Article

Assessing the Economic-Environmental Efficiency of Energy Consumption and Spatial Patterns in China

Chenyu Lu [1,*], Peng Meng [1], Xueyan Zhao [1], Lu Jiang [2,3], Zilong Zhang [2] and Bing Xue [4,*]

[1] College of Geography and Environmental Science, Northwest Normal University, Lanzhou 730070, China; 18394163936@163.com (P.M.); zhaoxy@nwnu.edu.cn (X.Z.)

[2] College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China; jianglu@iae.ac.cn (L.J.); zhangzl@lzu.edu.cn (Z.Z.)

[3] Key Lab for Environment Computation and Sustainability of Liaoning Province, Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110016, China

[4] Institute for Advances Sustainability Studies e. V., 14467 Potsdam, Germany

* Correspondence: luchenyu@nwnu.edu.cn (C.L.); xuebing@iae.ac.cn or bing.xue@iass-potsdam.de (B.X.)

check for updates

Abstract: The improvement of energy consumption efficiency represents a significant task and a critical step toward sustainable energy transformations. This study uses a data envelopment analysis (DEA) and spatial autocorrelation method to conduct comprehensive measurement and assessment research on the economic-environmental efficiency of energy consumption in 31 Chinese provinces. It then carries out a synthetic study on energy consumption efficiency in the context of temporal and spatial dimensions, analyzes the characteristics and patterns related to temporal and spatial evolution, and systematically summarizes the temporal and spatial evolution processes associated with China's economic-environmental efficiency in energy consumption. The results show that economic efficiency and environmental efficiency, both directly related to energy consumption, are positively correlated and display a parallel and synchronizing relationship. China's energy consumption efficiency displays an upward trend in general, although differences exist between economic efficiency and environmental efficiency about the growth rate and overall development level. In other words, economic efficiency is generally higher than environmental efficiency. A positive spatial correlation occurs between economic and environmental efficiency in energy consumption across all the Chinese provinces studied. Furthermore, some cluster characteristic can be identified. Accurately, the eastern coastal area of China with a higher efficiency represents a spatial cluster of high values, whereas the midwestern inland area of China with a lower efficiency represents a spatial cluster of low values. Therefore, a descending pattern is displayed from the east to the west. As time goes by, the extent of clustering could become more prominent, accompanied by an increasing spatial cluster of high values and a decreasing spatial cluster of low values. Accordingly, China needs to improve its energy consumption efficiency further and promote sustainable energy transformations.

Keywords: energy transition; energy efficiency; data envelopment analysis; spatial autocorrelation; China

1. Introduction

Energy consumption is a global issue that affects the extent of climate change and environmental pollution. Moreover, it determines whether the goal of global sustainable development can be achieved successfully. One of the core aspects of sustainable energy transformations is to improve energy consumption efficiency, or ensure that the intensity of energy consumption and resource utilization is in line with the Earth's capacity [1]. By doing so, high socioeconomic-ecological values could be achieved at

a relatively low cost of energy consumption, environmental alternation, and ecological damage. Given the continuous expansion of the demand for energy, rapid growth in energy consumption and low growth in energy production, one of the top priorities for sustainable development and environmental protection is to reduce energy usage and improve energy consumption efficiency [2]. The economic efficiency of energy consumption represents the economic benefits that energy consumption can provide. Under such circumstances, research on economic-environmental efficiency in energy consumption should not only include an assessment of economic efficiency and environmental efficiency, both closely related to energy consumption issues, but also comprise an assessment of energy consumption efficiency based on economic and environmental factors [3]. China is a vast country with uneven regional development and significant differences exist across its regions regarding energy consumption efficiency [4]. Therefore, the narrowing of the gap in energy consumption efficiency across its regions will help improve the overall energy consumption efficiency at a national level and promote the full realization of sustainable development.

This study uses a data envelopment analysis (DEA) and spatial autocorrelation method to quantify the economic-environmental efficiency of energy consumption in 31 Chinese provinces. Based on a comparative analysis of their evolutionary characteristics and patterns, we further systematically analyze the temporal and spatial evolution processes associated with China's economic-environmental efficiency in energy consumption. On the one hand, this study can help enrich and expand theories of human-land relationships and strengthen China's research on topics related to sustainable energy transformations. On the other hand, it could help the government to scientifically formulate China's sustainable energy transformation and development strategies and effectively coordinate the relationship between energy consumption, economic development, and environmental protection. As a result, the demands of Low-Carbon Green Growth could be met, and the goal of sustainable development could be fully achieved. Therefore, this study is both theoretically meaningful and of practical significance.

