autocorrelation analysis methods are used to estimate and analyse the evolution of the spatial heterogeneity pattern of TFEE in 30 provincial administrative regions of China from 2008 to 2017.

The direct and cross-driving effects of different policies on the spatial heterogeneity and agglomeration characteristics of regional energy efficiency in China are evaluated by using the GeoDetector method.

During the study period, regional energy efficiency in China is proven to have strong spatial agglomeration characteristics but these are especially significant in areas with low energy efficiency.

Urbanisation is proven to be the leading policy driving the spatial heterogeneity of regional energy efficiency in China, and the factors of this policy create the most significant overlapping spatial interaction effects.

Based on the development characteristics of different regions in China, targeted policy recommendations are proposed to optimise China's regional energy efficiency.

The remainder of the paper is organised as follows. '2' section reviews the relevant literature on energy efficiency measurement and analysis in China. In the '3' section, the energy efficiency measurement method and the GeoDetector method are briefly introduced. The '6' section measures China's regional energy efficiency from 2008 to 2017 and analyses the evolution of its spatial pattern. The '11' section evaluates the direct and cross-driving effects of the five policies on the spatial heterogeneity and the agglomeration characteristics of regional energy efficiency in China. The '14' section summarises the main conclusions of this paper and offers policy recommendations to optimise China's regional energy efficiency on this basis.

Literature review

Abundant studies exist on energy efficiency in China, mainly focusing on its measurement and analysis, influential factors and regional differences.

Measurement and analysis of energy efficiency and its influential factors. TFEE focuses on analysing the relationship between multiple inputs, such as energy, labour and capital, and economic output, allowing it to effectively compensate for the limitations of studying single-factor energy efficiency (Chang & Hu, 2010). Therefore, TFEE has been widely used to measure and analyse energy efficiency. Azam (2019, 2020) used relevant diagnostic testing methods to explore the impact of energy, environmental pollution, human capital, financial development and physical capital on economic growth in four BRICS countries and later studied the impact of energy use on economic growth in 10 developing economies in Asia. The empirical results show that energy is an important production factor in addition to human and physical capital, while environmental pollution attenuates economic growth. Zhang et al. (2011) used DEA to analyse the change trends of TFEE in 23 developing countries from 1980 to 2005, and the results showed that amongst the five countries with continuous growth in TFEE, China experienced the fastest growth. Hu and Wang (2006) took labour, capital stock, energy consumption and total sown area of crops as inputs and GDP as the single output and used DEA to measure the TFEE of 29 regions in China. Most existing studies only consider the expected output when measuring energy efficiency. Zhang and Choi (2013) included carbon dioxide, sulphur dioxide and chemical oxygen demand as undesirable output indicators in the DEA model and measured the TFEE of China from 2001 to 2010, showing that undesirable outputs had a significant impact on energy efficiency measurements. Wu et al. (2012) constructed static and dynamic indices to measure industrial energy efficiency by taking carbon dioxide emissions into account in the DEA model, and their empirical study shows that the energy efficiency improvement in China's industrial sector was mainly driven by technological progress. Li and Shi (2014) measured

the energy efficiency of various industrial sectors in China from 2001 to 2010 based on the improved Super-SBM model and then applied the Tobit regression model and found that enterprise scale, industry concentration, industrial structure and government regulation affected energy efficiency. Wang et al., (2013a) measured China's TFEE under three production scenarios, and the results proved that technological energy change was the main driving force of China's energy efficiency growth.

Evaluation of regional differences in energy efficiency. By measuring overall energy efficiency in China, Wang et al. (2013b) found that it was not high and had significant regional differences. Li et al. (2012) and Shi et al. (2010) measured the regional TFEE of China by using the SBM model and DEA model and fixing nonenergy inputs. The results showed that the eastern area had the highest energy, followed by the central area. Wang et al., (2013c) used improved DEA models to measure the energy and environmental efficiency of 29 administrative regions in China from 2000 to 2008, and the empirical results showed that the development of energy and environmental efficiency in eastern China was more balanced than that in central and western China. Wei et al. (2007) decomposed energy efficiency improvement into technological change and technological efficiency change using Malmquist Index Decomposition, and the calculation results showed that the energy efficiency gap amongst provincial iron and steel sectors had widened during the study period.

By reviewing the existing studies, it can be found that the current studies only calculate and analyse regional energy efficiency and its influential factors from the time dimension, while few studies analyse the evolution of regional energy efficiency from the spatial dimension, and thus, existing studies ignore the possible impact of interregional interaction on energy efficiency. With the passage of time and technological progress, connections between regions will inevitably have a spatial effect on changes in energy efficiency. Therefore, by measuring China's regional TFEE, this paper analyses the evolution of its spatial heterogeneity pattern and further explores the driving effect of different policy factors on the spatial agglomeration characteristics of regional energy

efficiency using GeoDetector. The results are of great significance for comprehensively and effectively improving China's regional energy efficiency.

Methodology

Energy efficiency measurement method

DEA is one of the most commonly used methods for efficiency evaluation (Cook & Seiford, 2009). In this model, linear programming and duality theorem are used to calculate the production frontier of the unit to be evaluated. The efficiency value of decision-making units (DMUs) that fall on the boundary is 1; the efficiency values of other DMUs that do not fall on the boundary are between 0 and 1. Since DEA can effectively deal with multiple inputs and outputs and can directly measure energy efficiency and input redundancy, it has advantages that cannot be underestimated in avoiding subjective factors, simplifying algorithms and reducing errors. Taking into account data characteristics, processing difficulty and result analysis, this paper selects an input-oriented variable returns to scale (VRS) DEA model to avoid the classification consistency problem of the constant returns to scale (CRS) DEA model (Boljuncic, 2006).

In addition to economic value indicators, in this paper, energy efficiency also takes into account undesired outputs such as environmental pollutants. In the DEA model, undesired outputs such as environmental pollutants appear as negative outputs, so undesired outputs must be addressed. At present, the methods for doing so in DEA models mainly include the curve measurement evaluation method, pollutant input processing method, data conversion function processing method and directional distance function method. This paper adopts the linear data transformation method, which converts pollutants into expected outputs through a linear data conversion function and offers great advantages for the VRS DEA model (Sarra et al., 2017).

