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Factors Affecting Wind Power Efficiency: Evidence from Provincial-Level Data in China

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Abstract: As a significant energy consumer, China is under tremendous pressure from the international community to address climate change issues by reducing carbon emissions; thus, the use of clean energy is imperative. Wind power is an essential source of renewable energy, and improving the efficiency of wind power generation will contribute substantially to China's ability to achieve its energy-saving and emission reduction goals. This paper measured the wind power efficiency of provinces in China from 2012 to 2017 using the data envelopment analysis (DEA) method. Moran's I index and the spatial Durbin model were applied to analyse the spatial distribution of the wind power efficiency and the spatial effects of influencing factors. The results show obvious differences in the spatial distribution of wind power efficiency in China; specifically, the wind power efficiency in the eastern and western regions is higher than that in the central areas. Moreover, wind power efficiency has a significant positive spatial correlation between regions: the eastern and western regions show certain high-high clustering characteristics, and the central area shows certain low-low clustering characteristics. Among the influencing factors, the fixed asset investment and carbon emission intensity of the wind power property have a negative impact on the efficiency of regional wind power production, while the urbanization process and carbon emission intensity have significant spatial spillover effects. The optimization of the economic structure, technological innovation and the construction of energy infrastructure are expected to improve the regional wind power efficiency. The results present a new approach for accurately identifying the spatial characteristics of wind power efficiency and the spatial effects of the influencing factors, thus providing a reference for policymakers.

Keywords: wind power efficiency; DEA; spatial econometric model; China

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1. Introduction

With the need to reduce global carbon emissions and mitigate climate change, the development of renewable energy (RE) has aroused widespread interest because it offers multiple benefits, such as improved energy security, enhanced technological competitiveness, and reduced greenhouse gas emissions [1]. At the Paris climate conference in 2015, China proposed specific carbon emission reduction targets, committing to reducing its carbon emission intensity by 60–65% by 2030, and a series of emission reduction plans have been formulated to achieve this goal [2]. To this end, China has begun to prioritize the use of RE, and its energy system is developing in a clean and low-carbon direction [3].

Compared with other types of RE, the technologies employed in wind power (WP) generation are mature and broadly available at a lower cost, making WP a significant source of RE [4–6]. WP plays an essential role in promoting China's green energy transformation and reducing carbon emissions [7,8]. Nevertheless, with the large-scale development and widespread use of WP, problems related to WP consumption, large-scale grid connections and excessive investment are starting to appear in China, increasing concerns about the prospects for WP utilization and representing a bottleneck in the sustainable development of China's power system [1,9–11]. Notably, during the period 2014–2015, the installed capacity of WP achieved a steady growth, but the amount of WP generation declined to a greater extent (Figure 1). Specifically, the average utilization hours of WP in 2014 were only 1905 h, a decrease of 120 h compared to 2013. Moreover, it achieved a continuous decline in 2015. This phenomenon may be due to the fact that Jilin and Gansu provinces, with enormous wind energy resources, have not effectively solved the problem of WP curtailment, and there are still insufficient WP transmission channels [12]. At the end of 2014, the relevant government departments raised the feed-in tariff of WP, and applicable policies were implemented in 2016, which led to excessive investment in wind farms (WFs). Although WP generation has gradually increased, it still lags behind the development of WP installed capacity [11]. As of 2020, the WP installed capacity accounted for 12.79%, while WP generation accounted for 6.12%, which means that nearly half of the wind turbines were wasted (Figure 1). In this study, WP efficiency is defined as the difference between the actual power generation and the maximum power generation output in a specific province under a certain level of production input (WP installed capacity). WP efficiency falls into the conceptual category of relative efficiency, focusing on the distance between a province and the region with the best WP development. The data envelopment analysis (DEA) model is used in this research to measure the relative efficiency, reflecting the development of WP at the provincial level in China.

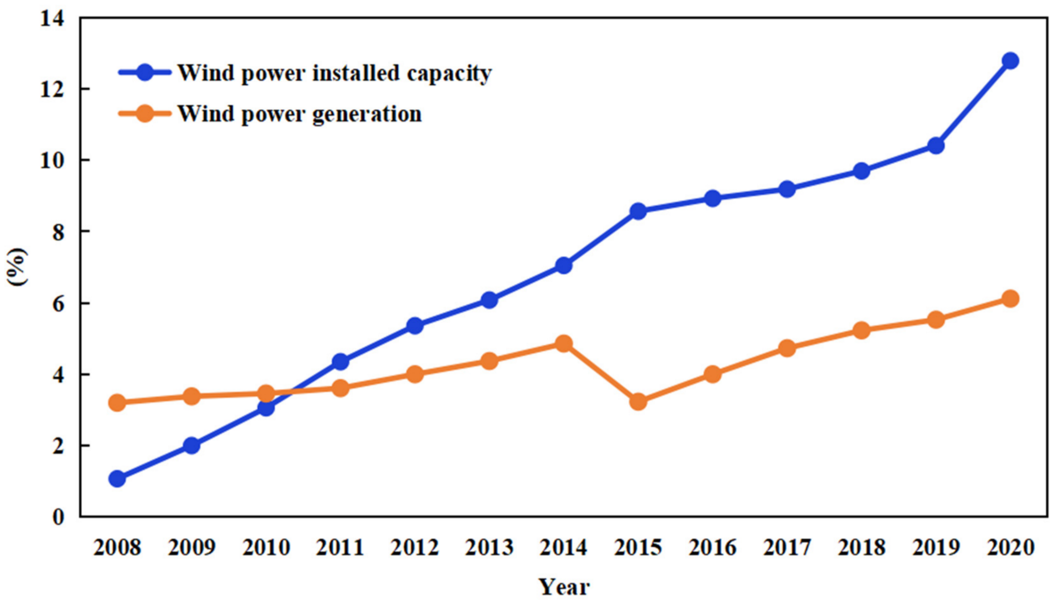

Figure 1. Share of WP installed and generated in China.

Furthermore, China's provinces have different wind energy resource endowments, and WP construction differs significantly among provinces. Specifically, there is a certain degree of regional heterogeneity in the construction of WFs, leading to different WP development characteristics in various provinces [13,14]. Under these circumstances, exploring the geographical differences and spatial distribution of WP efficiency among provinces and accurately identifying the degree of influence of key factors are of fundamental importance to the Chinese government's ability to implement a low-carbon and clean-energy strategy, which is crucial for the country's efforts to achieve its carbon emission reduction targets and fulfil its international responsibilities.

