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Analysis of the generation efficiency of disaggregated renewable energy and its spatial heterogeneity influencing factors: A case study of China

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A B S T R A C T

The world has witnessed a surge in renewable power installed capacity in recent years, and there is an emerging trend of renewable penetration in electricity production. However, there is a lack of quantitative comparative study on disaggregated renewable power sources concerning their generation efficiency performance, regional heterogeneity, development potential, and influencing mechanism in the existing literature. In the case of China's 30 provinces, this paper evaluates the hydropower, solar power, and wind power generation efficiency by stochastic frontier analysis method, and then reveals the distribution characteristics and deployment potential of different renewable sources. Furthermore, from the perspective of spatial heterogeneity, geographical detector model is utilized to study the influence mechanism of the generation efficiency of different renewable sources. The main results are as follows. Firstly, production inefficiency prevails in hydropower, solar power, and wind power generation industries. The installed capacity, utilized hours, and auxiliary power consumption have positive impacts on the three renewable energy sources. Every 1% increase in auxiliary power consumption leads to 0.16% increase in solar power generation, which is quite larger than the increase in hydropower and wind power. Secondly, on average, hydropower has the highest level of generation efficiency, followed by wind power and solar power. Kernel density curves indicate the generation efficiency of hydropower, solar power, and wind power displays distinct aggregation characteristics. Different energy types show significant regional differences in deployment potential. Thirdly, annual precipitation accounts for 76% of the spatial heterogeneity in hydropower generation efficiency, followed by hydropower technology innovation and power structure. As for solar power generation efficiency, the most important influencing factors are electricity investment and economic development. By contrast, wind power generation efficiency is primarily affected by power structure, electricity investment, and urbanization. Additionally, there exist distinct synergistic effects among different variables. These results provide insightful policy support for the improvement of renewable power generation efficiency. The study can be extended to the global scale using country-level data.

1. Introduction

The electric power industry is the fundamental industry of the national economy. Electricity production and sufficient supply provide an indispensable guarantee for economic development, social progress, and the improvement of people's living standards [1]. At the global level, coal is the dominant fuel for power generation, and its share reached 36.4% in 2019 [2]. The power sector is an important contributor to the growth of global carbon emissions. For example, in China, the power industry accounts for 40% of total CO_2 emissions and 60% of total SO_2 emissions [3]. Given that fossil energy has serious negative environmental externalities, renewable energy has become a priority of energy development strategy and increasingly important in power production. The power industry plays an increasingly important role in energy saving and emissions reduction [4]. The electricity supply is to shift towards a low-carbon and clean mode. The substitution of renewable

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electricity for thermal power not only reduces the consumption of fossil energy but also effectively alleviates environmental pollution.

Renewable energy has become a strategic emerging industry in the world [5]. Among different fuels, renewables provided the largest increment to power generation (340 TWh) in 2019 [2]. It is predicted that renewables will overtake coal as the biggest source of electricity generation by 2025 globally, and renewable power generation will make up about 50% of total electricity generation by 2050 [6]. According to the U.S. Energy Information Administration (EIA),[1] from the production perspective, the share of renewables in global electricity generation was 26.6% in 2018, and renewable electricity generation showed an increase rate of 79% during 2008–2018. By contrast, from the investment perspective, EIA indicated that the global renewable electricity installed capacity accounted for 32.8% of the total power installed capacity in 2018, indicating an increase rate of 126% from the 2008 level. Obviously, the development pace of renewable electricity generation is incompatible with the deployment pace of the corresponding installed capacity. Efficiency distortion has become a severe challenge for the sustainable development of renewable power industry. In this paper, renewable power generation efficiency (RPGE) refers to achieving maximum power generation under the given inputs, including installed capacity, utilized hours, and auxiliary power consumption. At the same time, there exist considerable regional differences in resource endowment, public policies, technology, energy regime, and economic development, etc, which brings great challenges to regional policy formulation for renewable electricity. For example, there is evidence to show the spatial differences significantly influence UK solar photovoltaic (PV) deployment [7]. There are considerable regional differences in renewable electricity penetration. Regionally, EIA data show that Iceland had the largest renewables share of power generation over 90% in 2018, while India and Egypt reported the penetration at 18% and 9%, much lower than the global average level of 26.6%. Thus, it is of great significance to make an in-depth understanding of the regional heterogeneity of renewable power generation and the underlying influencing factors.

At present, China relies heavily on fossil energy especially coal, forming a power structure dominated by thermal power generation [8]. For example, in 2017, thermal power generation contributed 71% of total electricity production in China [9]. China aims to peak its emissions by 2030 and achieve carbon neutrality before 2060 [10], and it has incorporated the development and utilization of renewable energy into the legal system. China set the differentiated responsibility weight of renewable power consumption for each provincial administrative region in 2019 [11]. The proportion of non-fossil energy in primary energy consumption will be mandated to reduce to 20% in 2030 [12]. In 2019, China's renewable electricity installed capacity accounted for 30% of the global renewable installed capacity [13]. However, generation in China does not match its installed capacity. From the production perspective, China's renewable electricity generation contributed a proportion of 27.9% in its total power production in 2019, while its renewable electricity installed capacity accounted for 39.5% of the total power installed capacity [14]. A striking feature of China's renewable electricity is that there is distinct regional heterogeneity in both development scale and generation efficiency [15]. It is expected that the case study of China will provide informative policy implications regarding promoting efficient and sustainable development of renewable electricity system, which serves as a benchmark for other economies in the process of power transition.

This paper focuses on hydropower, solar power, and wind power generation efficiency (i.e., HPGE, SPGE, and WPGE). Taking China as a case study, this paper aims to quantitatively evaluate HPGE, SPGE, and WPGE, and reveal their spatial differentiations and influencing factors. To be more specific, this paper tries to solve the following pressing issues: (i) How is the generation efficiency performance of three kinds of renewable sources? And how is the regional difference in efficiency performance across China's provinces? (ii) How is the development potential of disaggregated renewable power in different areas? (iii) What are the primary drivers of three kinds of RPGE from the perspective of spatial heterogeneity? That is, what contributes to the regional inequality in HPGE, SPGE, or WPGE? (iv) What targeted measures should be taken to improve efficiency performance and mitigate the regional heterogeneity of renewable power generation efficiency? Solving these problems is helpful to promoting the sustainable development of the renewable power industry and the deep decarbonization of the electricity system. Using the data set of China's 30 provinces, this paper employs the stochastic frontier analysis (SFA) method to evaluate HPGE, SPGE, and WPGE. Based on the efficiency evaluation results, we analyze the distribution characteristics and deployment potential of disaggregated renewable power. Furthermore, this paper investigates the influencing factors of HPGE, SPGE, and WPGE through geographical detector, thereby providing an in-depth understanding of conspicuous heterogeneity in HPGE, SPGE, and WPGE among different provinces.

Several knowledge gaps in the literature are remaining to be filled. (1) Although previous studies have analyzed the generation efficiency of renewable energy, there is a lack of comparative analysis regarding generation efficiency and its influencing factors between renewable power sources. (2) Little research tries to quantifying the regional deployment potential of renewable power. (3) The spatial heterogeneity influencing factors of the generation efficiency of disaggregated renewable power has not been revealed. This paper tries to quantitatively attribute the regional inequality in generation efficiency to the contributions of individual variables. Compared with the existing literature, this paper not only provides a comparative analysis of the accurately measured generation efficiency of disaggregated renewable power, but also quantifies the deployment potential of disaggregated renewable power in different areas. In addition, this paper obtains some new and meaningful findings with regard to the influencing factors of HPGE, WPGE, and SPGE from the spatial heterogeneity perspective. The methodology used in this paper has the following several advantages: (1) SFA is less affected by abnormal points and will not have the same efficiency value of 1. Its reliability and comparability are better than DEA. (2) The main advantage of SFA is that it considers the impacts of random factors on output; however, according to the DEA method, that the actual output is less than the frontier output is completely due to technical inefficiency. Essentially, in the DEA approach, the actual output is simply divided into production frontier and technology inefficiency, and the impacts of random factors on output are ignored. In fact, the process of renewable power generation is not only affected by production inefficiency, but also by random factors such as weather. This is one of the main reasons why we choose the SFA approach rather than the DEA method to evaluate disaggregated renewable power generation efficiency. (3) SFA can analyze the output elasticity of input factors (i.e., the contribution rate of various inputs to the output) and investigate returns to scale, while DEA does not set a specific production function form, which is equivalent to a black box. (4) Based on production function, the SFA method has a good economic connotation. We can get the frontier output of each decision-making unit, thus obtaining the development potential of disaggregated renewable power in different regions. This is of great importance for promoting the efficient and sustainable

[1] The data are derived from https://www.eia.gov/international/data/world.

development of renewable energy. (5) With several advantages over traditional regression analysis, the geographical detector is utilized to capture the driving factors behind the spatial heterogeneity of HPGE, SPGE, and WPGE. It provides a new perspective and scientific decision-making basis for policymakers to understand and narrow regional differences in HPGE, SPGE, and WPGE. This paper is of great significance in facilitating efficient and sustainable development of renewable power and low-carbon transition in China's power sector, meanwhile, it also provides a reference for other economies.

The rest of this study is divided into four sections. Section 2 provides the related literature review. Section 3 introduces the methodology used in this paper and describes the variables and their data sources. Section 4 presents the empirical results and discussion. Section 5 concludes this paper. The final part gives policy implications, challenges, and recommendations.

2. Literature review

Unlike conventional electricity sources, renewable power generation has few negative environmental externalities, notably CO_2 emissions. Energy use is an important driver of carbon emissions [16–24]. Climate change mitigation requires a fundamental increase of renewable energy supply [25–28]. Along with continuous progress in the global energy transition, renewable energy rises rapidly in energy supply, both in the absolute amount and the relative proportion [29]. Therefore, extensive studies on renewable energy are documented in the existing literature [30,31]. Some scholars focus on the influencing factors of renewable energy [32,33], in which some scholars investigate the causalities between renewable energy and economic growth [34–36] or carbon emissions [37–39]. In addition, the development mode of renewable energy has received extensive attention [40–43].

The studies on the evaluate the power generation efficiency are conducted at the industry level [44] and power plant level [45–49]. For example, from the perspective of ownership structure, Farer et al. [50] divide power enterprises in the US into publicly-owned and privately-owned electric utilities. They utilize the data envelopment analysis (DEA) method to measure their technical efficiency and find the technical efficiency of privately-owned electric utilities is significantly larger than that of publicly-owned utilities. The efficiency performance of renewable and non-renewable electricity generation has received some attention. Lam and Shiu [51] employ the DEA approach to estimate the technical efficiency of thermal power generation in China. The results show the highest technical efficiency is recorded in eastern coastal areas and some provinces with rich coal supply. Furthermore, using the super-efficiency DEA model, Zhou et al. (2011) evaluate the solar power generation efficiency in 20 countries during 2010–2016. They find solar power generation efficiency has positive effects on solar power generation and solar power storage. In addition, the technical efficiency of the bioenergy industry is also studied [52]. However, little attention has been paid to the efficiency of renewable power generation in China; besides, there is no comparative analysis of different renewable energy types, which is an important research topic to be studied. With regard to the efficiency evaluation method, DEA, as a nonparametric method, has been extensively applied in the literature. The boundary of the production function measured by the DEA method is definite, so it cannot distinguish between the influences of random factors and measurement errors. One of its most important shortcomings is that there is no clear form of the production function, which is equivalent to a black box, and there is no way to know the contribution rate of various inputs to production. The SFA method is also commonly used in efficiency evaluation [53]. When dealing with multi-output issues, this method is not as convenient as the DEA method. The SFA method requires that the output be a single variable, multiple outputs need to be combined into a comprehensive output. When there are too many input factors, the correlation between these indicators will affect the reliability of the results.