Suppose there are n independent DMUs; each DMU has m inputs x_i and s outputs y_i and k pollutant emissions b_i. First, the pollutant is converted by the linear data conversion function $b_i' = -b_i + v$, in which v is a sufficiently large vector, and then it is added to the conventional DEA model as expected output.

$$Min\theta_0 \tag{1}$$

$$\sum_{j=1}^{n} \eta_j x_{ij} + s_i^- = \theta_0 x_{i0}, i = 1,2,\cdots,m \tag{2}$$

$$\sum_{j=1}^{n} \eta_j y_{rj} - s_r^+ = y_{r0}, r = 1,2,\cdots,s \tag{3}$$

$$\sum_{j=1}^{n} \eta_j b_{tj} - s_t^+ = b_{t0}', t = 1,2,\cdots,k \tag{4}$$

$$\sum_{j=1}^{n} \eta_j = 1 \tag{5}$$

$$\eta_j, s_i^-, s_r^+, s_t^+ \geq 0 \tag{6}$$

where θ_0 is the effective value of DMU$_{j0}$; η_j is the combination ratio of the j-th DMUj in an effective DMU combination reconstructed relative to DMU$_{j0}$; and s_i^-, s_r^+ and s_t^+ are relaxation variables.

GeoDetector

GeoDetector is a spatial statistical analysis method used to study the leading drivers of spatial heterogeneity and their interactions (Wang et al., 2016). It has been widely used in remote sensing, meteorology, regional planning and public health. The basic principle of GeoDetector is that when the spatial heterogeneity pattern explained variable and the influential factors have the same spatial heterogeneity patterns, it indicates that there is a statistical correlation between them. Specifically, by performing a spatial layered overlay analysis of the same area, the value and direction of the q statistic are used to determine whether the explanatory factor is the dominant factor driving the spatial heterogeneity of the explanatory variable. Then, through a multispatial superposition analysis of different explanatory factors and explained variables, the key interactive factors in the spatial heterogeneity of the explained variables can be explored with the results of interactive factor q statistics. Compared with classical statistics, GeoDetector does not need to make a presupposition on the sample distribution and is immune to multicollinearity problems.

It also extends the setting of traditional econometric models, which are limited to multiplying variables when exploring interaction effects, and more accurately detects the interaction effects between variables through spatial superposition technology (Wang et al., 2019a). Unlike traditional analysis tools, GeoDetector does not require spatial continuity and can process both spatial surface data and point data, making it more flexible to use (Shrestha & Luo, 2017). Therefore, this method is better when analysing and evaluating the spatial heterogeneity pattern of regional energy efficiency in China, which is directly driven by single policy factors and cross-driven by multiple policy factors.

GeoDetector mainly conducts detection analysis through a factor detector and interaction detector.

A factor detector is used to analyse the determinants of influential factors on the spatial heterogeneity pattern of the explained variables. The q statistic is used for detection and identification, and its calculation formula is shown in Eq. (7).

$$q = 1 - \frac{\sum_{i=1}^{n} N_i \sigma_i^2}{N \sigma^2} \qquad (7)$$

where $i = 1, 2, \cdots, n$ is the subregion category in the 'layer' divided according to the attribute characteristic value represented by a certain influence factor; N_i represents the number of units in the i-th subregion; and σ_i^2 and σ^2 represent the variances of the explained variables in the i-th subregion and all subregions, respectively. $N_i \sigma_i^2$ represents the sum of the variances of the explained variables in the layer of the i-th subregion, and $N \sigma^2$ is the overall variance in the whole region. The value range of the q statistic is [0, 1]. The closer q is to 1, the more likely the influence factor is to be the dominant driving factor.

An interaction detector is used to determine the role of different influential factors in the spatial heterogeneity pattern of the explained variables, explore the key interaction factors and analyse their spatial superposition interaction effects. It is assumed that two influential factors A and B influence the explained variable Y, and spatial superposition is used to analyse the geographical partition where A, B and AB intersect and the spatial heterogeneity pattern of Y. To verify the interaction between A and B in region Y, $q(A)$, $q(B)$, and $q(A \cap B)$, which respectively represent the determinants of A, B and the spatial effect

of the superposition interaction between A and B on the spatial heterogeneity pattern of Y, are calculated and compared. When $q(A \cap B) = q(A) + q(B)$, A and B are independent of each other. When $q(A \cap B) < \text{Max}$ $(q(A), q(B))$, the interaction factor has a weakening effect; when $q(A \cap B) > \text{Max} (q(A), q(B))$, the interaction factor has an enhancing effect. $Q (A \cap B) \in [0,1]$, where the closer q is 1, the more likely $A \cap B$ is to be the key interaction factor.

China's regional TEFF measurement and the evolution of its spatial heterogeneity

Variable selection and data source

In this paper, the data of 30 provincial administrative regions in China from 2008 to 2017 are used as the DMUs of energy efficiency. Considering the consistency and availability of data, Xizang, Hong Kong, Macao and Taiwan are not included in the study. There are five input–output indicators for energy efficiency in this paper. In terms of output indicators, regional GDP is used as the desired output indicator. Taking into account the atmospheric pollutants generated in the use of fossil energy, this paper selects sulphur dioxide emissions as undesired output indicators. The input indicators are labour, energy consumption and fixed asset investment, and thus, the number of DMUs is more than twice the number of indicators, meeting the requirement of the DEA method (Meng et al., 2016).

The GDP of each region is converted from the absolute value for that year to the 2008 constant price as the base year in this paper. Sulphur dioxide emissions are converted into the desired output by the linear data conversion function, $w' = v - w$, where $v = 100$, and w' is added to the DEA model as the desired output. The labour force is calculated based on the average employment figure at the end of the current and previous year. Energy consumption data were converted into standard coal equivalents. The input–output indicator data of each region are all from the China Statistical Yearbook and China Energy Statistical Yearbook from 2009 to 2018.