Because WP is highly valued and is being actively developed, the study of WP efficiency calculation and its influencing factors has begun to attract an increasing number of researchers, who believe that improving WP efficiency is key to achieving carbon emission reduction goals and the sustainable development of the energy system. At present, most of the literature has focused on WFs, the operation of the WP industry and WP generation. Wu et al. [5] assessed the efficiency of large-scale WFs and found that development was at an acceptable level but that approximately 50% of WFs had an excessive investment. Sağlam [15] evaluated the production efficiency of WFs by employing the DEA and Tobit models in Texas and proposed that the technical level of wind turbines could have a significant impact on improving the efficiency of WFs. Iglesias et al. [16] measured the production efficiency of a group of WFs from 2001 to 2004 and made recommendations for the efficient operation of WFs. Niu et al. [17] evaluated the location of wind turbines in Chinese WFs, explored the relationship between efficiency and environmental variables and proposed that a rational environment can improve the efficiency of wind turbine production. Pieralli et al. [18] analysed WFs' efficiency by the nonconvex method in Germany and found that most losses in efficiency arise from changing wind conditions. Ederer [19] applied DEA to assess offshore wind energy's capital and operational efficiency and determined the best cost frontier. Li and Wu [20] analysed the impact of financial support on WP efficiency based on the DEA-Malmquist index and proposed that the financial investment in China's WP properties has a low success rate. Papież et al. [21] assessed WP efficiency in the EU, focusing on the impact of policy measures on the efficiency value, and proposed that the implemented RE economic policies can effectively improve the efficiency of WP production. Sağlam [22] evaluated the WP efficiency in 39 states in the US and found that WP is effective in more than half of the states, and it was proposed that investment policies and the technical level of WP equipment can affect WP efficiency. Pan et al. [13] measured the efficiency value by DEA and symbolic regression to analyse the degree of influence of selected factors, and they found that there is a large discrepancy in the WP efficiency among areas in China and that factors such as geographic location, technological progress and carbon regulation can affect WP efficiency. Using an approach derived from the improved Super-SBM and LSTM network models, Li et al. [3] measured and predicated the employment potency of WP in 30 regions in China and found that the general utilization potency of WP is low, with square measure regional variations; however, low-efficiency areas have greater potential for improvement.

The above studies have provided valuable insights into WP efficiency, but some problems must be further discussed. Most previous studies have advocated that the regions are independent and that there is no significant spatial correlation. Therefore, when traditional regression models are used to explore the degree of influence of different factors on the efficiency value, the impact of spatial factors is rarely considered. In other words, there is insufficient research on the spatial distribution characteristics of provincial WP efficiency or the influence of spatial factors. This deficiency could lead to certain deviations in the research results and a lack of regional specificity in the formulation of policies. To compensate for the lack of research on the spatial distribution of WP efficiency and the spatial effects of influencing factors at the provincial level, we explore the factors that affect the WP efficiency from the perspective of spatial spillover effects and increase the influence of spatial factors considering traditional regression models. The results of this study can provide approaches for accurately identifying the influencing factors of WP efficiency and narrowing the gaps among provinces. Moreover, the results can provide practical suggestions and references for national policymakers and implementers.

The remainder of the paper is arranged as follows. Section 2 presents the research methods and data. Specifically, the DEA model and the spatial econometric model are used to measure the WP efficiency and the spatial spillover effects of the influencing factors. The description of the data mainly details the variables considered and the data sources. Section 3 shows the results and provides a discussion. Section 4 presents the conclusions and proposes corresponding policy suggestions.

2. Research Methods and Data

2.1. Research Methods

In this study, an output-oriented DEA model is built to gauge the efficiency of WP generation in 30 provinces of China from 2012 to 2017. We use the calculated WP efficiency value as the explained variable and establish a spatial measurement regression model to accurately identify the impact of different levels of factors, considering the spatial spillover effect of WP efficiency. The specific research method framework is shown in Figure 2.

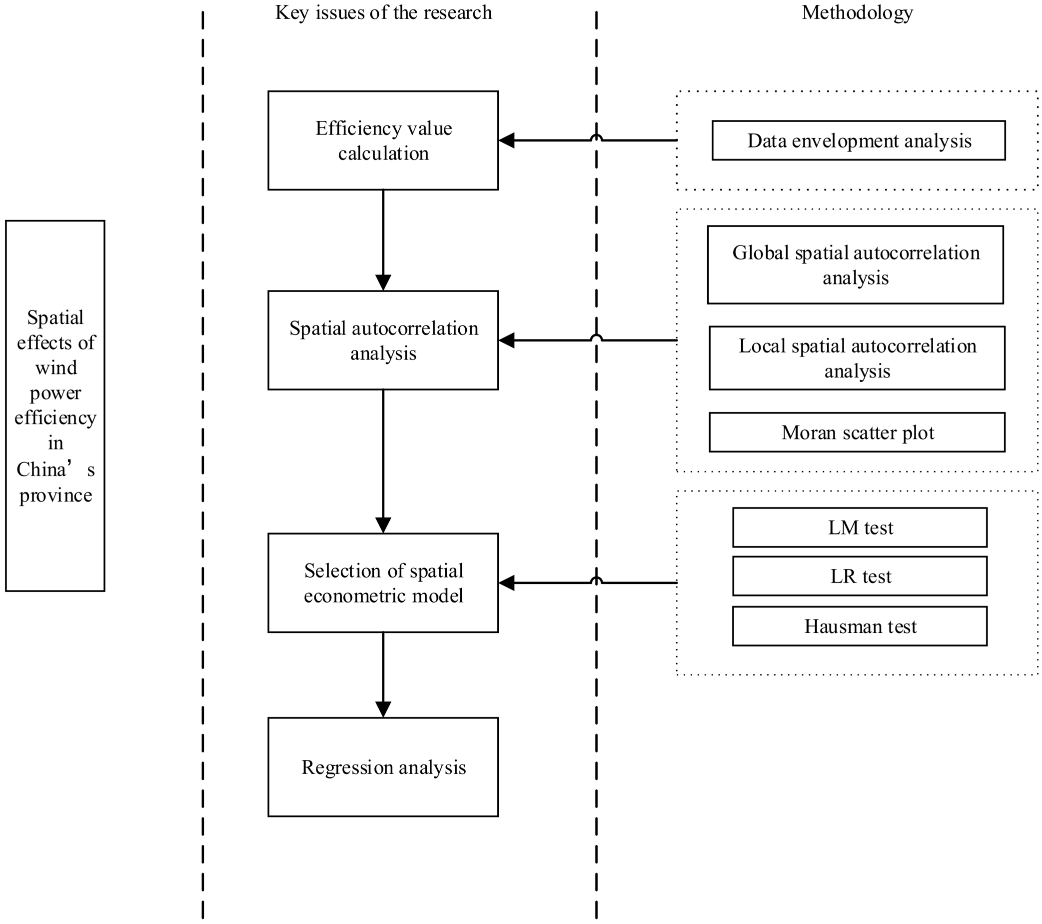

Figure 2. Framework of this paper.