To improve power generation efficiency, the determinants of technical efficiency have generated considerable research interest. The effects of some socio-economic factors have been investigated in the literature. Sun and Wu [53] utilize an improved SFA method to analyze the effects of price and quantity regulations on the efficiency of the power generation sector in China. According to Lam and Shiu [51], fuel efficiency and the capacity factor have significant impacts on the technical efficiency of thermal power generation in China, while foreign investment does not significantly influence efficiency. There is evidence to show that ownership significantly influences the efficiency of thermal power plants [54]. By contrast, Wu et al. [55] find the ownership of the wind farm has no significant effect on productive efficiency. Besides, introducing competition is conducive to facilitating performance improvements in the electricity generation industry [56,57]. Similarly, Fabrizio et al. [58] suggest market-based industry structure leads to efficiency gains compared with a regulated monopoly. In general, environmental factors will influence renewable power generation. Using a three-stage efficiency analysis method, Wang et al. [59] demonstrate temperature plays the most important role in influencing the operational efficiency of solar photovoltaic plants, however, precipitation and wind speed have no significant impact. On the whole, the factors that influence the technical efficiency of power generation are quite complicated. Compared with thermal power generation, renewable power generation is more sensitive to external random shocks and inefficiency factors, such as environmental uncertainty. The driving mechanism of the RPGE deserves in-depth analysis.

Most scholars adopt different econometric methods to study the determinants of technical efficiency [52,55]. Nevertheless, the traditional econometric approach has strictly linear assumptions and high requirements of data, and it may be ineffective in dealing with multi-collinearity problems when there are multiple independent variables. Moreover, it can only account for the temporal variations of the variable of interest, but cannot explain the mechanism of spatial heterogeneity. When studying the interactive influences of two variables, the econometric model strictly sets the form of the interaction as a product between two determinants. The traditional two-stage DEA-Tobit framework cannot consider the impacts of external random shocks such as environmental uncertainty, and it fails to reveal the formation mechanism for the spatial heterogeneity of efficiency.

This paper contributes to the literature in the following ways. First, it focuses on the regional RPGE and compares the RPGE of different renewable sources. Specifically, regional RPGE in China is quantitatively measured by the SFA method. Second, based on the evaluation results of RPGE, this paper provides a comprehensive analysis of the regional deployment potential of three different renewable sources in China's provinces. In addition, this paper sheds light on the distribution aggregation characteristics of China's RPGE by Kernel density estimation. Third, the geographical detector, originally developed in geographical research, is applied in this study to identify the contributions of various factors to the spatial differentiation of RPGE among different regions in China.

3. Methodology and data

3.1. Assessment model of RPGE through stochastic frontier analysis

The production frontier approach (PFA) is currently the main method in empirical research on efficiency and productivity issues. This approach is originally developed by Farrell [60] and can be divided into two major branches, i.e., parametric and non-parametric estimation methods. The parametric estimation method constructs a specific production function form and then estimates the function parameters on the production frontier through appropriate methods. The parametric PFA includes the deterministic frontier model [61] and the stochastic frontier model. The former utilizes linear programming to solve the production frontier without considering the influences of random factors; the latter assumes that the production frontier is influenced by both deterministic and random factors, and it can not only measure the technical efficiency of the evaluation decision unit, but also investigate the impacts of external random shocks and inefficiency factors on potential output. Non-parametric PFA does not specify the form of production function. Specially, DEA is the most commonly used non-parametric method. However, the efficiency value obtained by the DEA method may be biased since it does not consider the impacts of random factors (i.e., uncertainty) on efficiency. What's more, statistical tests are ignored by the DEA method as well. As a parametric method, SFA is an important method used in efficiency evaluation [62]. This study utilizes the SFA approach to measure the efficiency of renewable power generation in China's 30 provinces.

Stochastic frontier analysis (i.e., SFA) is proposed by Aigner et al. [63] and Meeusen and Den Broeck [64] independently. The original model is specified for cross-sectional data. Then, a stochastic frontier production function model for panel data is developed by Battese and Coelli [65]. The basic specifications of the SFA model are shown in Appendix A.

Let $f(x_i,\beta)=e^{\beta_0}\cdot {x_1}^{\beta_1}\cdot {x_2}^{\beta_2}\cdots {x_k}^{\beta_k}$ (i.e., production function with k inputs), taking the natural logarithmic transformation of Eq. (A1) (see Appendix A) will yield:

$$\ln y_i=\ln f(x_i,\beta)+v_i-u_i \tag{1}$$

Different from thermal power generation based on fossil fuels, renewable power generation needs little raw material. Installed capacity, utilized hours, auxiliary power consumption are primarily technical and economic indicators during the process of renewable power generation. In this paper, renewable power generation is regarded as the output, while renewable installed capacity, utilization hours, and auxiliary power consumption during the power generation process are taken as three production inputs. We have that:

$$\ln RPG_{ij}=\beta_0+\beta_1\cdot\ln IC_{ij}+\beta_2\cdot\ln UH_{ij}+\beta_3\cdot\ln APC_{ij}+v_{ij}-u_{ij} \tag{2}$$

Where i represents the region, j denotes the type of renewable power generation (RPG); IC represents renewable power installed capacity, UH is utilization hours, APC indicates auxiliary power consumption of renewable power plants. As the distribution of the composite disturbance term (v_i-u_i) is asymmetric, the maximum likelihood estimation (MLE) method rather than the OLS method is utilized to estimate the model. Based on Eq. (2), the following models are to be estimated.

$$\ln HPG_i=\beta_0+\beta_1\cdot\ln IC_i+\beta_2\cdot\ln UH_i+\beta_3\cdot\ln APC_i+v_i-u_i \tag{3}$$

$$\ln SPG_i=\beta_0+\beta_1\cdot\ln IC_i+\beta_2\cdot\ln UH_i+\beta_3\cdot\ln APC_i+v_i-u_i \tag{4}$$

$$\ln WPG_i=\beta_0+\beta_1\cdot\ln IC_i+\beta_2\cdot\ln UH_i+\beta_3\cdot\ln APC_i+v_i-u_i \tag{5}$$

Where HPG, SPG, and WPG indicate hydropower, solar power, and wind power generation, respectively.

3.2. Calculation of frontier and potential renewable power generation

According to Eq. (A4) (see Appendix A), coupled with the data of generation efficiency and the actual quantity of renewable energy generation, we calculate the frontier renewable energy generation as follows:

$$HPG_i^*=\frac{HPG_i}{HPGE_i} \tag{6}$$

$$SPG_i^*=\frac{SPG_i}{SPGE_i} \tag{7}$$

$$WPG_i^*=\frac{WPG_i}{WPGE_i} \tag{8}$$

Where HPG*, SPG*, and WPG*denote the frontier power generation in terms of specific energy sources; HPGE, SPGE, and WPGE represent their power generation efficiency. At the same time, based on the evaluation of frontier renewable energy generation, the potential power generation can be obtained by:

$$\varDelta HPG_i=HPG_i^*-HPG_i \tag{9}$$

$$\varDelta SPG_i=SPG_i^*-SPG_i \tag{10}$$

$$\varDelta WPG_i=WPG_i^*-WPG_i \tag{11}$$

Where δHPG, δSPG, δWPG represent potential power generation of specific energy sources. The indicator of potential power generation considers the gap between the frontier and real renewable power generation.

3.3. Study on the driving mechanism of RPGE by geographical detector

Geographical detector [66] is a new tool for the exploratory analysis of spatial data. In recent years, this method has been applied in some research on energy and environmental issues [67,68]. The application of the geographical detector model is to reveal the reasons for the spatial differentiation of RPGE among different regions, thereby finding the main driving factors of RPGE. The theoretical core is to detect the consistency of the spatial distribution patterns between the dependent variable and the independent variables through spatial heterogeneity analysis, obtaining the explanatory degree of the independent variable to the dependent variable. In other words, if an independent variable has an important effect on the dependent variable, the spatial distribution of the independent variable and the dependent variable should be similar. Compared with traditional statistical analysis methods, the geographical detector approach has several advantages. First, this method has no linear assumption. Second, it can reveal the interaction between two independent variables on the dependent variable, and can effectively overcome the limitations of traditional regression analysis methods regarding the product form of interaction. Third, this method is particularly effective in addressing the relationship between the independent variable and categorical variables. Fourth, it is free from collinearity problems when there are multiple independent variables. In this paper, RPGE is a continuous numerical variable, its determinants should be categorical variables in geographical detector. However, the estimation results of this approach are sensitive to the classification algorithm of the data. The main classification algorithms include the equal interval method, quantile method, K-means, etc.

In the factor detector model, the q-statistic is utilized to evaluate the impact of a specific factor on RPGE. The larger the q-statistic, the stronger the influence of the driving factor on the spatial differentiation of RPGE. The q-value is calculated as follows:

$$q = 1 - \frac{\sum_{l=1}^{L} N_l \sigma_l^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \quad (l = 1, 2, \cdots, L) \tag{12}$$

Where l indicates the strata of determinantx_i, meanwhile, RPGE is also composed of L strata based on a categorical $l(x_i)$. N is the number of units in China (i.e., 30 provinces), and N_l is the number of units in strata l. σ^2 is the variance of RPGE in China, σ_l^2 is the variance of RPGE in strata l. SSW represents the within sum of squares, and SST represents the total sum of squares. The geodetector q-value reflects the effect of the driving factor on the spatial differentiation of RPGE. The value of q-statistic is between 0 and 1, which implies x_i accounts for 100q% of the spatial heterogeneity of RPGE. That $q = 0$ means there is no association between x_i and RPGE, while $q = 1$ shows RPGE is completely determined by x_i. This paper establishes three geographical detector models. The variables considered in each model are presented in Table 1.

Interaction detector can be used to investigate the interaction between two detection factors. Their interaction influence on RPGE may be larger or smaller than the effect of a single factor. Nevertheless, there are some possibilities that their impacts on RPGE are independent of each other. Based on Eq. (12), the q-values of x_i and x_j (i.e., $q(x_i)$ and $q(x_j)$) are calculated, respectively. At the same time, the interaction influence of x_i and x_j, $q(x_i \cap x_j)$, can also be quantified. The categories of interaction detector are shown in Table 2.

3.4. Variables and data sources

This paper first utilizes the SFA method to estimate RPGE (i.e.) in China and then reveals the distribution characteristics and deployment potential of disaggregated renewable power. Furthermore, the geographical detector model is employed to study the influencing factors leading to the spatial heterogeneity of RPGE. In the stochastic production frontier model, the output is renewable

Table 1
Variables used in geographical detector models.

Variables	Dependent Variable: HPGE	Dependent Variable: SPGE	Dependent Variable: WPGE
Annual precipitation	✓		
Annual sunshine hours		✓	
Economic development	✓	✓	✓
Power structure	✓	✓	✓
Environmental regulation	✓	✓	✓
Electricity investment	✓	✓	✓
Financial development	✓	✓	✓
Urbanization	✓	✓	✓
Carbon emissions	✓	✓	✓
Renewable electricity technology innovation	✓	✓	✓

Table 2
The categories of interaction detector.

Criteria	Interaction
$q(x_i \cap x_j) < Min(q(x_i), q(x_j))$	Nonlinear weakening (NW)
$Min(q(x_i), q(x_j)) < q(x_i \cap x_j) < Max(q(x_i), q(x_j))$	Univariate weakening (UW)
$q(x_i \cap x_j) > Max(q(x_i), q(x_j))$	Bivariate enhancement (BE)
$q(x_i \cap x_j) = q(x_i) + q(x_j)$	Independent (IN)
$q(x_i \cap x_j) > q(x_i) + q(x_j)$	Nonlinear enhancement (NE)

Table 3
Definitions of variables used in the SFA model.