Table 1 TFEE of 30 provincial administrative regions in China from 2008 to 2017

Region	Year									
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.813	0.736	0.869	0.937	0.904	0.926	0.886	0.858	0.827	0.770
Shanxi	0.724	0.696	0.710	0.772	0.706	0.668	0.657	0.671	0.660	0.893
Nei Mongol	0.921	0.884	0.888	0.965	0.901	0.780	0.724	0.844	0.806	0.661
Liaoning	0.640	0.647	0.664	0.717	0.720	0.757	0.776	0.945	1.000	1.000
Jilin	0.660	0.679	0.686	0.738	0.733	0.739	0.765	0.771	0.767	0.709
Heilongjiang	0.733	0.660	0.635	0.693	0.669	0.684	0.802	0.976	0.920	0.841
Shanghai	0.985	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.870	0.872	0.840	0.870	0.885	0.824	0.864	0.889	0.878	0.887
Zhejiang	0.853	0.864	0.836	0.831	0.828	0.838	0.852	0.807	0.806	0.808
Anhui	0.698	0.724	0.719	0.741	0.745	0.737	0.735	0.721	0.698	0.668
Fujian	0.891	0.891	0.856	0.824	0.812	0.848	0.834	0.820	0.773	0.759
Jiangxi	0.794	0.773	0.742	0.728	0.717	0.705	0.696	0.672	0.679	0.674
Shandong	0.911	0.911	0.876	0.908	0.902	0.880	0.879	0.867	0.834	0.791
Henan	0.783	0.758	0.772	0.777	0.784	0.818	0.799	0.802	0.787	0.771
Hubei	0.732	0.690	0.678	0.665	0.682	0.655	0.642	0.656	0.665	0.657
Hunan	0.780	0.757	0.727	0.735	0.743	0.796	0.789	0.800	0.920	0.884
Guangdong	1.000	1.000	1.000	1.000	1.000	0.961	0.943	0.927	0.879	0.863
Guangxi	0.742	0.721	0.710	0.760	0.751	0.741	0.747	0.745	0.737	0.666
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chongqing	0.633	0.621	0.614	0.586	0.562	0.578	0.562	0.548	0.533	0.516
Sichuan	0.636	0.585	0.605	0.662	0.672	0.657	0.666	0.628	0.632	0.814
Guizhou	0.671	0.647	0.626	0.608	0.571	0.541	0.526	0.518	0.499	0.490
Yunnan	0.590	0.549	0.532	0.537	0.530	0.542	0.545	0.574	0.549	0.540
Shaanxi	0.655	0.663	0.714	0.731	0.740	0.724	0.720	0.721	0.710	0.713
Gansu	0.704	0.657	0.643	0.664	0.644	0.596	0.563	0.534	0.538	0.695
Qinghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ningxia	0.892	0.875	0.850	0.895	0.889	0.885	0.853	0.838	0.892	1.000
Xinjiang	0.699	0.685	0.733	0.758	0.712	0.697	0.676	0.638	0.652	0.505

Measurement of regional TFEE based on DEA model

Using DEAP 2.1 software, the TFEE of 30 provincial administrative regions in China from 2008 to 2017 was calculated, as shown in Table 1.

Table 1 shows that amongst the 30 provincial administrative regions in China investigated in this paper, Beijing, Tianjin, Shanghai, Hainan and Qinghai had the highest TFEE. The TFEEs of the above regions from 2008 to 2017 were all 1, and together, they constituted China's energy efficiency frontier. The TFEEs of Ningxia, Hunan, Heilongjiang and Liaoning show a rising trend, and Liaoning and Ningxia reached the efficiency frontier in recent years. The TFEE of 8 regions, including Guangdong and Nei Mongol, showed a declining trend, while the TFEEs in the other 13 regions showed a fluctuating trend, amongst which the TFEEs of Chongqing, Sichuan, Guizhou, Yunnan and Gansu were below 0.7 throughout the years.

Evolution of the spatial heterogeneity in regional energy efficiency

Based on the calculation results in the previous section, this paper analyses the evolution of the spatial heterogeneity pattern of China's regional energy
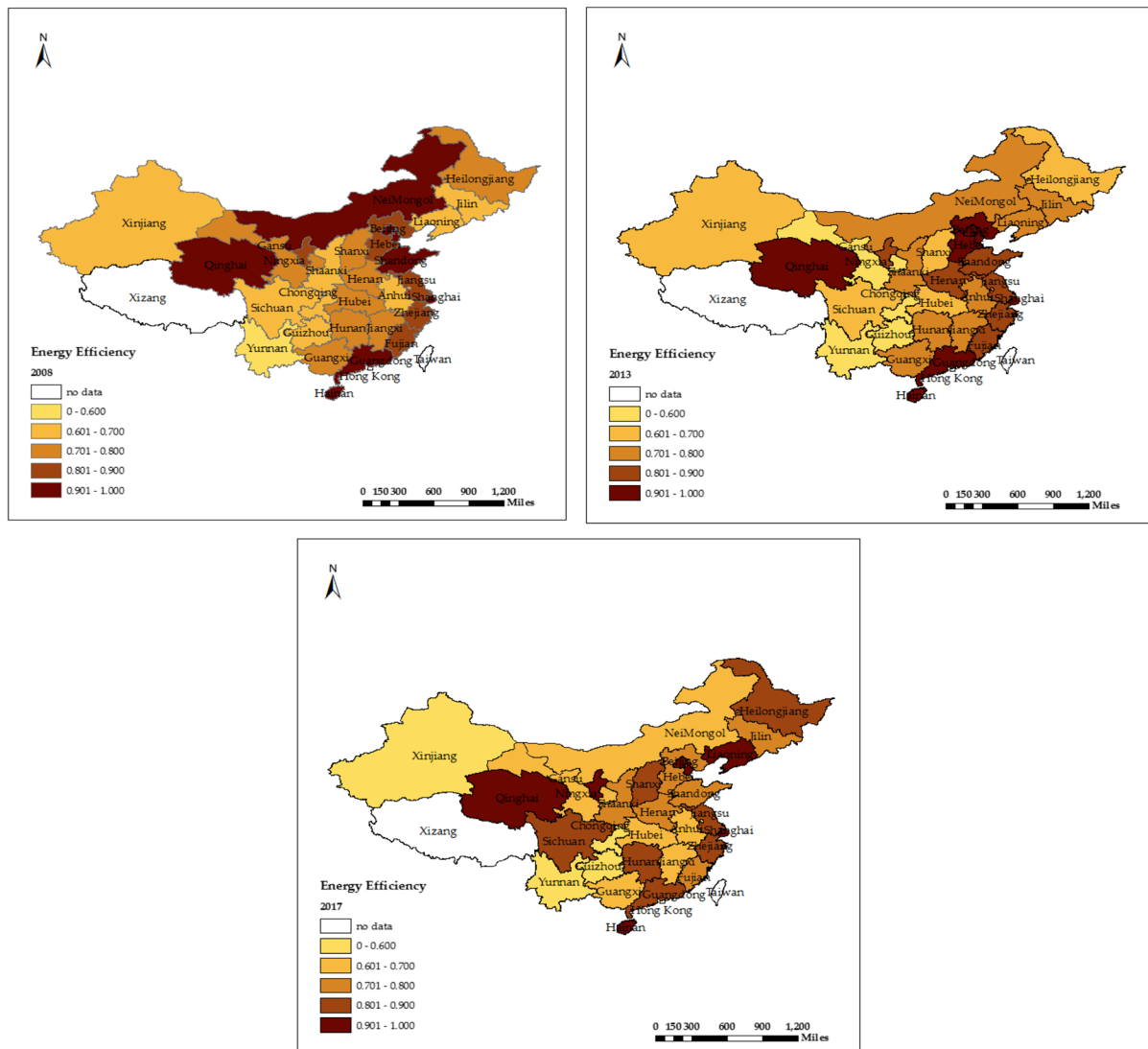
Fig. 3 Spatial heterogeneity pattern of regional energy efficiency in China in 2008, 2013 and 2017

efficiency spatial heterogeneity pattern in 2008, 2013 and 2017, as shown in Fig. 3. The evolution of energy efficiency in eastern, central and western China from 2008 to 2017 is shown in Fig. 4.