2.1.1. Evaluation Model of WP Efficiency

In the early development of DEA, two conventional measurement methods were mainly used [23]. The two conventional methods [2] are CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper). Among them, CCR is primarily used to measure the total efficiency under a fixed return to scale. BCC differs in that it is primarily used to measure pure technology and scale efficiency [21]. Related research has mainly focused on environmental efficiency [24,25], economic and ecological efficiency [26], energy efficiency [27,28], RE [29], water efficiency [30] and other variables.

Tone added slack variables to the conventional CCR or BCC model and built a slack-based measure model (SBM) to measure efficiency [13]. In contrast to the traditional model, the goal of the SBM is to maximize the actual profit and not just the benefit ratio. In other words, the efficiency value is more comprehensive and effective than that measured by the ordinary model [31]. To avoid the shortcomings of the conventional DEA model and provide a more objective WP efficiency value that is closer to reality, our research adopts the SBM and considers slack variables. The formula of the SBM is as follows [32]:

$$\begin{array}{c} \mathrm{E_{wp}} = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 + \frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}} \\ \text{s.t. } X\lambda + s^- = x_k \\ Y\lambda - s^+ = y_k \\ \lambda, s^-, s^+ \geq 0 \end{array} \tag{1}$$

where $\mathrm{E_{wp}}$ represents the efficiency value, x_{ik} represents the input variable, and y_{rk} represents the output variable. s_i^- represents the redundancy of the i-th input, and s_r^+ represents the redundancy of the r-th output. λ is the adjustment matrix, $X\lambda$ is the amount of input on the frontier, and $Y\lambda$ is the amount of output on the frontier.

Model (1) measures the WP efficiency from both the input and output perspectives. In the process of WP generation, the goal is to improve the output efficiency and increase power generation. To capture the actual situation of WP production, the output-oriented SBM is adopted to measure the efficiency. The formula of the output-oriented SBM is as follows [32]:

$$\begin{array}{c} \mathrm{E_{wp}} = \min \frac{1}{1 + \frac{1}{q}\sum_{r=1}^{q}\frac{s_r^+}{y_{rk}}} \\ \text{s.t. } X\lambda \leq x_k \\ Y\lambda - s^+ = y_k \\ \lambda, s^+ \geq 0 \end{array} \tag{2}$$

2.1.2. Spatial Autocorrelation Analysis

When analysing spatial data, regardless of which spatial econometric model is adopted, it is essential first to check whether there is a spatial correlation between economic variables. There are two main methods to test the spatial correlation of selected variables: the spatial autocorrelation analysis of the whole area and the spatial autocorrelation analysis of the local area [2,33].

The global Moran's I index is used to explain the spatial correlation of all data selected in the entire study area [8]. Its value is generally between −1 and 1. When the calculated Moran's I index is less than 0, the WP efficiency values between different provinces have a negative spatial relationship, and the closer to −1 it is, the greater the difference or the less concentrated the distribution. When the calculated Moran's I index is 0, the WP efficiency between different provinces is spatially irrelevant. When the calculated Moran's I index is greater than 0, the efficiency of different provinces is positively correlated in space. The closer the value is to 1, the closer the efficiency relationship between different provinces and the more similar its nature. The formula for calculating Moran's I index is as follows [8]:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\mathcal{W}_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\mathcal{W}_{ij}\right)\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{3}$$

in which x_i and x_j are the observed efficiency values, and $\overline{x}$ is the average of the observed variables. $\mathcal{W}_{ij}$ is the spatial weight matrix, which describes the spatial adjacency relationship of each province. In this part, a binary adjacency matrix is used, that is, when province i and province j are adjacent, the value is 1; otherwise, it is 0 [34].

The local Moran's I statistic can detect spatial agglomeration features in local space [33]. Its value is generally between −1 and 1. When its value is greater than 0, it means that the efficiency values of province i and its neighbouring provinces are positively correlated. When its value is less than 0, it means that the efficiency of province i and its neighbouring provinces are negatively correlated. The formula for the local Moran's I index is as follows [35]:

$$I_i = \frac{n(x_i - \overline{x}) \sum_i \mathcal{W}_{ij}(x_i - \overline{x})}{\sum_i (x_j - \overline{x})^2} \tag{4}$$

To further evaluate the spatial aggregation characteristics of different provinces, we use Moran scatter plots to analyse the provincial WP efficiency. For the plots, the X-axis represents the standardized WP efficiency value, and the Y-axis represents the spatial lag value of the WP efficiency. The Moran scatter chart includes four quadrants, which represent the four specific types of clusters between different provinces in space (Figure 3).

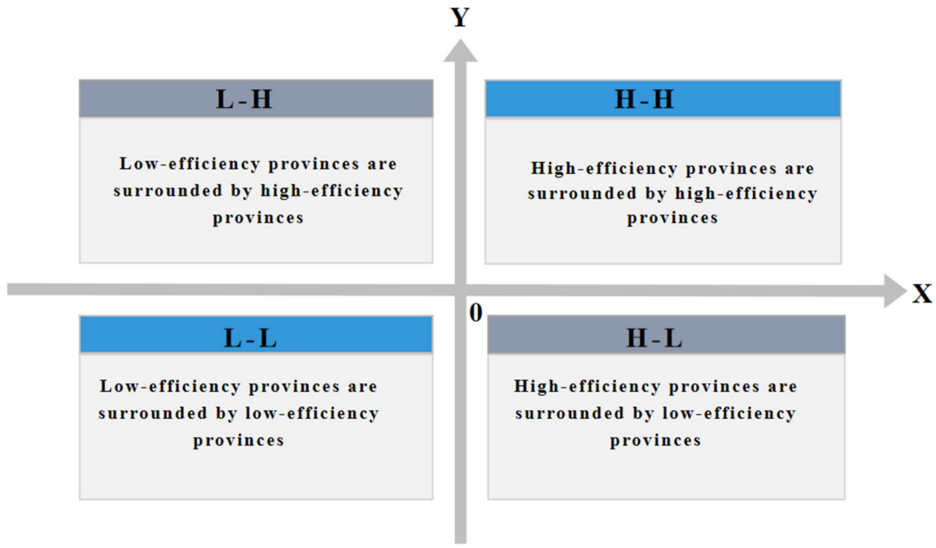

Figure 3. Moran scatter plot of the WP efficiency.