Variables	Definition	Symbol	Data source
Installed capacity	Renewable installed capacity	IC	China Electric Power Yearbook
Utilized hours	Hours of capacity utilization	UH	China Electric Power Yearbook
Auxiliary power consumption	Electricity consumption of the auxiliary equipment during power generation process	APC	National Energy Administration, China Electric Power Yearbook
Renewable power generation	Hydropower, solar power, and wind power generation	HPG, SPG, WPG	China Electric Power Yearbook
Wind power generation efficiency	Generation efficiency of the wind power industry	WPGE	Obtained from the SFA model
Hydropower generation efficiency	Generation efficiency of the hydropower industry	HPGE	Obtained from the SFA model
Solar power generation efficiency	Generation efficiency of the solar power industry	SPGE	Obtained from the SFA model

Table 4
Definitions of variables used in geographical detector model.

Variables	Definition	Symbol	Data source
Meteorological conditions	Annual sunshine hours	AS	China Statistical Yearbook
	Annual precipitation	AP	China Statistical Yearbook
Power structure	The share of thermal power generation in total electricity generation	PS	China Electric Power Yearbook
Electricity investment	The ratio of electricity investment to GDP	INV	Almanac of China's Water Power, China Statistical Yearbook
Financial development	The ratio of total loans of banking financial institutions to GDP	FD	Almanac of China's Finance and Banking, China Statistical Yearbook
Economic development	GDP per capita	GPC	China Statistical Yearbook
Environmental regulation	The ratio of industrial pollution control investment to industrial added value	ER	China Statistical Yearbook on Environment, China Statistical Yearbook
Carbon emissions	Total carbon emissions	C	Carbon Emission Accounts and Datasets for Emerging Economies
Renewable electricity technology innovation	Number of hydropower-related patents granted	HTI	Baiten database
	Number of solar power-related patents granted	STI	Baiten database
	Number of wind power-related patents granted	WTI	Baiten database
Urbanization	The share of urban population in total population	URB	China Statistical Yearbook

Table 5
Estimation results through the MLE method.

Variables	Hydropower	Solar power	Wind power
	Model (1)	Model (2)	Model (3)
ln *IC*	0.9853*** (0.0262)	0.9282*** (0.0663)	0.9503 (0.6217)
ln *UH*	0.9420*** (0.0442)	0.8938*** (0.2025)	0.9731** (0.4448)
ln *APC*	0.021 (0.0303)	0.1606** (0.0733)	0.0595 (0.6885)
Cons	8.6361*** (0.4456)	−8.0284*** (1.7323)	8.7418*** (0.9934)
σ^2	0.0372** (0.0167)	0.0942 (0.1026)	0.0229 (0.2095)
γ	0.9769*** (0.0198)	0.957*** (0.0652)	0.9825 (0.9593)
μ	−0.3813 (0.2754)	−0.0602 (0.5664)	−0.0125 (0.9965)
χ^2	1.4e+10***	36.13***	3.9e+09***
LOG	37.2992	10.8526	31.7195
LR statistic	10.4925***	2.4653	13.7878***

Note: (1) Standard errors are presented in parentheses. (2) *** indicates p < 0.01, ** indicates p < 0.05. (3) LOG represents log-likelihood function value.

power generation, and the inputs comprise renewable installed capacity, utilized hours, and auxiliary electricity use during the power generation process. In geographical detector model, 12 variables are considered to reveal the spatial heterogeneity influencing factors of RPGE. Renewable power comprises hydropower, solar power, and wind power. The summary of variables used in this paper is presented in Table 3 and Table 4. The data set used in this paper covers China's 30 provinces (except for Hong Kong, Macau, Taiwan, and Tibet) in 2017 due to data availability and completeness. Specially, the data of renewable power-related patent granted are collected from the Baiten database (i.e., https://www.baiten.cn/), which provides all kinds of patent information in China. China's provincial carbon emissions are derived from the CEADs (Carbon Emission Accounts and Datasets for Emerging Economies) [69]. The emission inventory includes 47 socio-economic sectors and 17 types of fossil energy-related emission data; compared with other data sets, its carbon emissions accounting scope is more comprehensive, covering emissions related to fossil fuel combustion and emissions related to the cement production process. The calculation process of auxiliary power consumption is as follows:

$$APC = RPG \cdot \eta \tag{13}$$

Where η represents the power consumption rate of power generation enterprises, which is obtained from *2018 National Electricity Price Regulatory Bulletin* issued by the National Energy Administration [70]. Equivalently, auxiliary power consumption is equal to renewable electricity generation minus the corresponding on-grid quantity.

4. Results and discussion

4.1. Results of the SFA model

Table 5 shows the estimation results of the SFA model by using the maximum likelihood estimation (MLE) approach. All variables are on the natural logarithm scales. The SFA model is performed through FRONTIER Version 4.1 developed by Tim Coelli. Specially, the results of hydropower, solar power, and wind power are presented in Models (1)–(3) respectively. If the production inefficiency u_i does not exist, then the estimation of the model becomes a simple least square method. The main method to judge whether the model is appropriate is to check the value of γ. When γ is close to 1, it shows that the composite disturbance term of the frontier production function mostly comes from the technical inefficiency variables. In this case, the stochastic frontier model is required. According to Models (1)–(3), the γ statistic is at least 0.957, indicating that the application of the SFA model is appropriate. Production inefficiency prevails in the renewable power generation industry.

As shown in Models (1)–(3), the elastic coefficient of installed capacity is quite large and positive in all models, but it is not statistically significant for wind power. It specifies that the increasing renewable installed capacity plays an important role in promoting renewable power generation. With the continuous increase of electricity demand in recent years, China's renewable installed capacity has grown rapidly. In 2017, the total installed capacity of renewable electricity in China reached 636.33 million KW. In addition, the elastic coefficient of utilized hours is positive and it is statistically significant at least 5% level, showing that utilized hours are an important factor in increasing hydropower, solar power, and wind power.

As for auxiliary power consumption, its elastic coefficient is positive in all models, but it is only statistically significant in Model (2). Specially, the elastic coefficient of auxiliary power consumption in Model (2) is distinctly larger than that in Model (1) and Model (3). It indicates that compared with hydropower and wind power, every unit increase of solar power generation requires less auxiliary

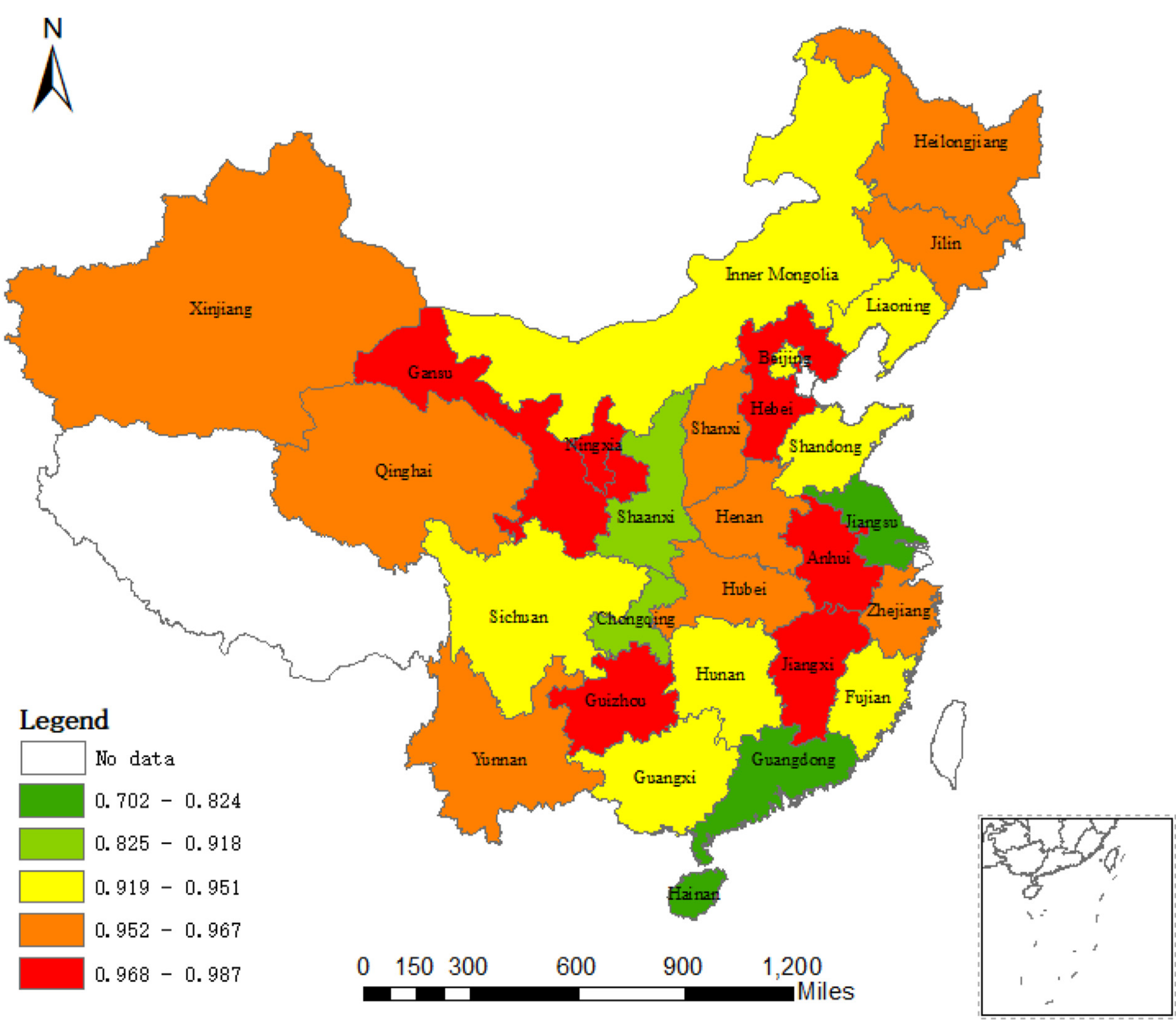

Fig. 1. Geographic distribution of China's hydropower generation efficiency in 2017.

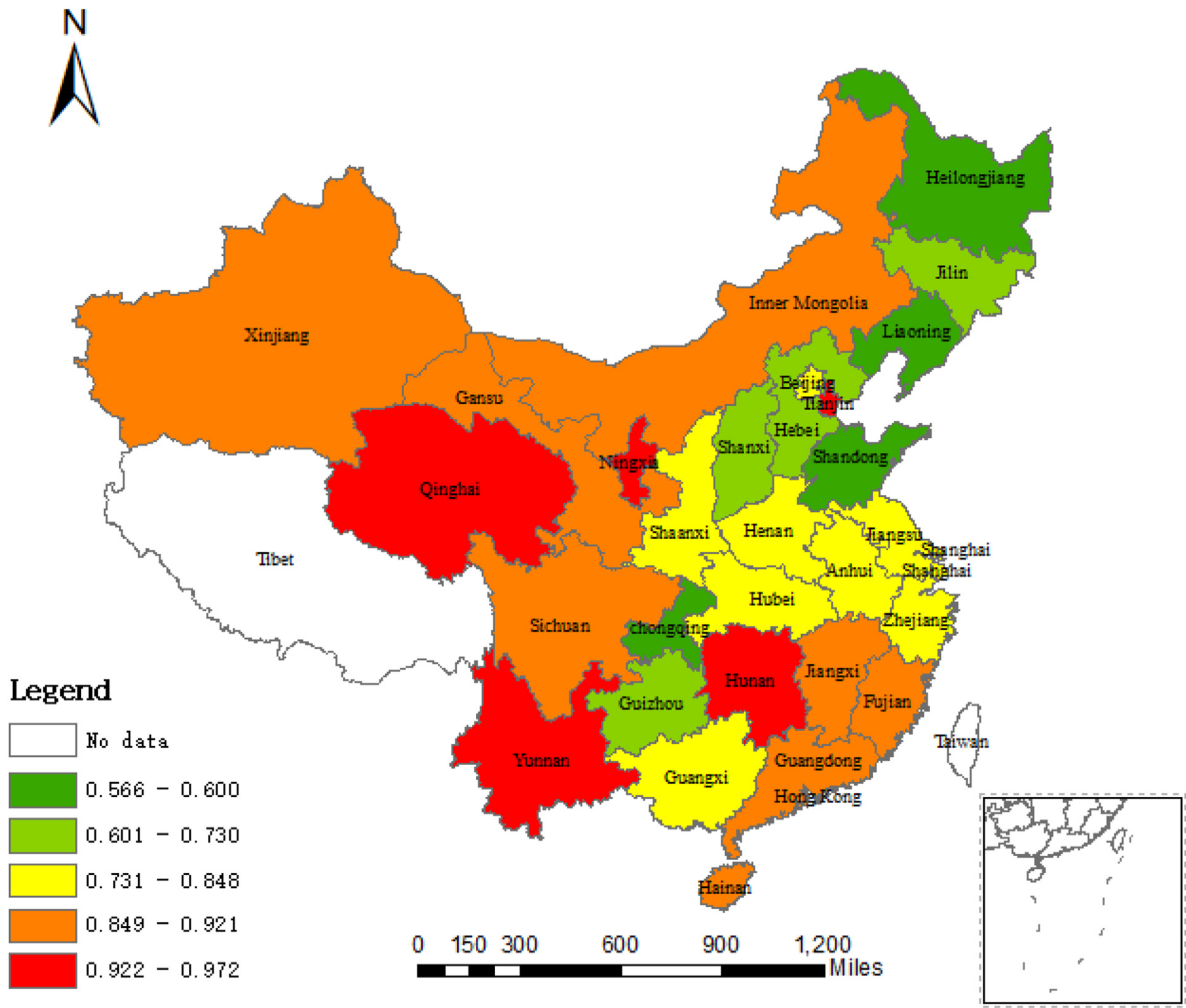

Fig. 2. Geographic distribution of China's solar power generation efficiency in 2017.