2. Literature Review

Generally speaking, energy consumption efficiency is the maximum output with certain energy input or the minimum energy input with a specified output [5]. The measurement of energy consumption efficiency can be categorized into two major types: Single-factor energy efficiency measurement and total-factor energy efficiency measurement. Single-factor energy efficiency is a partial factor productivity indicator that measures energy consumption and economic efficiency. For a specific economy, it usually refers to the ratio of the effective output to the energy input, as represented by the index of energy consumption per GDP. For example, Jimenez et al. [6] decomposed energy consumption intensity into changes in aspects such as economic structure, production levels, the extent of efficiency and fuel sources. Filippini et al. [7] believed that changes in economic structure, efficiency, technology, and the environment could all lead to changes in energy consumption intensity. Thus, energy consumption intensity was not a good indicator of energy efficiency. Proskuryakova et al. [8] concluded that, although energy consumption intensity could, to some extent, reflect energy consumption conditions, it did not represent energy efficiency effectively. Indeed, the single-factor energy efficiency method only measures a proportional relationship between energy inputs and outputs and fails to take into account all the other factors that function in the process of production, or the combined impacts of these input factors on energy efficiency. By contrast, the total-factor energy efficiency method is based on the theory of total factor productivity (TFP). It considers not only energy input factors that function in the process of production, but also the impacts of other input factors, such as technology, capital, and labor. Thus, it has some distinct advantages over the traditional single-factor energy efficiency method. To some extent, it compensates for the weaknesses of the single-factor energy efficiency method. At present, the measurement method of total factor energy efficiency is mainly based on DEA. According to the measurement scales for a specific study, it belongs to either a large-, medium-, or small-scale type.

At the national level, quite a few studies have been conducted. For example, Gökgöz et al. used the DEA method to measure energy consumption efficiency in EU countries [9]. Simsek [10]

quantified energy consumption efficiency in 23 OECD countries and demonstrated that countries such as Ireland, Japan, Norway, Switzerland, the UK, and the US display the highest level of energy consumption efficiency. Borozan [11] also analyzed energy consumption efficiency in the EU region. Wrigley et al. [12] used Australia as an example to address how to improve the energy consumption efficiency of rental properties. Huang et al. [13] studied the driving force of China's energy intensity. Guan et al. [14] measured China's energy and environmental efficiency and analyzed the associated spatial distribution characteristics and evolution patterns. Huang [15] measured China's energy and environmental efficiency and ascertained the characteristics of China's spatial association networks related to energy and environmental efficiency, as well as the associated influencing factors. Also, Suzuki [16], Jebali [17], Wang [18], and other scholars also researched the measurement of energy efficiency at the national level. By contrast, at the provincial or state level, Bhat et al. [19] calculated the energy consumption efficiency and estimated energy saving potential for each Indian state. Ghiyasi [20] quantified the energy consumption efficiency for each Iranian province. Ruizfuensanta [21] conducted a comparative analysis of energy consumption efficiency within the internal regions of Spain and concluded that significant differences existed among the various regions regarding the optimization of energy consumption. Martínez et al. [22] analyzed and evaluated the energy usage and efficiency characteristics of the manufacturing sector across the different regions of Colombia. Xu et al. [23] measured the energy consumption efficiency of nine provinces along the Silk Road Economic Belt and found that this region had a high potential for energy savings. Zhang et al. [24] analyzed the energy consumption efficiency in Xinjiang and pointed out that technological progress was one of the main reasons for improvements in this area. In addition, Sağlam [25], Wu [26], Qin [27], and other scholars also researched the measurement of energy efficiency at either the provincial or state level. Finally, for relatively small-scale studies, Poggi et al. [28] explored how to improve the energy consumption efficiency of Portuguese cities at the municipal level. Mohseni et al. [29] studied the energy flow patterns and environmental impacts of the grape production systems for 58 vineyards in Arak County, Iran. Raheli et al. [30] assessed the sustainability and energy consumption efficiency of tomato production industries in the Malan region of East Azerbaijan, Iran. Goto et al. [31] evaluated the operational and environmental efficiency of regional industries in Japan based on surveys of manufacturing and non-manufacturing industries across 47 counties. Zhang et al. [32] analyzed the energy consumption efficiency among prefecture-level cities in the Jiangsu province and found that the overall energy consumption efficiency of these cities displayed a downward trend. Jiang [33] analyzed the energy consumption efficiency and associated influencing factors of 110 Chinese prefecture-level cities, and proposed "one city and one policy" as part of energy development strategies. Also, Imran [34], Sun [35], Huang [36], and other scholars have also researched the measurement of energy efficiency at the city or smaller levels.