2.1.3. Spatial Econometric Model

We consider the influence of spatial factors when selecting factors and then establish a spatial regression model derived from conventional regression models to measure the spatial effects of selected factors. Depending on how the spatial autocorrelation term is introduced into the regression model, it can be separated into the spatial lag model (SLM) and the spatial error model (SEM), and the SLM can be further separated into a spatial autoregressive model (SAR) and a spatial Durbin model (SDM) [2]. The SDM is widely used in spatial econometric analysis because it can be degenerated into its SAR and SEM. The formula of the SDM is as follows [34]:

$$WPE = \rho \mathcal{W} * WPE + X\beta + \mathcal{W}\,\overline{X}\delta + \varepsilon \tag{5}$$

where WPE is the WP efficiency, X is the explanatory variable, $\mathcal{W}\,\overline{X}$ is the spatial lag explanatory variable, and ε represents the random term. When $\delta = 0$, the SDM degenerates to the SAR; the formula of the SAR is as follows:

$$WPE = \rho \mathcal{W} * WPE + X\beta + \varepsilon \tag{6}$$

Based on Formula (6), when $\rho = 0$ and $\varepsilon = \lambda \mathcal{W} \varepsilon + \upsilon$, the model degenerates to the SEM, and the formula of the SEM model is as follows:

$$WPE = X\beta + \lambda \mathcal{W} \varepsilon + \upsilon \tag{7}$$

where λ is the spatial error coefficient and υ represents random error.

When selecting a spatial measurement model, first, it is necessary to perform a Lagrange multiplier (LM) test and use the result as a criterion for determining which spatial model is more realistic [2]. In the spatial effect test process, we must compare the significance of the LM test results. When the significance of LMLAG is greater than that of LMERR, and only R-LMLAG passes the significance test, we conclude that the SLM is appropriate and the SEM is suitable. After a suitable model is selected, the Hausman test is used to choose the effect of the model [33].

2.2. Description of Variables and Data Sources

When analysing the factors affecting WP efficiency at the regional level in China, the analysis is mainly separated into two stages: efficiency measurement based on the SBM-DEA model and spatial econometric analysis considering spatial effects. It is indispensable to ensure that complete research data are selected, and this study compiles data from 30 provinces in China between 2012 and 2017. Our study area does not include Taiwan, Tibet, Hong Kong, and Macao because it is difficult to obtain complete data in these areas. The economic data involved in this study were deflated according to the price index.

2.2.1. Description of Input and Output Variables

The selection of variables in measuring WP efficiency in this study was derived from the literature [13,21,22]. The WP property has particularities among traditional industries, and the investment in capital and technology is directly reflected in the installed WP capacity. To reduce the collinearity between input variables and reduce measurement errors, this study uses the installed capacity as the input variable and WP generation as the output variable. The data are obtained from the China Electric Power Yearbook (CEPY) (2013-2018), and the variables and statistical descriptions are presented in Table 1.

Table 1. Efficiency measurement variables and descriptive statistics.

Variables	Description	Unit	Number of Samples	Mean	Max	Min
Input	Installed wind capacity	GW	180	3.759	26.700	0.020
Output	WP generation	GWh	180	6280.278	55,100.000	20.000

2.2.2. Selection of Influencing Factors

The selection of influencing factors in the spatial econometric analysis mainly includes five categories: economy, environment, technology, policy, and space. The most commonly selected economic influencing factors are economic structure, urbanization rate, and investment level because urbanization promotes improvement in the quality of life of residents, and changes in industrial structure will change the terminal energy consumption composition [2], thereby affecting the efficiency of WP production. Environmental impact factors are primarily based on regional carbon emission intensity as a measurement indicator, which measures whether the mechanisms adopted by China's provinces to control carbon emissions have effectively driven improvements in WP efficiency. The technological influencing factor includes the level of WP technology progress as the measurement index [36], which primarily measures the impact of the technical level of the WP industry on the efficiency of WP production. The policy-influencing factor includes infrastructure construction, which primarily measures the current level of the regional power grid level influencing WP efficiency. The spatial factor is the introduction of a spatial weight matrix to measure the spatial spillover effect of the WP efficiency. The economic data and population data are from the National Bureau of Statistics (NBS), carbon emissions data are from the China Emission Accounts & Database (CEADs), patent data are from the China National Intellectual Property Administration (CNIPA), and transmission grid data are from CEPY (2013–2018). The specific variable descriptions and statistics are presented in Table 2.

Table 2. Descriptive statistics of independent variables in the spatial econometric model.

Symbol	Variables	Description	Unit	Max	Min	Mean	Data Sources
ES	Economic structure	Industrial added value as a proportion of GDP	%	50.736	11.838	37.125	NBS
UR	Urbanization rate	The percentage of the urban population in the total population	%	89.607	36.424	57.130	NBS
IL	Investment level	Total investment in fixed assets in the wind power property	one hundred million yuan	510.929	0.321	63.662	NBS
CEI	Carbon emission intensity	Carbon emissions per unit of GDP	t/million yuan	718.588	42.902	205.622	CEADs
TP	Technology progress	Number of wind power patents	item	381.000	2.000	55.544	CNIPA
TGD	Transmission grid density	The ratio of the length of the transmission line above 110 KV to the administrative area	m/km^2	924.121	23.007	267.351	CEPY (2013–2018)
LLR	Line loss rate	Transmission line loss rate of each province	%	14.950	1.690	6.433	CEPY (2013–2018)
W	Spatial weight matrix	When province *i* and province *j* are adjacent, the value is 1; otherwise, it is 0					

3. Results and Discussion

3.1. WP Efficiency

The WP efficiency at the provincial level in China during the 2012–2017 period is calculated by the SBM-DEA model. Specifically, the installed WP capacity is the input variable, and the WP generation is the output variable. For China's WP properties, although the selected input and output indicators are relatively simple, they can effectively reflect the actual level of WP development, and the results are presented in Figure 4.

Examining the time scale reveals that, for the national average, the WP efficiencies from 2012 to 2017 were 0.736, 0.784, 0.756, 0.713, 0.819 and 0.792, respectively, showing a gradually increasing trend with inevitable fluctuations, which indicates that the development of WP in China is improving. Still, some issues and challenges prevent it from achieving a high-quality development [37], such as wind abandonment, power rationing and lagging power grid construction, causing the WP generation efficiency to fluctuate [11]. From the perspective of individual provinces, the WP efficiencies of Inner Mongolia, Shanghai and Fujian are stable and effective, probably because Inner Mongolia has vibrant wind energy resources, a sparse population and natural advantages for the construction of large-scale WFs. With relevant government policies, wind energy in the region has been effectively utilized and shows a stable development [38]. Shanghai and Fujian are located in the eastern coastal areas, with abundant offshore wind energy resources and a high WP technology level, and because of these resources, the development of WP is stable, and the WP efficiency is high. The WP efficiencies of Yunnan, Beijing, Qinghai, Tianjin and Hebei are relatively stable and effective. The plausible cause is that provinces like Yunnan and Qinghai are rich in wind energy resources and have relatively superior natural geographical conditions. However, Beijing, Tianjin, Hebei and other regions have developed economies and a high technological level, providing adequate technical support and financial backing for WP in these regions. The WP efficiencies of other provinces, such as Hainan and Chongqing, show a gradual upward trend. The likely cause is that the development of WP in these regions started late. With the support of government policies, the installed capacity of WP increased rapidly, which led to a rapid improvement in WP efficiency. The WP efficiencies in provinces such as Jiangsu and Shandong show a gradual decline. These provinces are located in the eastern coastal areas, with abundant offshore wind energy resources, and the early development of WP is relatively stable. However, the power structure of Jiangsu and Shandong is dominated by thermal energy, and the terminal power consumption potential is tremendous [10]; thus, the large-scale stable power demand will inhibit the development of WP to a certain extent. The WP efficiencies of Jilin, Heilongjiang, Liaoning, Shanxi, Anhui, Henan, Guangxi and Gansu fluctuate considerably. A possible reason is that although the development of WP in the northeast and northwest regions started early, owing to the lag in power grid construction, there has been a significant degree of WP abandonment in this area, and the use of wind energy is unstable [39]. Provinces such as Shanxi, Anhui, Henan and Guangxi are located in the central region, with fewer wind energy resources and low WP technology, which inhibits the steady improvement in their WP efficiencies to a certain extent and results in fluctuations in WP efficiency fluctuations.