power consumption. In terms of coefficient magnitudes, the impacts of installed capacity and utilized hours are distinctly larger than that of auxiliary power consumption. Furthermore, the production functions are tested for constant returns to scale. The null hypothesis that the sum of their output elasticities is 1 can be rejected. As shown in Table 5, the χ^2 statistics are all significant, which suggests that under the condition that the technical level and factor prices remain unchanged, the output will not increase in the same proportion if all factor inputs increase by a certain proportion. This also reflects the existence of power generation inefficiency to a certain extent.

4.2. Analysis of disaggregated renewable power generation efficiency

Coupled with the MLE estimation results in Table 5, Frontier 4.1 software can directly give the calculation results of the generation efficiency of hydropower, solar power, and wind power in China's provinces. Figs. 1–3 display the spatial distribution characteristics of HPGE, SPGE, and WPGE, respectively. In terms of the mean value, hydropower has the highest level of generation efficiency of 0.9378, followed by wind power (0.9033) and solar power (0.8145). The standard deviation of solar power is larger than that of hydropower and wind power, indicating there are significant differences in the SPGE among 30 provinces. There are significant differences in the generation efficiency of different renewable sources among China's provinces.

As shown in Fig. 1, hydropower generation efficiency varies from 0.702 to 0.9872. Jiangxi has the highest level of hydropower generation efficiency, while the least level is recorded in Guangdong. Specifically, in 25 provinces, the hydropower generation efficiency is larger than 0.9. However, when it comes to solar power, there are only 11 provinces with SPGE greater than 0.9 (see Fig. 2). The values lower than 0.7 are reported by five provinces, including Chongqing, Shandong, Heilongjiang, Jilin, and Liaoning. The group of provinces with slightly high levels of SPGE between 0.7 and 0.9 contains 14 provinces. As for wind power in Fig. 3, WPGE also displays distinct spatial heterogeneity across different provinces. WPGE ranges from 0.6888 to 0.9898. WPGE larger than 0.9 is reported by 21 provinces. The largest WPGE is reported by Shanghai, slightly lower levels of WPGE are recorded in Tianjin, Inner Mongolia, Jilin, Hainan, and Gansu.

Fig. 4 plots the distributional differences of HPGE, SPGE, and WPGE through the Kernel density estimation. As for the wind

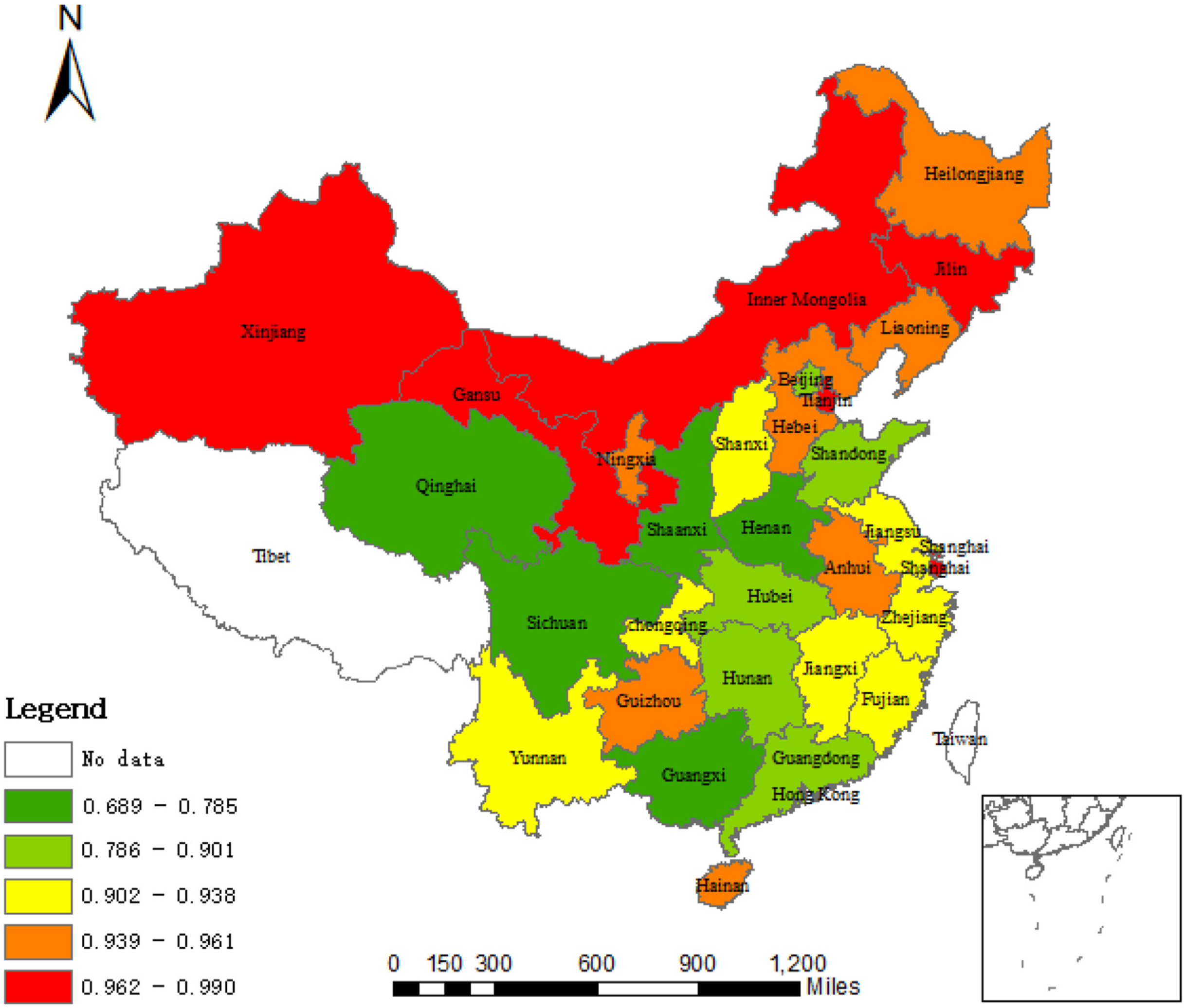

Fig. 3. Geographic distribution of China's wind power generation efficiency in 2017.

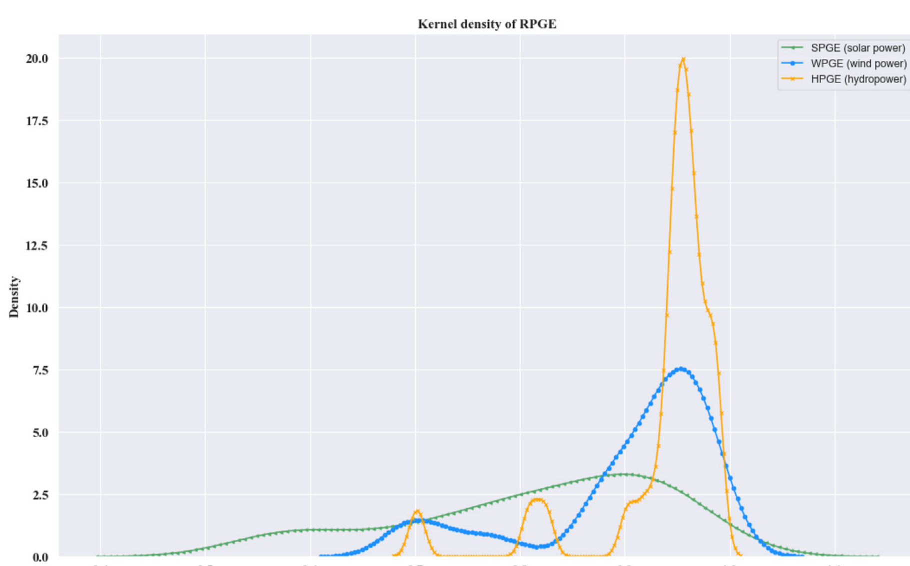

Fig. 4. Kernel density of HPGE, SPGE, and WPGE.

Table 6
Results of Spearman and Kendall rank correlation coefficients.

	HPGE	SPGE	WPGE
Spearman's rank correlation	−0.1221	0.4218**	0.5869***
Kendall's rank correlation	−0.0821	0.3176**	0.4429***

Note: *** and ** indicate the 1% and 5% significant levels, respectively.

power, the Kernel density curve presents a bimodal shape, which shows the development of regional WPGE has become polarized. The provincial WPGE displays distinct agglomeration characteristics and can be divided into two clusters. It can be seen that HPGE displays three peaks. In detail, the peak on the right is the highest, indicating most provinces are concentrated in the high-HPGE group. In addition, the distribution of SPGE presents a more dispersed pattern, and there is only one low peak. Compared with WPGE and HPGE, the value range of SPGE is larger. This means the spatial distribution of SPGE is more scattered. Different provinces exhibit significant differences in SPGE. On the whole, SPGE, WPGE, and HPGE display distinct aggregation characteristics.

On the whole, China's total renewable energy resources are very rich, but the regional distribution is uneven. For example, the regional distribution of wind energy resources is uneven, and Inner Mongolia, Xinjiang, Heilongjiang, and Gansu account for 50% of the total wind energy resources [71]. Most areas with abundant renewable energy resources are located in western China where economic development and transportation are relatively backward. The distribution of renewable energy in China is unbalanced, and the geographical obstacles between resource areas and load areas are relatively large. Besides, due to on-grid access, intermittency, volatility, and randomness of renewable energy, the curtailment problems hinder the green transformation of the power industry.