Overall, the pattern in the spatial heterogeneity pattern of regional energy efficiency in China during the study period is relatively obvious, and this result is consistent with the research results of relevant literature on regional differences in energy efficiency in the '2' section. The TFEE in the eastern region was significantly higher than that in the central and western regions from 2008 to 2017, where the average

TFEE of provinces in eastern China reached 0.909, 23.53% higher than that in central China and 28.00% higher than that in western China. Further analysis shows that during the study period, the areas with high energy efficiency are mainly located in parts of the Bohai Rim region (Beijing, Tianjin, Liaoning, Hebei), the middle reaches area of the Yellow River (Shanxi, Henan), the eastern and southern coastal areas (Jiangsu, Zhejiang, Fujian, Guangdong, Hainan) and parts of the northwest area (Qinghai, Ningxia). The areas with low energy efficiency are mainly located in parts of the southwest area
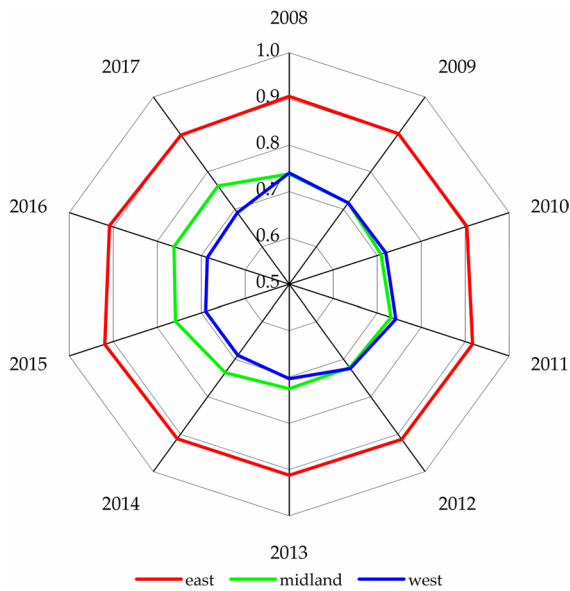
Fig. 4 Energy efficiency trends in eastern, central and western China from 2018 to 2017

(Chongqing, Guizhou, Yunnan) and in the middle reaches area of the Yangtze River (Anhui, Jiangxi, Hubei). It is worth noting that the provinces of Nei Mongol and Shandong gradually shifted from high energy efficiency to low energy efficiency during the sample period.

From the perspective of each study section, there are fluctuations in the spatial heterogeneity pattern of China's regional energy efficiency. The internal variation in regions with TFEEs below 0.6 and regions with TFEEs between 0.6 and 0.7 are particularly significant. In 2008, examining the spatial heterogeneity pattern of China's regional energy efficiency, only Yunnan had a TFEE below 0.6, and provinces with heavy industry as the pillar, such as Liaoning and Jilin, and provinces whose energy structure was dominated by raw coal, such as Shaanxi and Guizhou, had TFEEs between 0.6 and 0.7; this latter group of provinces also included provinces such as Anhui, Sichuan and Chongqing that have developed rapidly or whose energy consumption structure is based on raw coal. From 2008 to 2017, the TFEE of western China dropped from 0.740 to 0.691, resulting in a significant expansion in TFEEs below 0.6 for the two research periods of 2013 and 2017.

Analysis of the spatial agglomeration characteristics and policy effects of regional energy efficiency in China

Spatial agglomeration characteristics of regional energy efficiency

To investigate whether there are spatial agglomeration characteristics in China's regional energy efficiency, this paper uses Geoda 1.10 software to perform global and local spatial autocorrelation analysis based on the rook contiguity space weight matrix defined by the common boundary. The general Moran index, Moran scatter plots and LISA cluster maps of energy efficiency are shown in Table 2 and Fig. 5.

It can be seen from Table 2 and Fig. 5 that during the study period, the Moran index statistics are all positive, the z values all reach 1.96, and they all pass the significance test at the 5% significance level, indicating that China's regional energy efficiency is not a random distribution in space, there is significant positive spatial dependence, and there are strong features of spatial agglomeration. Provinces with high (low) energy efficiency are often adjacent to other provinces with high (low) energy efficiency, showing the characteristic of 'neighbouring areas are similar'. The large positive spatial correlation indicates that the spatial difference in energy efficiency in China is gradually narrowing, and this trend is continuing over time.

With reference to Fig. 6, the spatial agglomeration characteristics between a central area and other adjacent areas can be further clarified, where the high–high agglomeration area or low–low agglomeration area indicates that the TFEE of a central area has a higher or lower degree of spatial agglomeration than its surrounding area, there is a strong positive spatial correlation, and the spatial units are homogeneous. When located in a low–high agglomeration area or a high–low agglomeration area, respectively, the TFEE of a central area is lower or higher than that of its surrounding area, there is a strong negative spatial correlation, and the spatial units are heterogeneous. The specific analysis shows that the spatial agglomeration characteristics of China's low energy efficiency regions are particularly significant. The TFEEs of Yunnan, Guizhou, Sichuan, Chongqing, and Gansu in western China are consistently relatively low. The provinces of eastern China have higher TFEE overall,

Table 2 Moran index test results for regional energy efficiency in China from 2008 to 2017

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Moran index	0.231	0.255	0.304	0.321	0.309	0.306	0.333	0.298	0.225	0.218
Z value	2.23	2.36	2.76	2.90	2.79	2.78	2.98	2.69	2.11	2.07

but the spatial agglomeration characteristics are not significant at the 5% significance level, showing that there are few high–high agglomeration regions. The spatial heterogeneity and agglomeration characteristics of regional energy efficiency are driven by national macroeconomic and social development policies and micro-industrial development policies. Therefore, it is necessary to analyse and evaluate the effects of different policies on the evolution of the spatial heterogeneity pattern of regional energy efficiency in China and, based on this, introduce more targeted policies and measures in accordance with regional development characteristics to further enhance the spatial agglomeration characteristics of regional energy efficiency in China; in particular, this can help form a wide range of energy efficiency high–high agglomeration areas to effectively promote the overall improvement of regional energy efficiency in China.