Province	2012	2013	2014	2015	2016	2017	Mean value	Ranking
Beijing	0.853	1.000	0.958	1.000	1.000	1.000	0.969	5
Tianjin	0.836	1.000	0.904	1.000	1.000	1.000	0.957	7
Hebei	1.000	0.932	0.891	0.926	0.989	1.000	0.956	8
Shanxi	0.953	0.906	0.826	0.805	0.872	0.835	0.866	14
Inner Mongolia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Liaoning	0.865	0.856	0.859	1.000	1.000	0.917	0.916	9
Jilin	0.671	0.715	0.687	0.682	0.638	0.729	0.687	25
Heilongjiang	0.789	0.824	0.768	0.778	0.761	0.810	0.788	17
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Jiangsu	1.000	0.888	0.886	0.830	0.847	0.791	0.874	12
Zhejiang	0.902	0.925	0.816	0.894	0.991	0.837	0.894	10
Anhui	0.639	0.720	0.724	0.696	0.869	0.736	0.730	21
Fujian	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
Jiangxi	0.662	0.702	0.692	0.663	0.766	0.720	0.701	24
Shandong	1.000	0.911	0.855	0.912	0.882	0.700	0.877	11
Henan	0.946	0.763	0.760	0.567	0.755	0.500	0.715	22
Hubei	0.617	0.668	0.927	0.910	0.821	0.751	0.782	18
Hunan	0.595	0.610	0.484	0.571	0.772	0.742	0.629	28
Guangdong	0.803	0.823	0.758	0.937	0.896	0.749	0.828	16
Guangxi	0.339	1.000	1.000	0.630	0.825	0.658	0.742	20
Hainan	0.638	0.821	0.724	0.984	1.000	1.000	0.861	15
Chongqing	0.142	0.214	0.281	0.603	1.000	1.000	0.540	30
Sichuan	1.000	0.500	0.564	0.571	0.746	0.654	0.673	26
Guizhou	0.382	0.592	0.474	0.815	0.772	0.749	0.630	27
Yunnan	0.993	1.000	1.000	0.944	1.000	1.000	0.990	4
Shannxi	0.724	0.468	0.684	0.624	0.672	0.577	0.625	29
Gansu	0.868	0.825	0.598	0.584	0.561	0.779	0.703	23
Qinghai	1.000	1.000	1.000	1.000	1.000	0.779	0.963	6
Ningxia	0.748	1.000	0.816	0.756	0.890	1.000	0.868	13
Xinjiang	0.848	0.620	0.898	0.565	0.726	0.827	0.747	19
Mean value	0.736	0.784	0.756	0.713	0.819	0.792	-	

Figure 4. WP efficiency calculation results from 2012 to 2017.

Regarding the spatial scale, at the regional level, there are differences in the WP efficiencies among provinces (Figure 5). The provinces with low WP efficiencies are mainly concentrated in the central areas and are represented by Guizhou and Hunan.

These provinces are far from the east's offshore wind energy resource-rich areas and the onshore wind energy resource-rich areas in the west and north. In other words, the wind energy resources within the central area are comparatively scarce, and therefore the performance of WP is relatively low [13]. The eastern, central and western provinces have dual competition for economic benefits and environmental goals. There are certain regional obstacles, and the construction of cross-regional power grids is lagging. Some local governments sacrifice ecological benefits to drive their economic development, leading to the ineffective implementation of promotion policies related to WP development and insufficient support for the WP industry [4]. The provinces with higher WP efficiencies are mainly concentrated in the western areas, represented by provinces such as Inner Mongolia and Qinghai, and in the developed eastern regions, characterized by Beijing and Shanghai. Mainly because the western region is rich in wind energy resources and has received support from China's policy for developing large-scale WFs, the WP in the west region has developed rapidly [14,39]. The eastern developed regions have a relatively high level of economic development, a high concentration of technological innovation and a significant demand for terminal power [10], which has promoted WP efficiency improvements. In general, the WP efficiency at the provincial level in China presents a significant variability in spatial distribution, and interregional barriers are the main reason for differences in the WP efficiencies. The eastern region has a more advanced economy, numerous scientific and technological talents and strong financial support. In contrast, the western region is rich in natural resources, and the central region has moderate technical and natural resources. Therefore, the complementarity of resources between regions can promote WP efficiency.