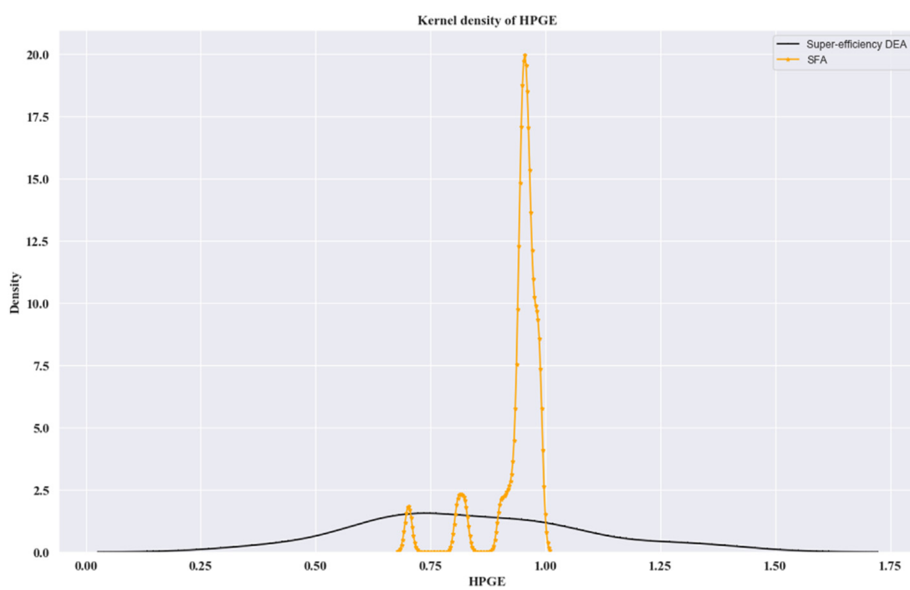

Fig. 5. Kernel density of HPGE by SFA and super-efficiency DEA.

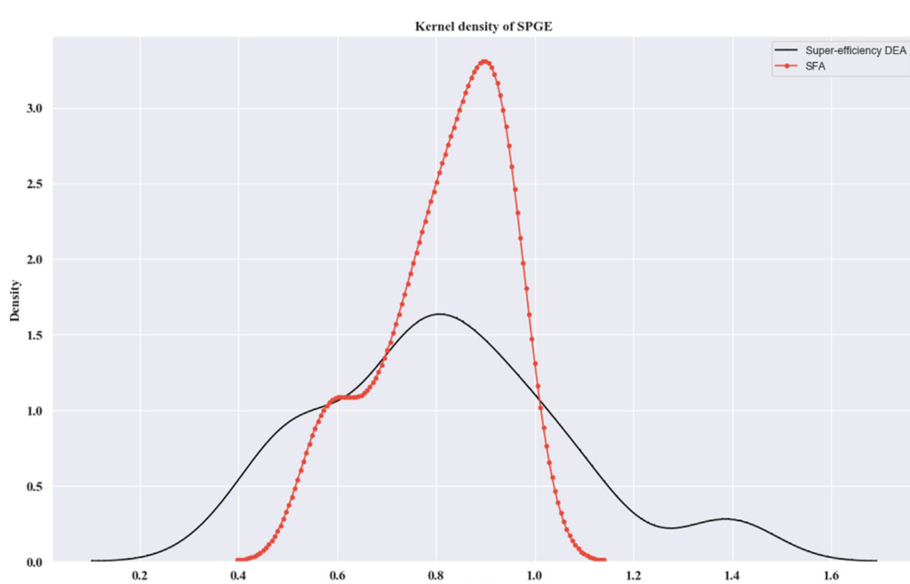

Fig. 6. Kernel density of SPGE by SFA and super-efficiency DEA.

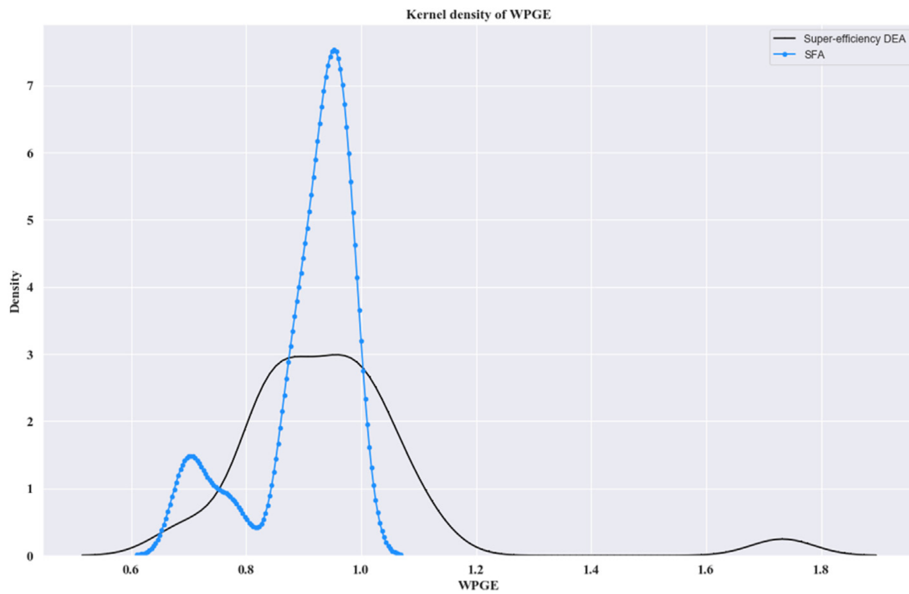

Fig. 7. Kernel density of WPGE by SFA and super-efficiency DEA.

4.3. Comparative analysis between SFA and DEA methods

What is the difference between DEA and SFA results? This paper compares the results of SFA and super-efficiency DEA (i.e, the BCC model with variable returns to scale). In this paper, the super-efficiency DEA model is output-oriented. It can distinguish multiple effective decision-making units whose efficiency value is 1, which avoids the loss of information in some effective decision-making units. Since the SFA model assumes that the inefficiency term is greater than 0, it can also consider the ranking of efficient DMUs at the function frontier.

Accordingly, a question naturally emerges, is the difference between DEA and SFA results statistically significant? Different from the correlation coefficient, the coefficient of rank correlation is calculated on the basis of rank, which is more suitable for reflecting the correlation of sequence variables. In this paper, Spearman's and Kendall's rank correlation coefficients are estimated. According to the results of rank correlation coefficients in Table 6, both Spearman and Kendall coefficients of HPGE are not statistically significant, which shows the null hypothesis that HPGE obtained through DEA and SFA are independent should be accepted. That's to say, the two efficiency estimation methods lead to completely different results for HPGE. The reason is that renewable power generation is greatly affected by random factors, while the DEA approach does not consider the influence of random factors, which results in a large difference between its estimation results and SFA. For SPGE and WPGE, the statistics are statistically significant at least at the 5% level, indicating there is a significant correlation between the results of DEA and SFA methods. That is to say, for solar power and wind power, the efficiency assessment results show minor differences despite different approaches.

To illustrate the difference more clearly, this paper utilizes Kernel density estimation to shed light on the distribution characteristics of HPGE, SPGE, and WPGE. The results are depicted in Figs. 5–7. As shown in Fig. 5, the Kernel density distributions of HPGE by SFA and DEA present significant differences in both skewness and kurtosis. The distribution of HPGE obtained by the DEA method is relatively even, while the efficiency obtained by the SFA approach shows a clear agglomeration form. Fig. 6 presents that the Kernel density distribution of SPGE by DEA is very close to that by SFA, with a main peak. However, from Fig. 7, it is found that although the shapes of the two curves are different for WPGE, the efficiency values are mostly concentrated between 0.6 and 1. As supplementary evidence, this part analyzes the specific distribution patterns of HPGE, SPGE, and WPGE, and uncovers how the differences between the two methods arise. The DEA and SFA methods evaluate renewable electricity generation efficiency from different perspectives, and their distributions display distinct differences.

4.4. Analysis of frontier and potential renewable power generation

In the previous section, this paper evaluates China's generation efficiency of hydropower, solar power, and wind power by using the SFA method. Inefficiency needs to be further eliminated, and there is still a large amount of renewable potential remaining to be exploited. The greater the generation efficiency, the closer the actual output level is to the frontier out level. Based on the results of the SFA model, we compare the frontier and potential renewable power generation among different provinces.

(1) Hydropower

According to Eq. (6), Fig. 8 depicts the frontier hydropower generation of China's 30 provinces in 2017. Obviously, Sichuan has the highest levels of frontier hydropower generation (more than 333.5 TWh), followed by Yunnan (261.1 TWh) and Hubei (154.7 TWh). In addition, among the rest provinces, the group of provinces with slightly high levels of frontier hydropower generation between 42.9 TWh to 74.4 TWh includes Guangxi, Guizhou, Hunan, Guangdong, and Fujian. It can be seen that southwestern provinces have relatively larger frontier hydropower generation, while most provinces located in northern China have a minor

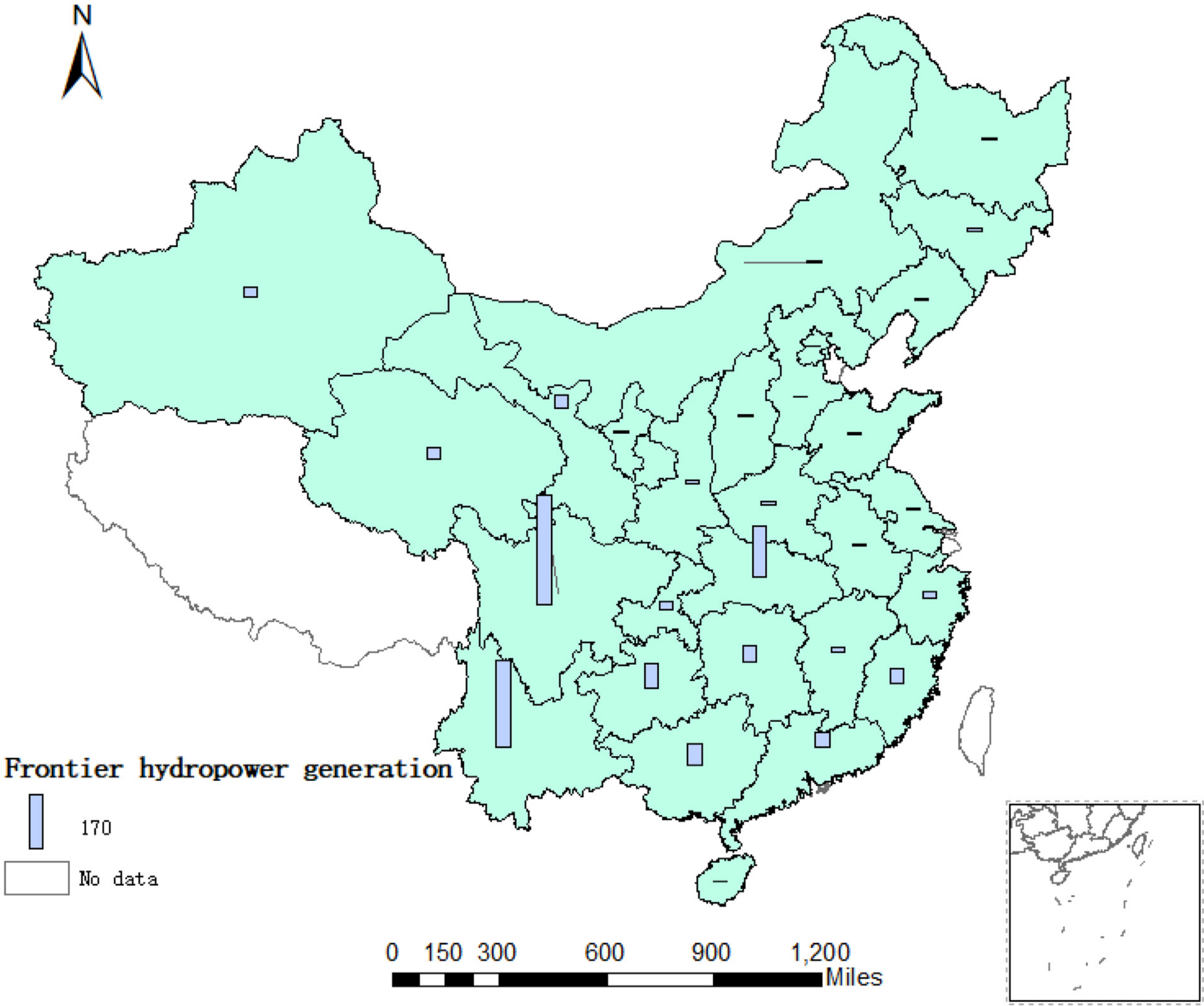

Fig. 8. Frontier hydropower generation in 2017 (unit: TWh).

frontier hydropower generation with little hydropower resources to develop, including Beijing, Tianjin, Xinjiang, and Inner Mongolia. However, hydropower generation efficiency is quite high in most north provinces such as Hebei, Gansu, Xinjiang, Inner Mongolia, and Ningxia, indicating these provinces have made better use of existing renewable resources to improve power-generating efficiency and control the excessive growth of installed capacity.