Analysis of direct driving effect

This paper selects representative policies and measures from the five policy areas of the economy, society, energy, technology and industry to analyse and evaluate the direct and cross-driving effects of

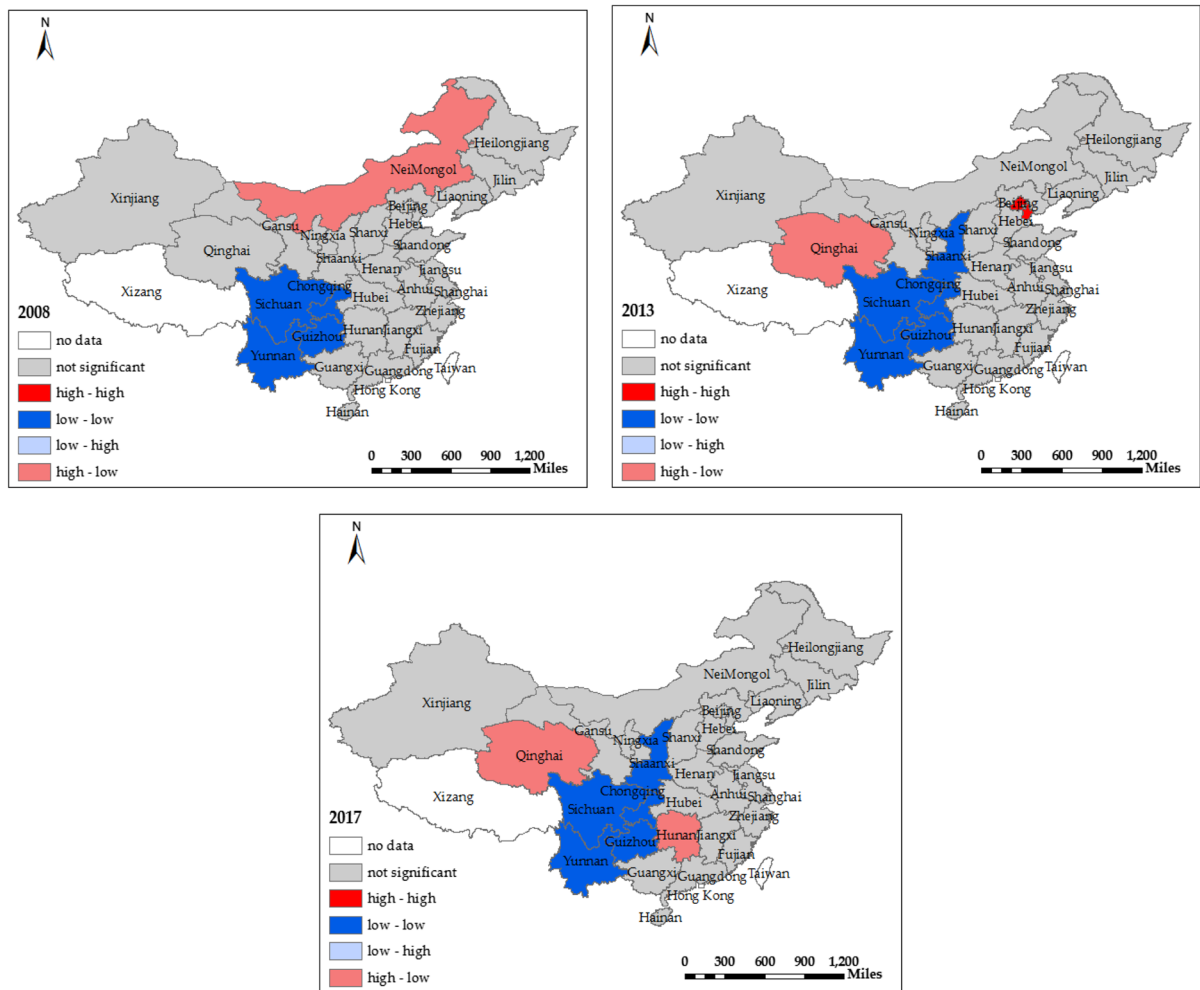**Fig. 5** Moran scatter plots of regional energy efficiency in China
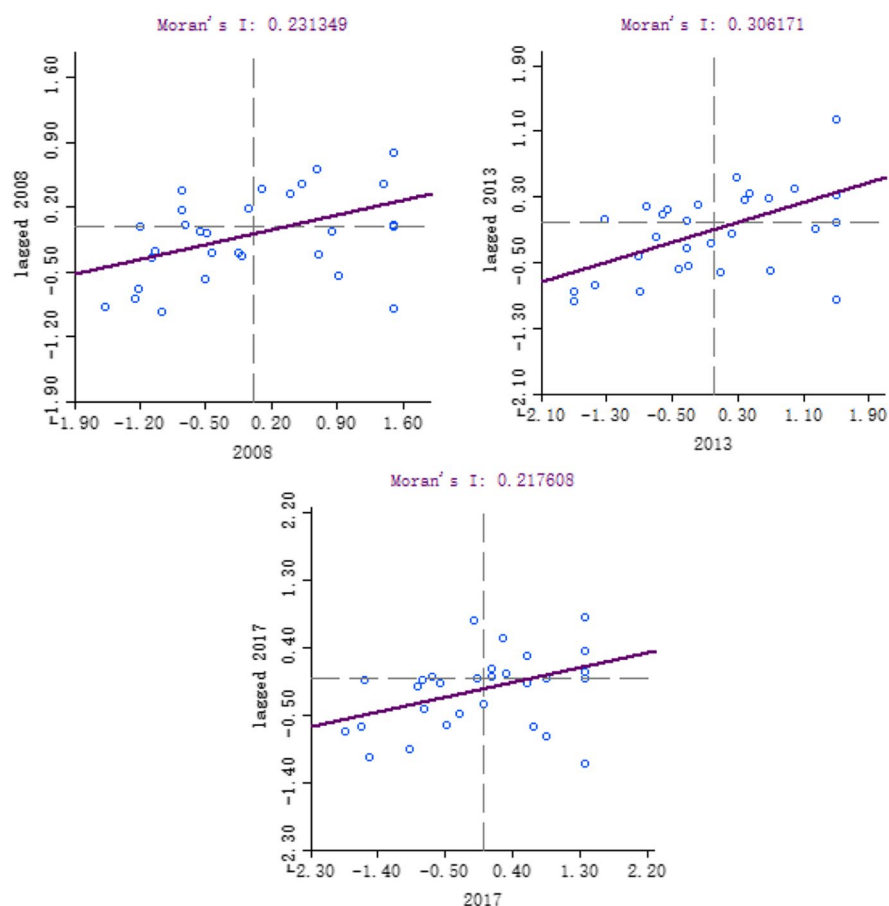
Fig. 6 LISA cluster maps of regional energy efficiency in China

different types of policies on spatial heterogeneity and on the agglomeration characteristics of regional energy efficiency in China. At the same time, combined with existing studies on the factors influencing energy efficiency, typical indicators are selected to represent the implementation intensity of various policies, given comprehensive consideration of data availability. The selection and description of policies and indicators are shown in Table 3.