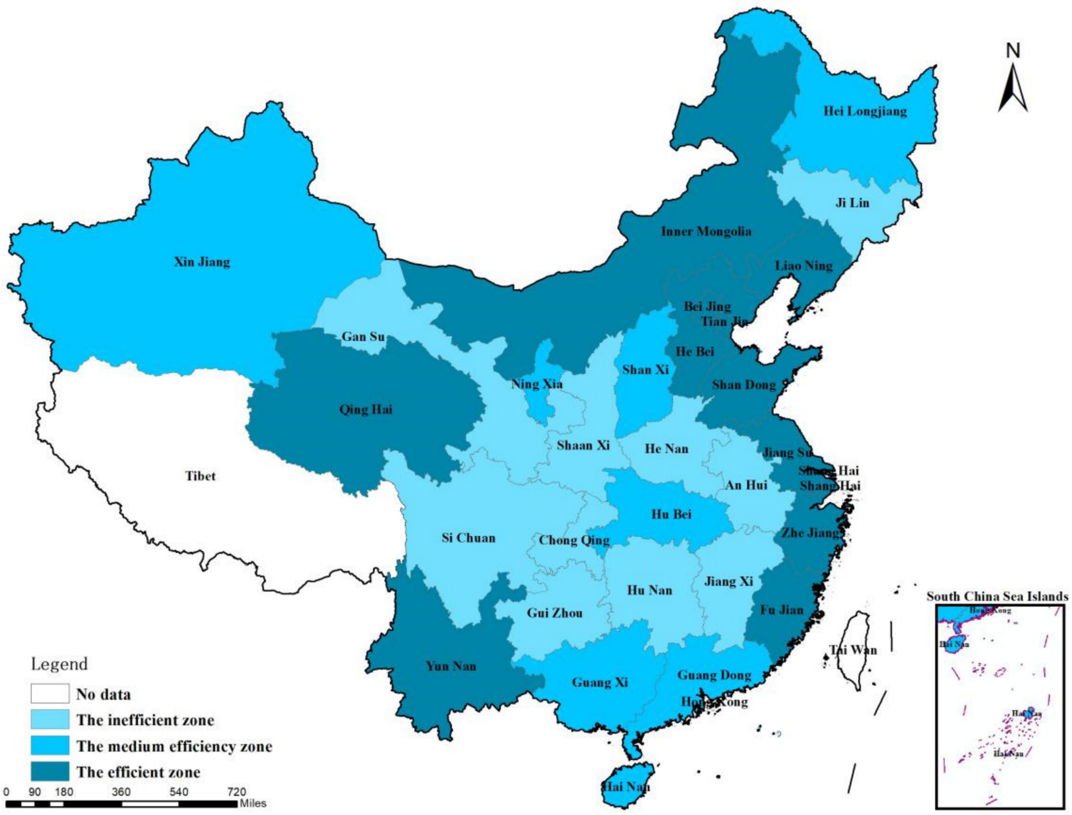

Figure 5. Spatial distribution of the WP efficiencies in China.

3.2. Spatial Correlation of the WP Efficiency

The WP efficiency at the provincial level in China has regional heterogeneity and specific spatial aggregation characteristics, as shown in Figure 5 [13]. Therefore, we further analyse the spatial aspects of WP efficiency at the regional level in China. Table 3 shows the global Moran's I index results for China from 2012 to 2017. Moran's I index for all years passes the significance test and fluctuates continuously over time. These results indicate that the WP efficiencies of the provinces in China are not randomly distributed in space, and there is a significant spatial correlation. Therefore, spatial factors should be taken into consideration when analysing the WP efficiency.

Table 3. Moran's I and statistical tests of the WP efficiency.

Year	Moran's I	Z-Value	*p*-Value
2012	0.228 **	2.266	0.021
2013	0.283 ***	2.753	0.007
2014	0.230 **	2.269	0.020
2015	0.400 ***	3.651	0.000
2016	0.361 ***	3.273	0.001
2017	0.159 *	1.636	0.061

Note: ***, ** and * indicate significant differences at the 1%, 5% and 10% levels, respectively.

A scatter plot of the local Moran's I index can be used to analyse the regional agglomeration characteristics of the WP efficiency. The points in the first quadrant indicate that high-efficiency provinces are surrounded by high-efficiency provinces, showing the spatial distribution characteristics of high and high clustering (H-H). The points in the second quadrant indicate that low-efficiency provinces are surrounded by high-efficiency provinces, showing the spatial distribution characteristics of low and high clustering (L-H). The points in the third quadrant indicate that inefficient provinces are surrounded by weak provinces, showing the spatial distribution characteristics of low and low clustering (L-L). The points in the fourth quadrant indicate that high-efficiency provinces are surrounded by low-efficiency provinces, showing the spatial distribution characteristics of high and low clustering (H-L). The WP efficiencies in 2013, 2014, 2015 and 2016 are selected to draw a local Moran's I scatter plot (Figure 6a–d). Most of China's provinces are distributed in the first or third quadrant of the graph (Table 4), indicating that China's WP efficiency has a significant positive spatial correlation, and over time, the trend towards spatial correlation has gradually increased; that is, China's WP efficiency shows significant spatial agglomeration characteristics. In addition, the distribution of provinces in each quadrant is relatively stable, with fewer changes in provinces, and the links between provinces tend to be tough. H-H clustering is mainly distributed in provinces such as Beijing, Hebei, Liaoning and Inner Mongolia, which are rich in wind energy resources, with a more developed economy and a higher technological level. L-L clustering is mainly distributed in provinces such as Sichuan, Chongqing, Hunan and Hubei. These areas have relatively low wind energy resources and are located in the south western and central regions of China, which are characterized by a complex geological environment. China's provincial WP efficiencies exhibit spatial agglomeration characteristics, which means that the WP progress in one province may affect that in other provinces. Therefore, the WP progress in surrounding areas should be considered to promote improvements in WP efficiency and the collective development of WP between regions.

Table 4. The distribution of provinces in different quadrants of Moran's I scatter plots.

Year	Type	Quantity	Province
2013	H-H	12	Beijing, Tianjin, Hebei, Liaoning, Shanxi, Shandong, Inner Mongolia, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Hainan
	L-H	3	Jilin, Guangdong, Xinjiang
	L-L	9	Hunan, Hubei, Shaanxi, Sichuan, Anhui, Jiangxi, Henan, Chongqing, Guizhou
	H-L	6	Yunnan, Fujian, Guangxi, Gansu, Ningxia, Qinghai
2014	H-H	12	Beijing, Tianjin, Hebei, Liaoning, Shanxi, Shandong, Inner Mongolia, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Ningxia
	L-H	4	Jilin, Guangdong, Henan, Gansu

Table 4. *Cont.*

Year	Type	Quantity	Province
	L-L	10	Hunan, Hubei, Shaanxi, Sichuan, Anhui, Jiangxi, Chongqing, Guizhou, Qinghai, Hainan
	H-L	4	Yunnan, Fujian, Guangxi, Xinjiang
2015	H-H	8	Beijing, Tianjin, Hebei, Liaoning, Shanxi, Inner Mongolia, Heilongjiang, Guangdong
	L-H	4	Jilin, Henan, Zhejiang, Ningxia
	L-L	13	Hunan, Hubei, Shaanxi, Sichuan, Anhui, Jiangxi, Chongqing, Guizhou, Qinghai, Gansu, Xinjiang, Shanghai, Guangxi
	H-L	5	Yunnan, Fujian, Hainan, Shandong, Jiangsu
2016	H-H	11	Beijing, Tianjin, Hebei, Liaoning, Shanxi, Shandong, Shanghai, Jiangsu, Zhejiang, Guangdong, Guangxi
	L-H	5	Jilin, Henan, Jiangxi, Heilongjiang, Guizhou
	L-L	9	Hunan, Hubei, Shaanxi, Sichuan, Anhui, Qinghai, Gansu, Xinjiang, Ningxia
	H-L	6	Yunnan, Fujian, Hainan, Anhui, Chongqing, Inner Mongolia