Based on Eq. (9), Fig. 9 presents the potential hydropower generation in 2017. From a regional perspective, there are distinct differences in potential hydropower generation among different provinces. It is found that the spatial distribution of potential hydropower generation is similar to that of frontier hydropower generation in Fig. 8. The provinces concentrated in north China generally have lower potential hydropower generation, compared with those in southern China. Sichuan, Yunnan, and Hubei have a large level of potential hydropower generation (more than 5.3 TWh). Although Guangdong has a low level of frontier hydropower generation, it ranks second in terms of potential hydropower generation (12.8 TWh), which shows there is still a large amount of hydropower generation that can be expanded in Guangdong. Furthermore, with both high frontier and potential hydropower generation, Sichuan, Yunnan, and Hubei have huge room for hydropower growth in the future. Overall, in 2017, the total hydropower generation in China was up to 1187.8 TWh, while there are nearly 1253.9 TWh of hydropower potential yet to be exploited. Therefore, it is of great importance to promote the deployment of hydropower and improve the power generation efficiency, especially in Sichuan, Yunnan, Hubei, and Guangdong.

(2) Solar power

Fig. 10 plots the spatial distribution of frontier solar power generation in 30 provinces in 2017. There is distinct spatial heterogeneity across different provinces. On the whole, the provinces located in northern China have significantly higher frontier solar power generation than those located in southern China, which means most solar power sources are in northern China. For instance, Inner Mongolia has the greatest frontier solar power generation of 12.4 TWh. From the geographical perspective, this division is highly consistent with the Qinling Mountains-Huaihe

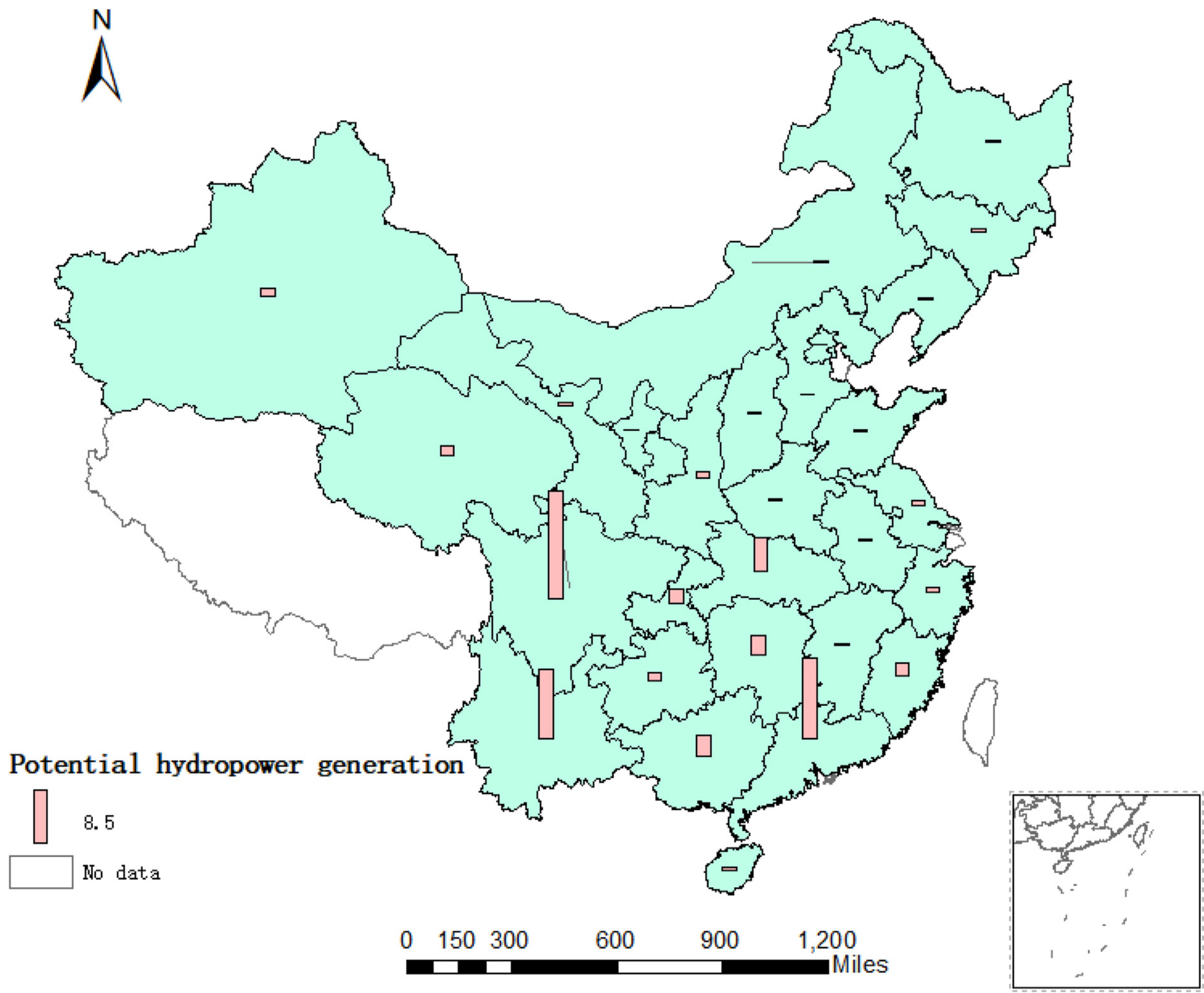

Fig. 9. Potential hydropower generation in 2017 (unit: TWh).

River Line (i.e., Qinling-Huaihe Line), which is an important geographical boundary in China. In the north and south of this line, natural conditions, geographical features, agricultural production, and people's consumption habits are significantly different.

As shown in Fig. 11, the regions with high potential solar power generation are concentrated in North China, including Shandong, Hebei, Henan, and Shanxi. For example, the largest value in 2017 was 4.9 TWh reported by Shandong, followed by Hebei (3.1) and Shanxi (2.1). The three provinces have high frontier and potential solar power generation, showing photovoltaic resources of these three provinces should be fully developed and utilized. It is worth noting that all provinces in southern China generally show both low frontier and potential solar power generation. Therefore, southern China is at no time a focus of photovoltaic power-related policies in the future.

(3) Wind power

As shown in Fig. 12, most provinces in northern China have a large frontier wind power. However, in south China, only Yunan has a high level of frontier wind power generation. That suggests China's wind power resources are mainly concentrated in the north. In particular, Inner Mongolia has the largest frontier wind power of 56.5 TWh, followed by Xinjiang (32.7 TWh) and Hebei (27.4 TWh).

It can be seen from Fig. 13 that most of the provinces have relatively large potential for wind power in China, but it does not mean that most provinces have not well developed and utilized wind power resources. Indeed, the value of potential wind power generation is low, that is, it merely accounts for a small proportion of frontier wind power generation. The total potential hydropower generation in China reaches 21.2 TWh. The highest level of potential wind power generation is recorded in Shandong (2.4 TWh).

4.5. Influencing factors of RPGE

4.5.1. Factor detection

The application of the SFA method is to evaluate the generation efficiency of hydropower, solar power, and wind power in China's 30 provinces. From the geographical perspective, China's provinces

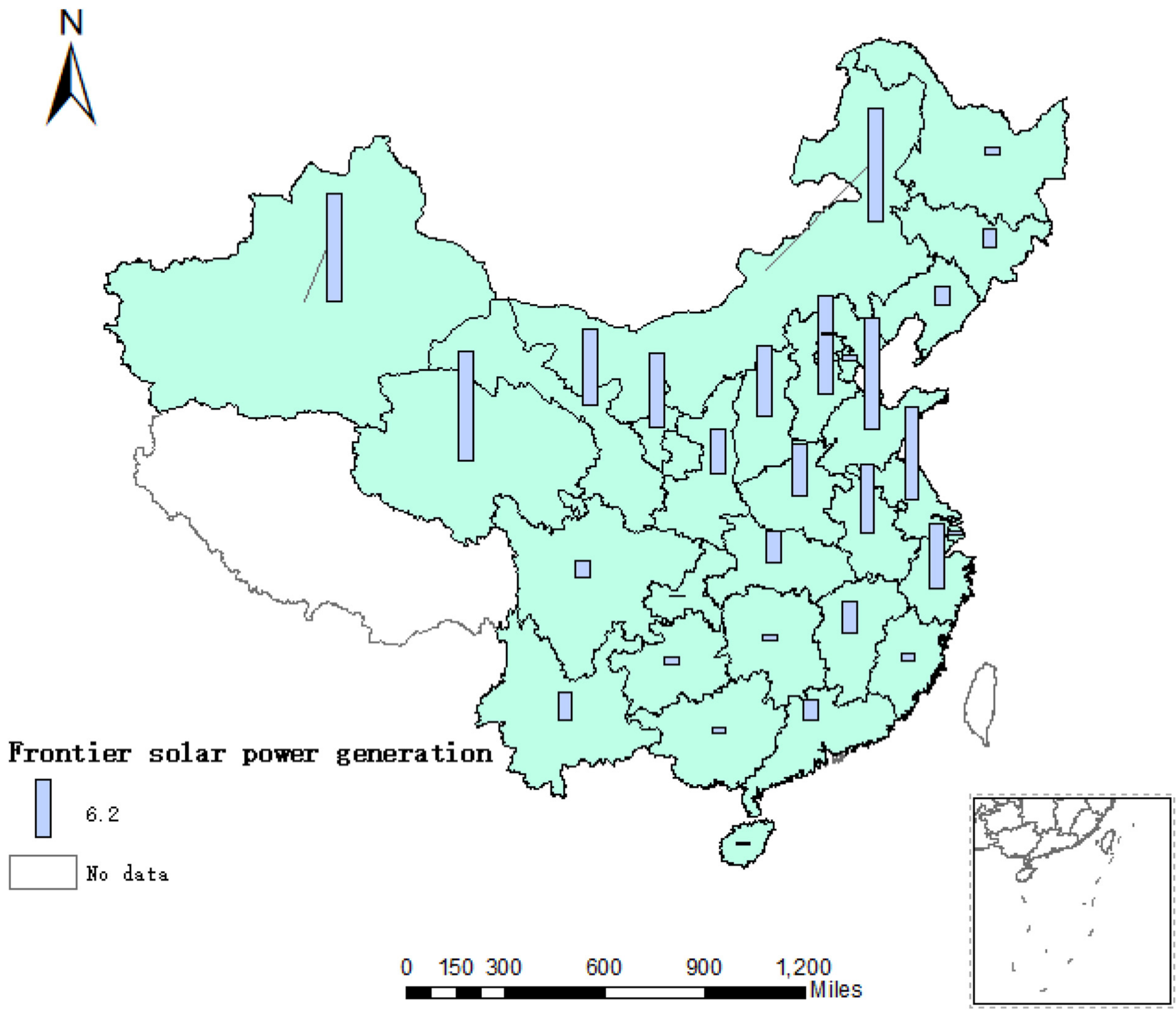

Fig. 10. Frontier solar power generation in 2017 (unit: TWh).

show distinct differences in energy resources, consumption structure, economic development, and climatic conditions. Due to the differentiated conditions across different provinces, HPGE, SPGE, and WPGE present conspicuous spatial heterogeneity and insufficient development. It is necessary to disclose the influence mechanism of HPGE, SPGE, and WPGE in China. The application of geographical detector is to provide adequate evidence regarding the issue of what contributes to the spatial differentiation of HPGE, SPGE, and WPGE, respectively. When using the geographical detector, RPGE is a numerical variable, its determinants should be categorical variables. In this paper, all independent variables are numerical variables, they are stratified and discretized into categorical variables through the quantile method.