Table 3 Policy and indicator description

Dimension	Representative policy	Indicator	Reference
Economy	Opening up	Proportion of foreign investment in fixed assets	Wang et al., 2019b
Society	Urbanisation	Proportion of urban population in total population	Li et al., 2018; Adom, 2019
Energy	Energy planning	Proportion of electricity consumption in primary energy consumption	Wei et al., 2009
Technology	Technical progress	Proportion of R&D expenditure in GDP	Cui et al., 2014
Industry	Industrial restructuring	Proportion of value added of tertiary industry to GDP	Yang & Wei, 2019

In this paper, the value added of tertiary industry, R&D expenditure, foreign investment, urban population and total population data of each region are all from the China Statistical Yearbook 2009–2018, and the coal consumption data of each region are from the China Energy Statistical Yearbook 2009–2018. Since GeoDetector is based on cross-sectional data for analysis, to ensure a comprehensive geographic exploration of the patterns of regional energy efficiency spatial heterogeneity and to better reflect the effects of different types of policies on regional energy efficiency spatial heterogeneity and agglomeration characteristics at different times, combining the actual data collection and sorting, this paper selects 2008, 2013 and 2017 as the focal years and carries out geographic detection and analysis of the spatial heterogeneity pattern of regional energy efficiency in China.

First, a factor detector is adopted to analyse the intensity with which various policies drive the spatial heterogeneity pattern of energy efficiency in China, to identify the leading driving policy and to evaluate the policy effects of the spatial heterogeneity pattern by comparing the effect intensity of each factor in different years. The factor detector results for the focal years calculated by the GeoDetector2015 software are shown in Table 4.

As seen from Table 4, all policies pass the test at the 5% significance level, indicating that the five types of policies, including opening up, urbanisation, energy planning, technological progress and industrial restructuring, have significant driving effects on the spatial heterogeneity and agglomeration characteristics of China's regional energy efficiency. This result also matches the research results of the relevant literature in Table 4. The ranking of policy effects in 2008 is urbanisation > opening up > technological progress > energy planning > industrial restructuring. The 2013 results differ from those in 2008; the

q statistic corresponding to technological progress in 2013 is smaller than that corresponding to energy planning and industrial restructuring, while the effects of all five policies have declined. The ranking of policy effects is energy planning > urbanisation > industrial restructuring > opening up > technical progress. In 2017, opening up had the strongest effect on the spatial heterogeneity pattern of regional energy efficiency, and the ranking of policy effects changed again: opening up > technological progress > urbanisation > energy planning > industrial restructuring. Overall, urbanisation has been the leading policy driving the spatial heterogeneity pattern of regional energy efficiency in China, and its effect has consistently been amongst the top three. The effects of opening up and technological progress show a trend of first declining and then increasing. Energy planning became the most decisive driving policy within the 2013 sample cross-section, while industrial restructuring consistently had a small effect.

Analysis of cross-driving effect

In this paper, the interaction detector is used to analyse the driving effects of the interaction factors formed by superpositioning the above policies on the spatial heterogeneity pattern of regional energy efficiency in China and to explore trends in the evolution of the driving effect of the interaction factors in different years. The interaction detector results for the focal years as calculated by GeoDetector2015 software are shown in Table 5.

Table 5 presents the q statistics of the interaction factors in the sample cross-sections formed by the superposition of each pair of policies. In summary, all the interaction factors have stronger effects on the spatial heterogeneity of regional energy efficiency than any single factor. In all sample cross-sections, the key

Table 4 Factor detector results for major years

Year Policy	2008		2013		2017	
	q	P value	q	P value	q	P value
Opening up	0.965895	0.00	0.913920	0.00	0.937717	0.00
Urbanisation	0.968654	0.00	0.947307	0.00	0.920414	0.00
Energy planning	0.961438	0.00	0.952747	0.00	0.914624	0.00
Technical progress	0.962724	0.00	0.806996	0.00	0.924801	0.00
Industrial restructuring	0.958580	0.00	0.947219	0.00	0.912779	0.00

Table 5 Interaction detector results for focal years

Interaction factor	q		
	2008	2013	2017
Opening up ∩ urbanisation	0.976631	0.963073	0.960148
Opening up ∩ unergy planning	0.977230	0.969033	0.966395
Opening up ∩ uechnical progress	0.971231	0.962572	0.967193
Opening up ∩ undustrial restructuring	0.974554	0.961856	0.943328
Urbanisation ∩ energy planning	0.984268	0.966595	0.952888
Urbanisation ∩ technical progress	0.980266	0.954129	0.943012
Urbanisation ∩ industrial restructuring	0.979295	0.962883	0.939695
Energy planning ∩ technical progress	0.968881	0.962807	0.952264
Energy planning ∩ industrial restructuring	0.973587	0.969639	0.954286
Technical progress ∩ industrial restructuring	0.970480	0.949747	0.948302

interaction factors with relatively large effects on the spatial heterogeneity of regional energy efficiency in China are urbanisation ∩ industrial restructuring, urbanisation ∩ energy planning, urbanisation ∩ technological progress, and urbanisation ∩ opening up, showing that the interaction factors containing urbanisation have important multiple spatial superposition interaction effects on the spatial heterogeneity of China's regional energy efficiency. At the same time, the effects of urbanisation on the spatial heterogeneity pattern of China's regional energy efficiency are closely intertwined with those of the four other policies. From 2008 to 2017, China's urban population increased from 624 to 813 million, representing an average annual growth rate of 2.99% and far exceeding the average annual growth rate of China's total population of 0.51%. The urbanisation rate increased from 46.99% in 2008 to 58.52% in 2017. The steady advancement of China's urbanisation process has concentrated capital and talent, improved the technology level and optimised the urban infrastructure, effectively enhancing the employment absorption capacity of cities and promoting rapid growth in electricity consumption demand.