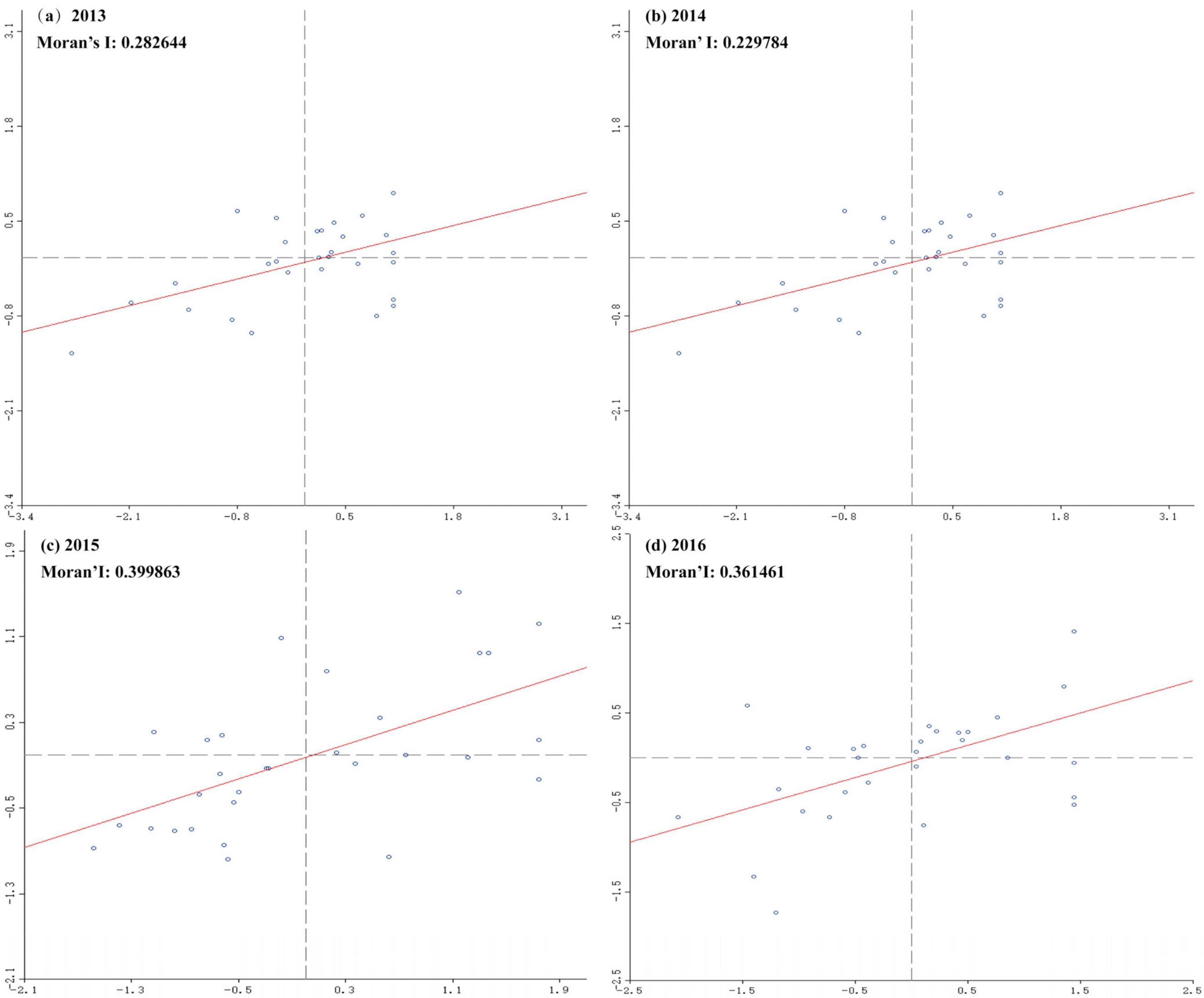

Figure 6. Moran's I scatter plots for the WP efficiencies of China's provinces.

3.3. Spatial Effects of WP Efficiency

China's WP efficiency has a significant positive spatial correlation; thus, an appropriate spatial measurement model is chosen to identify its spatial characteristics. The spatial spillover effects of various influencing factors are considered when performing the factor analysis. The test results of the spatial measurement model are shown in Table 5. First, the LM test results show that LMLAG, LMERR and R-LMLAG are significant at the 1% level, and R-LMERR is significant at the 5% level. When both the SEM and SLM are significant, the SDM should be selected. Second, according to the results of Hausman's test, the fixed effect is determined to be appropriate because its *p*-value is 0.000, which passes the significance test. Then, we further analyse the selection of the fixed effects model by employing the LR test. Table 5 shows that the fixed spatial effects pass the significance test; thus, the model is more appropriate. Based on the above test results, the SDM is used under spatial fixed effects to analyse the factors that affect the efficiency of WP production in China. The spatial lag of the spatial weight matrix W introduced by the SDM also reflects how a province's explanatory variables affect the WP efficiency of the surrounding area.

Table 5. Test results of spatial measurement model selection.

	Test Value	***p*-Value**	**Freedom**
LMLAG	16.4782 ***	0.000	
LMERR	10.9986 ***	0.001	
R-LMLAG	9.8935 ***	0.002	
R-LMERR	4.4139 **	0.036	
Hausman	364.8659 **	0.000	15
Spatial fixed effects (LR-SDM)	151.9164 **	0.000	30
Time-period fixed effects (LR-SDM)	9.3587	0.154	6

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

The LM, Hausman, and LR tests indicate that the SDM under spatial fixed effects is a suitable choice and has a solid ability to explain the factors affecting the WP efficiency at the provincial level in China. Consequently, we use the SDM under spatial fixed effects to analyse the influencing factors of WP efficiency in China, and the model estimation results are presented in Table 6.

Table 6. The estimation results of SDM under spatial fixed effects.

Variables	**Regression Coefficients**	**Variables**	**Regression Coefficients**
ln (ES)	0.1588 (0.5406)	Wln (ES)	−0.0516 (0.7324)
ln (UR)	0.6371 (0.5301)	Wln (UR)	1.6105 *** (0.0002)
ln (IL)	−0.2172 *** (0.0000)	Wln (IL)	−0.0174 (0.3907)
ln (CEI)	−0.5542 ** (0.0203)	Wln (CEI)	−0.7090 *** (0.0000)
ln (TP)	0.0351 (0.3458)	Wln (TP)	0.0047 (0.8147)
ln (TGD)	0.3945 (0.3319)	Wln (TGD)	−0.1599 (0.4348)
ln (LLR)	0.1205 (0.4071)	Wln (LLR)	0.0595 (0.4304)
R^2	0.5932		