Both meteorological and socio-economic factors are considered in the geographical detector model. Factor detection aims to investigate the separate impacts of individual factors on HPGE, SPGE, and WPGE. Table 7 shows the results of the factor detector. Given possible latent influencing factors and data availability, different models take into account different influencing factors. Judging from the q-values, individual detection factors show distinct differences with regard to their effects on the research objects.

As shown in Table 7, Model (1) displays the impacts of nine factors on HPGE. The q-statistics are shown in descending order as follows: Annual precipitation (0.760)> hydropower technology innovation (0.759)> power structure (0.617)> urbanization (0.401) > economic development (0.358)> financial development (0.309)> carbon emissions (0.258)> electricity investment (0.252)> environmental regulation (0.193). Specially, annual precipitation has the largest q-value, and it can account for 76% of the spatial heterogeneity in HPGE, indicating annual precipitation is the most important factor influencing the generation efficiency of hydropower. A slightly lower q-value is reported by hydropower technology innovation, which means the technology factor also takes a dominant place in explaining the spatial heterogeneity of HPGE. Therefore, it is of great significance to promote hydropower-related generation technologies diffusion in regions with low HPGE. In addition, power structure plays an important role in influencing

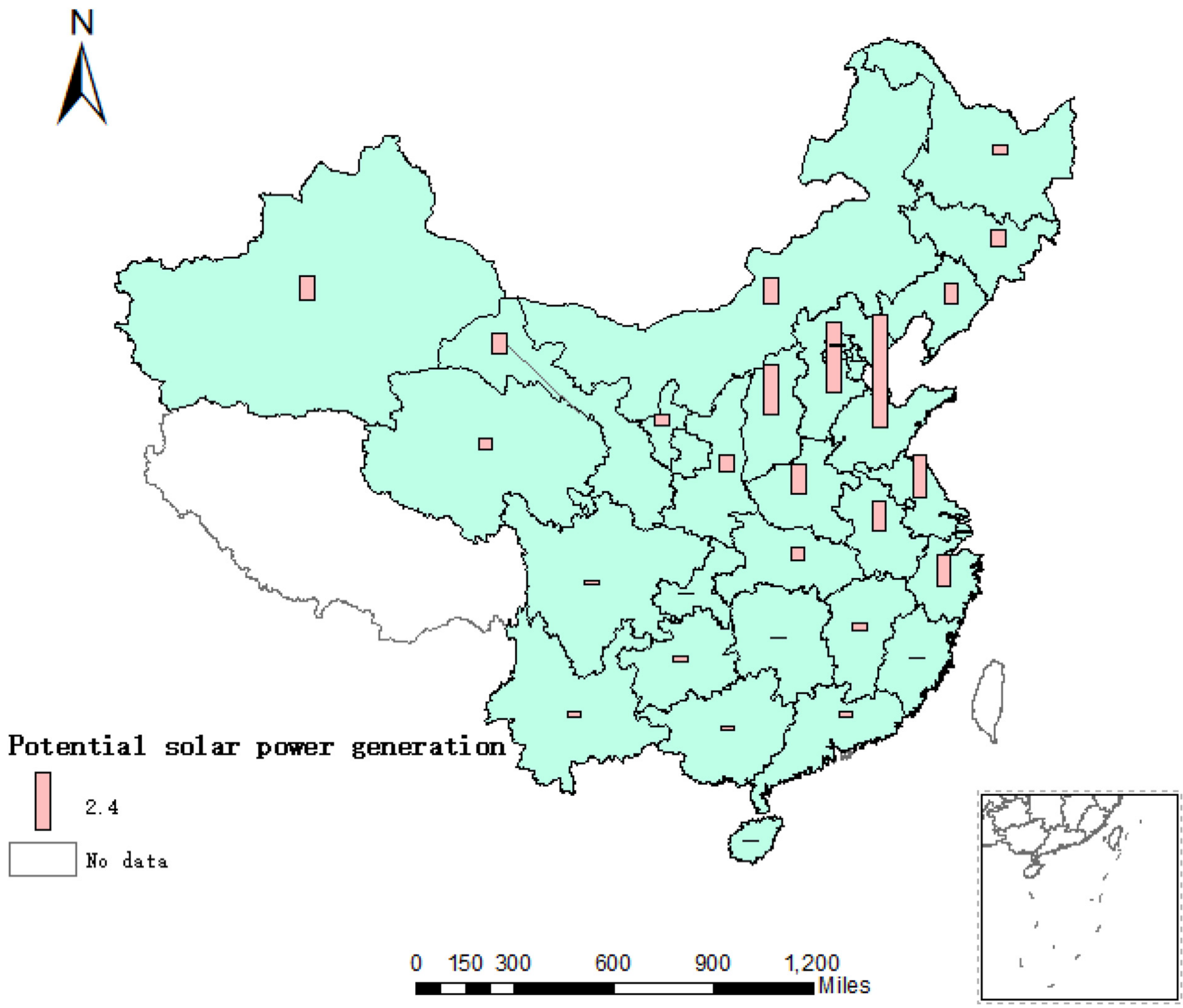

Fig. 11. Potential solar power generation in 2017 (unit: TWh).

HPGE, while other factors, including carbon emissions, electricity investment, and environmental regulation, have significantly lower explanatory power for HPGE.

From the detection results in Model (2), the driving strength of electricity investment on SPGE is the largest, compared with other factors. That is to say, electricity investment is the most important factor influencing SPGE, rather than meteorological factor, environmental pressure, or technology innovation. The main q-statistics are given in descending order: electricity investment (0.506)> economic development (0.477)> environmental regulation (0.460) > power structure (0.409)> urbanization (0.354). The results show economic development, power structure, and environmental regulation also have important effects on SPGE. Obviously, environmental regulation serves as an effective policy tool in driving solar power generation. The q-statistic of urbanization is 0.354, indicating it accounts for 35.4% of the provincial inequality of SPGE. Besides, financial development, annual sunshine hours, carbon emissions have little impact on SPGE. Compared with other factors, the q-value of solar power technology innovation is negligible, which shows China's solar power generation is not limited by the level of photovoltaic technology. On the whole, solar power generation efficiency in China is mainly influenced by economic factors, which means it is of great importance to improve funds support for the regional deployment of solar photovoltaic power.

Model (3) presents the impacts of eight factors on WPGE. It can be seen that the q-statistic of power structure is as high as 0.548, while the q-statistics of other factors are smaller than 0.5, showing generation efficiency of wind power is primarily affected by power structure. In this paper, power structure reflects the importance of thermal power generation in a region. In some regions, thermal power capacity is surplus and has a substitution effect on renewable electricity. It is necessary to reduce the excessive dependence on thermal power, thereby contributing to the improvement of WPGE. The results also suggest that electricity investment is the second-largest influencing factor of WPGE, it can explain 46.2% of provincial differences in WPGE. That confirms the importance of increasing power investment in wind power. Furthermore, urbanization is also a critical factor that accounts for 42.8% of the regional

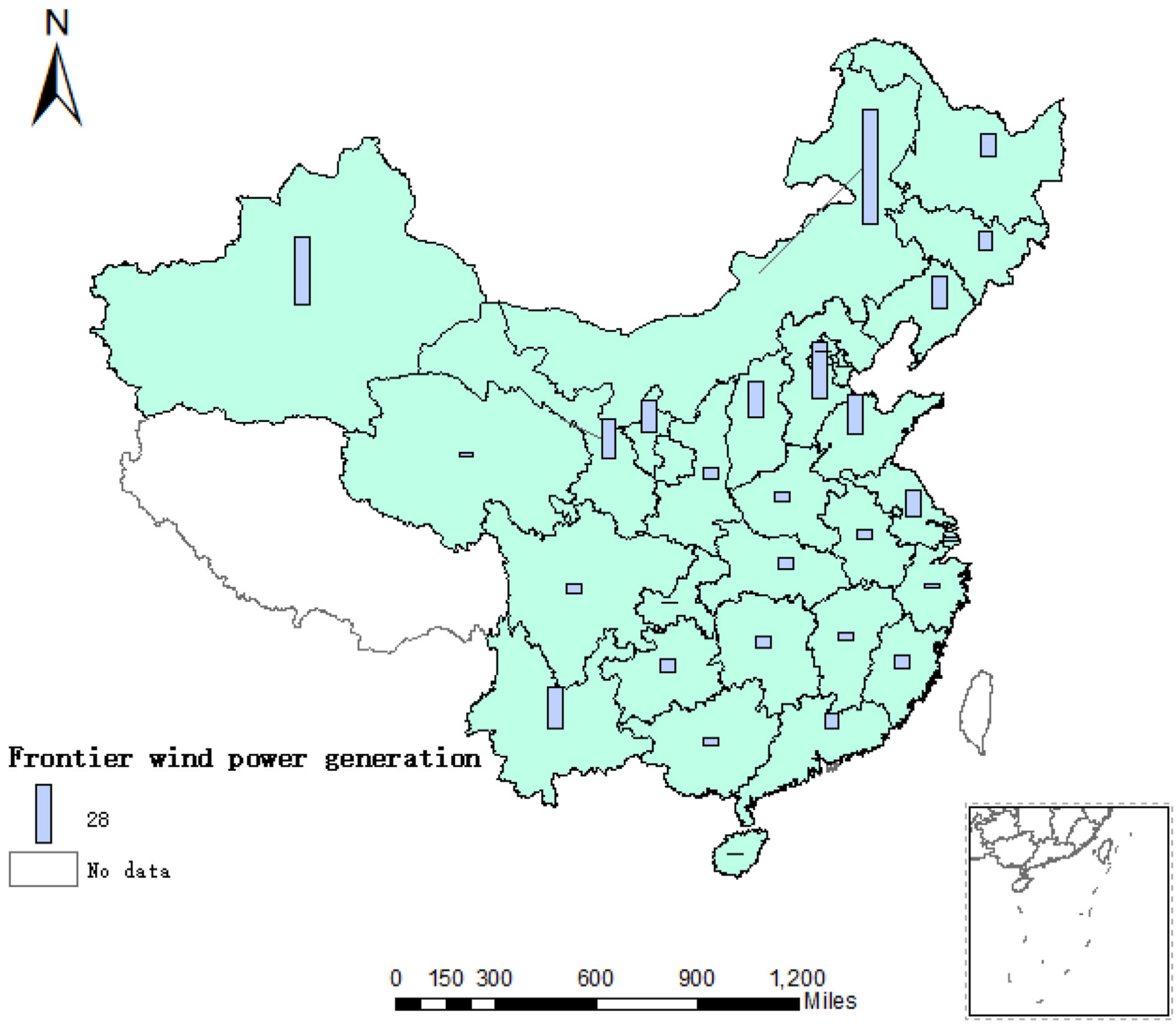

Fig. 12. Frontier wind power generation in 2017 (unit: TWh).

disparities of WPGE. Urbanization is closely related with energy use. In the process of urbanization, the awakened environmental awareness limits the scale of thermal electricity generation to some extent. The small towns facilitate the development of distributed renewable energy with little transportation costs. As shown in Model (3), the q-statistics of environmental regulation, financial development, and carbon emissions are between 0.35 and 0.4, and their effects are quite close. As for economic development, its impact is relatively small. Specially, wind power technology innovation has the smallest q-statistic of 0.228, which indicates the technical factor has the least impact on wind power generation efficiency in China.

4.5.2. Interaction detection

The interaction detector is performed to reveal the interactive effects of various factors on HPGE, SPGE, and WPGE in China. The results show that the interactive effects between any two driving factors present the nonlinear enhancement. The interactive effect of two factors is always greater than the sum of the effects of individual factors. When considering the interactions between different factors, the spatial disparities of HPGE, SPGE, and WPGE can be explained in a greater proportion.