Technological progress ∩ opening up maintained a relatively high effect for all three sample cross-sections. With the steady improvement in China's opening up level, advanced foreign technologies, equipment and management experience have increasingly been introduced to reduce China's energy consumption and sulphur dioxide emission intensity, thus improving regional energy efficiency. In addition, opening up can promote the learning of advanced environmental protection technology and

management experience. In particular, given the issue of climate change, the international cooperation mechanisms under the Kyoto protocol, such as the CDM, can effectively reduce pollutant emissions while promoting China's regional economic development.

Conclusions and policy recommendations

Conclusions

Considering sulphur dioxide emissions as undesired output, this paper uses DEA to calculate the TFEEs of 30 provincial administrative regions in China from 2008 to 2017 and analyses the evolution of their spatial heterogeneity pattern. Furthermore, global and local spatial autocorrelation analyses are used to explore the spatial agglomeration characteristics of China's regional energy efficiency. Then, the direct and cross-driving effects of five policies, including opening up, urbanisation, energy planning, technological progress and industrial restructuring, on spatial heterogeneity and the agglomeration characteristics are assessed by GeoDetector. The results show the following.

Regional energy efficiency in China overall presents a spatial heterogeneity pattern showing significantly higher TFEEs in the eastern area than in the central and western areas. During the sample period, the TFEEs of Beijing, Tianjin, Shanghai, Hainan and Qinghai were all 1, and thus, they constitute China's energy efficiency frontier. Chongqing, Sichuan, Guizhou, Yunnan and Gansu have relatively low

energy efficiencies. There are certain fluctuations in the spatial heterogeneity pattern of energy efficiency in each study period. The internal variation in regions with TFEEs below 0.6 and regions with TFEEs between 0.6 and 0.7 are particularly significant.

Regional energy efficiency in China is not randomly distributed in space but has significant positive spatial dependence and strong spatial agglomeration characteristics. However, the results of the local spatial autocorrelation test show that the spatial agglomeration characteristics of low energy efficiency regions in China are particularly significant, while the energy efficiency agglomeration characteristics in most eastern regions are not significant at the 5% significance level.

The five types of policies have significant direct driving effects on spatial heterogeneity and the agglomeration characteristics of regional energy efficiency in China. In general, urbanisation has been the leading driving policy. Compared with the direct driving effect of a single policy, the interactions of policy pairs show enhanced cross-driving effects, and the interaction factors that include urbanisation have the most significant multiple spatial superposition interaction effects on the spatial heterogeneity of China's regional energy efficiency.

Policy recommendations

The spatial heterogeneity pattern of regional energy efficiency in China shows that the energy efficiency levels in different regions are uneven, and different policies have different driving effects on spatial differentiation and the agglomeration characteristics of regional energy efficiency. However, each region, to different degrees, is characterised by an interweaving of urbanisation, opening up, energy planning, technological progress and industrial restructuring. Therefore, a 'one-size-fits-all' development strategy cannot effectively achieve the overall goal of energy efficiency improvement. While jointly undertaking national commitments on energy conservation and emission reduction, it is necessary for each region to choose policies and measures appropriate to its development reality according to its own pollutant emission conditions and regional development characteristics. Therefore, this paper makes the following policy recommendations.

China is in the late middle period of industrialisation and experiencing the rapid development of urbanisation, and some regions are producing large amounts of pollutants while their economic development level constantly improves. The five provinces of Shandong, Hebei, Shanxi, Henan and Liaoning accounted for 28.68% and 29.61% of China's total energy consumption and sulphur dioxide emissions in 2017, respectively, as these are typical regions with high energy consumption and high emissions. Considering that the energy endowment structure and consumption structure of the above regions are dominated by coal and that their industrialisation and urbanisation level is relatively high, it is necessary to promote the agglomeration of capital, talent, technology and other factors through urbanisation and gradually shift away from the extensive economic development model featuring high energy consumption and high emissions. By setting reasonable industrial policies, the direction and mode of factor allocation can be further optimised and the industrial structure can be transformed and upgraded into a more capital- and labour-intensive structure to effectively reduce energy consumption and pollutant emissions and improve energy efficiency.

Shaanxi, Xinjiang, Guizhou, Gansu, Qinghai, Ningxia and Nei Mongol have high energy intensity but relatively low levels of economic development, and they are currently in the midst of a rapid increase in industrialisation and urbanisation. The energy intensity of the above provinces is relatively rigid, and it will be difficult for their total energy consumption to decline in the short term. Considering the coal-based energy endowment and the low energy price of coal, it will be difficult to quickly change the coal-based energy consumption structure in these regions. The results of the global and local spatial autocorrelation analyses show that China's energy efficiency has a strong spatial agglomeration characteristic, so improvements in the energy efficiency in one region can radiating out to benefit the surrounding areas. In particular, Qinghai Province has become a prominent 'bright spot' in a region where energy efficiency has remained low, so Qinghai Province can be considered a 'growth pole' for regional energy efficiency to create good communication conditions for its surrounding areas, promote resource flows between regions and promote the improvement in regional energy efficiency from point to plane. At

the same time, the government can formulate reasonable tax and fiscal subsidy policies and strengthen its supervisory mechanism to encourage enterprises to introduce cleaner production technologies and equipment to reduce pollutant emissions as much as possible and further improve energy efficiency.

Tianjin, Shanghai, Jiangsu, Zhejiang and Guangdong relied on demographic dividends, geographical advantages and policy advantages to vigorously developed export manufacturing in their early stage of development and achieved rapid economic growth. However, excessive energy rigidity also led to a rapid increase in pollutant emissions. Considering that the urbanisation rate, technology level and degree of opening up of the above regions are all at the leading level in China, it is necessary to focus future policies and measures on energy consumption and industrial structure transformation to give full play to the cross-driving effects of different policies. With the demographic dividend gradually disappearing, these regions can make full use of the capital and technology accumulated over a long period of time to gradually change the status quo of extensive industrial development, realise the transformation and upgrading of export-oriented industries and reduce the rigid energy demand. At the same time, the greater the use of natural gas and other clean energy and innovations in energy use technology and equipment can help gradually transform their coal-based energy consumption structure and improve energy efficiency.

Declarations

Conflict of interest The authors declare no competing interests.

References

Adom, P. K. (2019). An evaluation of energy efficiency performances in Africa under heterogeneous technologies. *Journal of Cleaner Production, 209*, 1170–1181. https://doi.org/10.1016/j.jclepro.2018.10.320

Amoco, BP. (2019a). BP Statistical Review of World Energy 2019. Available online: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf. Accessed 9 March 2020.