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

Regarding the economic factors, the coefficient of the influence of the economic structure on WP efficiency is 0.1588, indicating that a specific industrial scale helps enhance WP efficiency. However, this impact is not significant, probably because some provinces have engaged in unreasonable large-scale industrial development. Consequently, the large-scale and rational development of WP properties can help improve the efficiency of WP production. The spatial spillover effect of the economic structure is negative and nonsignificant, which means that the economic form of a certain province has a restraining effect on the WP efficiencies of its neighbouring provinces, although the restraining impact is not apparent. The coefficient of influence of the level of urbanization on the efficiency of WP production is 0.637. The urbanization process has raised residents' awareness of consumption while also promoting the status of final energy consumption. The continuous consumption of conventional fossil energy and the daily problems caused by environmental pollution have brought increased attention to the development and utilization of WP. However, the statistical impact of this indicator is not significant, which indicates that the current level of urbanization has not significantly promoted the development of RE, and an improvement in the urbanization rate may worsen the financial subsidy gap for WP, making it difficult to enhance its efficiency. The spatial spillover coefficient of the urbanization level is 1.6105, indicating that the urbanization level of the focal province will increase the WP efficiencies of its neighbouring areas, because with the continuous increase in urbanization, increases in power consumption can accelerate power transactions and flows between regions, thereby promoting WP efficiency improvements. The government should use the spillover effects of urbanization to encourage the coordination of natural and social resources between regions. The influence coefficient of fixed asset investment on WP efficiency is −0.2172, which indicates that a fixed-asset investment has an inhibitory effect on WP efficiency. This result may be related to the excessive investment in WP properties at this stage. Investors can overvalue the expansion of the installed capacity [10] and ignore the potential for quality improvements in WP development, thereby reducing the efficiency of WP production. It is worth noting that the impact of fixed asset investment on WP efficiency is more significant than other factors. Driven by the price adjustment policy of WP, investors pay more attention to the increase in WP installed capacity but ignore the coordinated development of WP and grid construction, leading to large-scale wind curtailment. In this sense, China's WP industry's irrational investment and economically unviable production are very prominent [12]. The spatial spillover effect coefficient of fixed asset investment is −0.0174, indicating that the level of fixed asset investment in WP properties in the focal province will inhibit the WP efficiencies of the neighbouring provinces, although this effect is not apparent.

Regarding the environmental factors, the impact coefficient of the carbon emission intensity on the WP efficiency is −0.5542, which indicates that under severe pressure to reduce emissions and the implementation of related measures, the decline in the provincial carbon emissions is effectively driving WP efficiency improvements, which also shows that the development of RE can effectively reduce carbon emissions and support China in achieving its carbon emission reduction goals. The spatial spillover coefficient of the carbon emission intensity is −0.7090, indicating that a decrease in the carbon emission intensity of a province can enhance the WP efficiencies of the surrounding provinces. In addition, the spatial spillover effect of carbon emission intensity is more significant than that of other factors. Over time, as an atmospheric pollutant, CO_2 has high spatial mobility and is easily affected by the natural environment and geographic location. Specifically, for provinces with high carbon emissions, the carbon emissions of their surrounding areas are also at a relatively high level. Therefore, strengthening the coordination of low-carbon development between neighbouring provinces can effectively improve the efficiency of WP production, reduce the efficiency gap between provinces and promote the sustainable development of WP properties. Regarding the scientific and technological factors, the coefficient of influence for the WP technology level on WP efficiency is 0.0351, although this indicator is not significant, indicating that innovative WP technologies can enhance WP efficiency. However, the application of innovative technologies in RE, such as those included in WP patents, is lagging and depreciating [36], leading to minor improvements in WP efficiency. The spatial spillover coefficient of the WP technology level is 0.0047 and does not pass the significance test, indicating that the exchange of WP innovation technologies between provinces is insufficient, that effective technology sharing has not been achieved and that specific technical barriers still exist. At the policy level, the influence coefficient of the grid density on the WP efficiency is 0.3945, indicating that high-density high-voltage grid construction can promote WP efficiency improvements. However, this index is not significant, mainly because there is information asymmetry between power grid construction and power supply construction, which leads to a lag in power grid construction [40] and fails to support the efficient transmission of WP substantially. Therefore, accelerating the construction of a high-voltage power grid and coordinating the planning of power supply construction would improve the efficiency of WP production. The spatial spillover coefficient of the power grid density is −0.1599, which is not significant. This shows that the construction level of a province's transmission network has a restraining effect on the efficiency of WP production in the surrounding area. This effect can be explained by the potential institutional and interest conflicts in power grid construction and power transmission among provinces [38], which leads to the slow building of an interprovincial high-voltage transmission network that cannot provide infrastructure guarantees for the interprovincial information of WP [14].

4. Conclusions and Policy Implications

China is under pressure to tackle climate change, achieve carbon emission reduction and fulfil its international responsibilities. RE power generation represented by WP provides an effective way for China to achieve its carbon emission reduction targets [22]. Our research analyses the influencing factors of WP efficiency at the provincial level in China using spatial measurement. This study differs from the existing studies based on traditional regression models, providing a new perspective for improving WP efficiency. SBM-DEA and SDM are used to accurately identify the characteristics of WP efficiency at the provincial level and the spatial effects of its factors. The specific conclusions are as follows:

(1) The spatial distribution characteristics of the WP efficiency among provinces in China show that the efficiency is higher within the eastern and western regions and lower within the central regions. We suggest that the eastern, central and western regions break the barriers between provinces to promote the value of advantageous resources and the diffusion of innovative technologies.

(2) The WP efficiencies of the different provinces in China are positively correlated in terms of spatial attributes. Most provinces in the eastern and western areas show H-H clustering characteristics, and most provinces in the central area show L-L clustering characteristics. We suggest that the governments of provinces consider WP development in the surrounding provinces as part of their own WP development process and promote the improvement of WP efficiency and the joint advancement of WP properties among regions.

(3) Provincial-level mechanisms aimed at controlling carbon emissions have driven improvements in WP efficiency, although the negative impact caused by excessive investment in WP properties must also be recognized. Factors such as economic structure, urbanization level, WP technology innovation and power grid construction have not reached their full potential for improving WP efficiency in China. We suggest that relevant departments reduce blind investment and optimize the energy mix. Moreover, adjusting the economic structure, rationally distributing industrial configurations, improving the timeliness of WP patent applications, and accelerating the construction of cross-regional high-voltage power grids can further enhance the WP efficiency. In addition, the development of distributed WP can be considered in areas with low wind resources, especially the central provinces.

(4) The urbanization process and the decline in carbon emission intensity have effectively driven improvements in the WP efficiencies of surrounding provinces. Factors such as economic structure, investment level, transmission grid construction and WP technology innovation have not reached their full potential for enhancing the WP efficiencies of surrounding provinces. We suggest that decision-makers make full use of the superior resources of highly efficient provinces, break down regional barriers and promote the benign diffusion of advanced technologies and resources to the surrounding areas [14].

Our research considers the spatial effects of WP efficiency by selecting critical economic, environmental, technological and policy factors to analyse the spatial impacts of WP efficiency, which addresses the lack of research on provincial WP production efficiency and provides suggestions for policymakers. WP is a strategic emerging resource in China, and it is still in its infancy. The research time is relatively short due to data availability. Any outliers or measurement errors in the data set may affect the efficiency calculation and regression results. Therefore, as a future extension of this research, we will evaluate the WP efficiency, conduct a factor analysis using a more comprehensive range of data sets and perform comparative studies at different time scales.

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