Compared to a single policy, multi-policy interactions are more effective in improving power generation efficiency. For example, given the interactive influences of power structure and environmental regulation, it is feasible to limit the blind expansion of thermal power and eliminate backward production capacity by increasing environmental regulations. Also, it is necessary to reduce the thermal power generation rate and enhancing financial support jointly. Renewable power projects have huge initial investments, high risks, and a long cycle, which make project financing difficult. The traditional financing model cannot completely solve the problem of the shortage of initial investment funds. This will inevitably require the development of new

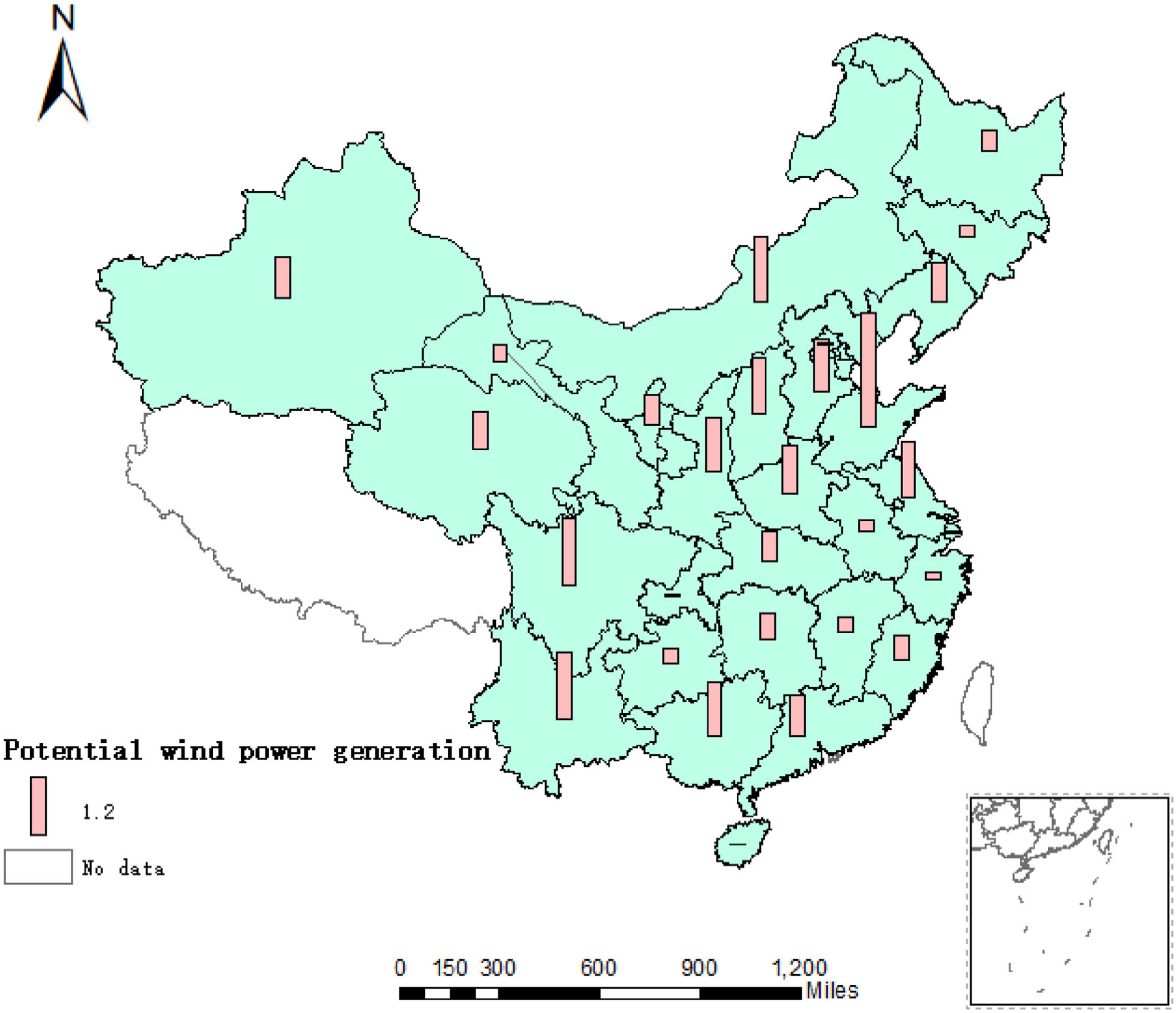

Fig. 13. Potential wind power generation in 2017 (unit: TWh).

Table 7
Results of factor detector.

Variables	Model (1)	Model (2)	Model (3)
	Dependent Variable: HPGE	Dependent Variable: SPGE	Dependent Variable: WPGE
AP	0.760		
AS		0.229	
GPC	0.358	0.477	0.280
PS	0.617	0.409	0.548
ER	0.193	0.460	0.350
INV	0.252	0.506	0.462
FD	0.309	0.144	0.392
URB	0.401	0.354	0.428
C	0.258	0.200	0.385
HTI	0.759		
STI		0.076	
WTI			0.228

Note: All variables are defined in Table 4; *q*-statistics are reported.

financing models for the renewable energy industry, thus solving the problem of insufficient development funds.

5. Conclusions

This study aims to reveal the spatial differentiation and influencing factors of hydropower, solar power, and wind power generation efficiency in China. The main conclusions of this research are as follows: (1) Production inefficiency prevails in hydropower, solar power, and wind power generation industries. The production functions do not satisfy constant returns to scale. The positive impacts of installed capacity and utilized hours on renewable energy generation are distinctly larger than that of auxiliary power consumption. Every 1% increase in auxiliary power consumption leads to 0.16% increase in solar power generation, which is quite larger than the increase in hydropower (0.02%) and wind power (0.06%). (2) The generation efficiency of three renewable sources shows distinct spatial differences and aggregation characteristics among China's provinces. In terms of the mean value, hydropower has the highest level of generation efficiency among China's provinces, followed by wind power and solar power. (3) China has nearly 1253.9 TWh of hydropower potential yet to be exploited. It is of great importance to promote the deployment of hydropower and improve the power generation efficiency, especially in Sichuan, Yunnan, Hubei, and Guangdong. In addition, the provinces located in northern China have significantly higher frontier and potential solar power generation than those located in southern China. Besides, wind power resources are mainly concentrated in north China. (4) Hydropower generation efficiency in China is mainly influenced by annual precipitation, hydropower technology innovation, and power structure. As for solar power generation efficiency, the most important influencing factors are electricity investment and economic development. By contrast, wind power generation efficiency is primarily affected by power structure, electricity investment, and urbanization. (5) Through the interaction detection of geographical factors, it is believed that there exist distinct synergistic effects among different variables, indicating the importance of multi-policy interactions.

6. Policy implications, challenges, and recommendations

This study provides the following policy implications for a high-efficiency renewable energy system in China. (1) It is necessary to scientifically plan power construction, increase the utilization hours and avoid the surplus renewable installed capacity. In addition, the power plants should reduce the electricity consumption of auxiliary equipment during power generation process. The renewable power projects with low operating costs should have priority access to the grid and are absorbed by the market. China has abundant coal resources, the long-term dependence on traditional fossil fuels will significantly affect the energy use patterns. From the source prevention perspective, there is a need to optimize the primary energy consumption structure and power supply structure. (2) It is imperative to increase financial support for renewable energy projects and adopt some new financial tools to promote the marketization of renewable energy, such as establishing renewable energy bidding trading mechanisms and promoting green power certificate transactions. With the deepening of market-oriented reforms in China's power industry, the original renewable energy subsidy policies will become increasingly unsustainable and the cancellation of protection policies is the general trend. (3) To gain market competitiveness, renewable power-generating companies should actively promote technological progress. Revolutionary technological breakthroughs are urgently needed in the fields of power generation, peak shaving, power transmission, energy storage, and distributed power grids. It is necessary to establish a market-oriented mechanism for technological innovation, strengthen the guidance of technological innovation in the power energy industry chain, and increase R&D expenditures in technological research of the entire power industry chain. In particular, it is of great urgency to promote the improvement and diffusion of hydropower-related generation technologies. (4) This paper provides critical policy implications for the development of alternative energy sources and the urbanization process in China. As China's urbanization process advances, the development model of small-sized cities and towns is expected to play an important role in facilitating the development of renewable energy. For example, the urbanization characterized by a large number of small towns is conducive to the development of distributed renewable energy such as wind power and solar photovoltaic power with little transportation costs. (5) It is imperative to adopt both economic and administrative environmental regulations to drive structural transformation in the power industry. Appropriate environmental regulations, such as emissions trading, resource tax, and environmental tax, are conducive to suppressing thermal power capacity, reducing the utilization of high-carbon energy, and improving renewable electricity technologies.

The regional disparities bring huge challenges to the coordinated development of the renewable power industry in China. Local conditions should be considered when formulating targeted policies for improving the generation efficiency of different renewable sources. It is necessary to improve the deployment of hydropower and its generation efficiency in Sichuan, Yunnan, Hubei, and Guangdong. For low-generation efficiency regions, due attention should be paid to optimize the dispatch and hierarchy of generation units. Besides, the potential solar power needs to be tapped, especially in north China where the frontier and potential solar power are both high. In particular, Inner Mongolia has the largest frontier wind power, followed by Xinjiang and Hebei. Therefore, based on the regional characteristics of different energy types, the individual authority should scientifically plan power construction and fully exploit the potential of disaggregated renewable power. The coordinated development of renewable power is achieving the targets of carbon peak by 2030 and carbon neutrality by 2060. There is a need to promote the regional allocation, trade, and consumption of renewable electricity with the interconnection and interoperability of regional power grids.

Given data availability, the study period is up to 2017, which is expected to be updated in the future. In addition, the research can be extended to the global scale using county-level data. It is necessary to consider more input factors, such as labor and total land area of power plants.

Credit roles

Bolin Yu: Conceptualization, Methodology, Software, Data curation, Writing − original draft, Writing − review & editing. Debin Fang: Conceptualization, Supervision, Visualization, Formal analysis, Writing − review & editing, Funding acquisition. Jingxuan Meng: Writing − review & editing.

Declaration of competing interest

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

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Appendix A

$$y_i = f(x_i, \beta)\exp(v_i - u_i),\ 0 < u_i \le 1 \tag{A1}$$

$$y_i^* = f(x_i, \beta)\exp(v_i) \tag{A2}$$

$$\sigma^2 = \sigma_v^2 + \sigma_u^2,\ \gamma = \sigma_u^2 \Big/ \left(\sigma_v^2 + \sigma_u^2\right) \tag{A3}$$

$$TE_i = \frac{y_i}{y_i^*} = \exp(-u_i) \tag{A4}$$

Where y_i is the actual output of the ith province, y_i^* indicates the stochastic frontier output.x_i represents the vector of inputs and β represents the vector of corresponding parameters. $(v_i - u_i)$ is the composite disturbance term comprising an idiosyncratic error and the inefficiency component. v_i is the random error term which represents the random external shocks that may influence the output, and it follows the *iid.* $N(0, \sigma_v^2)$. v_i is independent of the non-negative technical inefficiency u_i which is non-observed. u_i may follow a truncated-normal distribution $N^+(\mu, \sigma_u^2)$. The parameter γ represents the proportion of inefficiency term in the composite disturbance term. TE_i denotes technical efficiency, which is expressed as the ratio of actual output to stochastic frontier output. In this paper, technical efficiency refers to *RPGE*. Specifically, TE_i is determined by u_i. When $u_i = 0$, then $TE_i = 1$ and there is no technical inefficiency in the production process, the actual output can reach the frontier output; when $u_i > 0$, then $TE_i < 1$ and there exists technical inefficiency in the production process, that is, the actual output level is below the boundary of the production frontier.

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