Amoco, BP. (2019b). BP Sustainability Report 2019. Available online: https://www.bp.com/content/dam/bp/busin

ess-sites/en/global/corporate/pdfs/sustainability/group-reports/bp-sustainability-report-2019.pdf. Accessed 9 March 2020.

Azam, M. (2019). Relationship between energy, investment, human capital, environment, and economic growth in four BRICS countries. *Environmental Science and Pollution Research, 26*(33), 34388–34400. https://doi.org/10.1007/s11356-019-06533-9

Azam, M. (2020). Energy and economic growth in developing Asian economies. *Journal of the Asia Pacific Economy, 25*(3), 447–471. https://doi.org/10.1080/13547860.2019.1665328

Boljuncic, V. (2006). Sensitivity analysis of an efficient DMU in DEA model with variable returns to scale (VRS). *Journal of Productivity Analysis, 25*(1–2), 173–192. https://doi.org/10.1007/s11123-006-7139-5

Chang, T.-P., & Hu, J.-L. (2010). Total-factor energy productivity growth, technical progress, and efficiency change: An empirical study of China. *Applied Energy, 87*(10), 3262–3270. https://doi.org/10.1016/j.apenergy.2010.04.026

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA) – Thirty years on. *European Journal of Operational Research, 192*(1), 1–17. https://doi.org/10.1016/j.ejor.2008.01.032

Cui, Q., Kuang, H. B., Wu, C. Y., & Li, Y. (2014). The changing trend and influencing factors of energy efficiency: The case of nine countries. *Energy, 64*, 1026–1034. https://doi.org/10.1016/j.energy.2013.11.060

Hu, J.-L., & Wang, S.-C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy, 34*(17), 3206–3217. https://doi.org/10.1016/j.enpol.2005.06.015

Li, L.-B., & Hu, J.-L. (2012). Ecological total-factor energy efficiency of regions in China. *Energy Policy, 46*, 216–224. https://doi.org/10.1016/j.enpol.2012.03.053

Li, H., & Shi, J.-F. (2014). Energy efficiency analysis on Chinese industrial sectors: An improved Super-SBM model with undesirable outputs. *Journal of Cleaner Production, 65*, 97–107. https://doi.org/10.1016/j.jclepro.2013.09.035

Li, K., Fang, L., & He, L. (2018). How urbanization affects China's energy efficiency: A spatial econometric analysis. *Journal of Cleaner Production, 200*, 1130–1141. https://doi.org/10.1016/j.jclepro.2018.07.2

Meng, F., Su, B., Thomson, E., Zhou, D., & Zhou, P. (2016). Measuring China's regional energy and carbon emission efficiency with DEA models: A survey. *Applied Energy, 183*, 1–21. https://doi.org/10.1016/j.apenergy.2016.08.158

Sarra, A., Mazzocchitti, M., & Rapposelli, A. (2017). Evaluating joint environmental and cost performance in municipal waste management systems through data envelopment analysis: Scale effects and policy implications. *Ecological Indicators, 73*, 756–771. https://doi.org/10.1016/j.ecolind.2016.10.035

Shi, G.-M., Bi, J., & Wang, J.-N. (2010). Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energy Policy, 38*(10), 6172–6179. https://doi.org/10.1016/j.enpol.2010.06.003

Shrestha, A., & Luo, W. (2017). Analysis of groundwater nitrate contamination in the central valley: Comparison of the GeoDetector method, principal component analysis and geographically weighted regression. *Isprs*

International Journal of Geo-Information, 6(10), 297. https://doi.org/10.3390/ijgi6100297.

Wang, H., Zhou, P., & Zhou, D. Q. (2013a). Scenario-based energy efficiency and productivity in China: A non-radial directional distance function analysis. *Energy Economics, 40*, 795–803. https://doi.org/10.1016/j.eneco.2013.09.030

Wang, Q., Zhao, Z., Zhou, P., & Zhou, D. (2013b). Energy efficiency and production technology heterogeneity in China: A meta-frontier DEA approach. *Economic Modelling, 35*, 283–289. https://doi.org/10.1016/j.econmod.2013.07.017

Wang, K., Yu, S., & Zhang, W. (2013c). China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Mathematical and Computer Modelling, 58*(5–6), 1117–1127. https://doi.org/10.1016/j.mcm.2011.11.067

Wang, J.-F., Zhang, T.-L., & Fu, B.-J. (2016). A measure of spatial stratified heterogeneity. *Ecological Indicators, 67*, 250–256. https://doi.org/10.1016/j.ecolind.2016.02.052

Wang, H., Gao, J., & Hou, W. (2019a). Quantitative attribution analysis of soil erosion in different geomorphological types in karst areas: Based on the GeoDetector method. *Journal of Geographical Sciences, 29*(2), 271–286. https://doi.org/10.1007/s11442-019-1596-z

Wang, Z. H., Sun, Y. F., Yua, Z. Y., & Wang, B. (2019b). Does energy efficiency have a spatial spill-over effect in China? Evidence from provincial-level data. *Journal of Cleaner Production, 241*, 10. https://doi.org/10.1016/j.jclepro.2019.118258

Wei, Y.-M., Liao, H., & Fan, Y. (2007). An empirical analysis of energy efficiency in China's iron and steel sector. *Energy, 32*(12), 2262–2270. https://doi.org/10.1016/j.energy.2007.07.007

Wei, C., Ni, J. L., & Shen, M. H. (2009). Empirical analysis of provincial energy efficiency in China. *China & World Economy, 17*(5), 88–103. https://doi.org/10.1111/j.1749-124X.2009.01168.x

Wu, F., Fan, L. W., Zhou, P., & Zhou, D. Q. (2012). Industrial energy efficiency with CO2 emissions in China: A non-parametric analysis. *Energy Policy, 49*, 164–172. https://doi.org/10.1016/j.enpol.2012.05.035

Yang, Z., & Wei, X. (2019). Analysis of the total factor energy efficiency and its influencing factors of the Belt and Road key regions in China. *Environmental Science and Pollution Research, 26*(5), 4764–4776. https://doi.org/10.1007/s11356-018-3961-3

Zhang, N., & Choi, Y. (2013). Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. *Social Science Journal, 50*(2), 225–234. https://doi.org/10.1016/j.soscij.2013.01.003

Zhang, X.-P., Cheng, X.-M., Yuan, J.-H., & Gao, X.-J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy, 39*(2), 644–650. https://doi.org/10.1016/j.enpol.2010.10.037