Currently, most existing studies focus on the partial measurement of certain aspects of energy consumption efficiency, but research on the comprehensive measurement of both economic efficiency and environmental efficiency is minimal. The extant studies measure energy consumption efficiency on the temporal dimension, but the integration of spatial analysis is often lacking. In other words, systematic research on energy consumption efficiency that includes both temporal and spatial dimensions is very limited. Therefore, this study should compensate for the gap in the existing knowledge.

3. Research Method and Data

3.1. The Assessment of Economic-Environmental Efficiency in Energy Consumption

3.1.1. DEA

DEA is an assessment method used for studying the relative efficiency among organizations of the same type (decision units) with multiple inputs and outputs [5]. The basic principle is to first determine all the production possibility sets according to the original data, then compare a single decision unit with the determined optimal production frontier so that the relative efficiency of the decision unit can

be calculated. Based on the research results of Ewertowska [37], Borozan [11], Fang [38], and Wang [18], this study selects the slacks-based measure-undesirable (SBM-Undesirable) model to measure the economic-environmental efficiency in energy consumption.

The establishment of the SBM-Undesirable model is based on the following principles: Let us assume that there are n decision making units, m input indicators, s_1 expected outputs and s_2 non-expected outputs. Therefore, for the ith decision-making unit, the corresponding input matrix X, expected output matrix Y and non-expected output matrix Z are:

$$
\begin{aligned}
X &= (x_{i1}, x_{i2}, \cdots, x_{im}) \in R^{n \times m}, X > 0 \\
Y &= (y_{i1}, y_{i2}, \cdots, y_{iS_1}) \in R^{n \times S_1}, Y > 0 \\
Z &= (y_{i1}, y_{i2}, \cdots, y_{is_2}) \in R^{n \times s_2}, Z > 0
\end{aligned}
\tag{1}
$$

All production possibility sets based on the decision-making units are:

$$
P(x) = \{(x, y, z) | x \leq \lambda X, y \leq \lambda Y, z \leq \lambda Z, \lambda \geq 0\}
\tag{2}
$$

The mathematical form of the model is:

$$
\rho = min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{ik}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^Y}{y_{rk}} + \sum_{t=1}^{s_2} \frac{s_t^Z}{z_{tk}} \right)}
\tag{3}
$$

$$
st \begin{cases}
x_k = \lambda X + B^- \\
y_k = \lambda Y - B^Y \\
z_k = \lambda Z + B^Z \\
B^- \geq 0, B^Y \geq 0, B^Z \geq 0, \lambda \geq 0
\end{cases}
\tag{4}
$$

In these formulas: ρ is the objective function of the SBM-Undesirable model; x_k, y_k, and z_k represent the indicators of inputs, expected outputs and non-expected outputs, respectively; st represents that the objective function is subject to the set of restrictions; s^-, s^Y and s^Z represent the relaxation variables of inputs, expected outputs and non-expected outputs, respectively; B^-, B^Y and B^Z represent the relaxation vectors of inputs, expected outputs and non-expected outputs, respectively; and λ is the density vector, representing the weight of each element. If $\rho = 1$, and $s^- = s^Y = s^Z = 0$, this indicates that the decision making unit is valid; otherwise, it is invalid. In the latter case, there is room for further improvement with regard to inputs or outputs. The calculation of Formula 3 and 4 can not only measure the impact of energy consumption on economic development based on expected output, but also effectively evaluate the impact of energy consumption on the environment under non-expected output.

3.1.2. Indicators and Data

According to the researching findings of Yang [39], Chen [40], Suzuki [16], Zhu [41], and Guan [14], we select indicators that are used more frequently and conduct research based on 31 provinces, autonomous regions, and municipalities directly under the Chinese Central Government (regions in Hong Kong, Macao, and Taiwan are not considered due to the lack of relevant statistical data) between 2000 and 2017. The specific indicators include:

Input indicators:

(1) Energy input: The total amount of energy consumption, with relevant data obtained from China's Energy Statistics Yearbook.

(2) Capital investment: The investment in fixed assets of each province is based on the cost price in 1999, with relevant data obtained from China's Statistical Yearbook.

(3) Labor input: The number of employees (the average number of employees at the end of the year and the number of employees at the end of the previous year), with relevant data obtained from China's Statistical Yearbook.

(4) Technology input: The transaction amount of the technology market, with relevant data obtained from China's Statistical Yearbook.

Output indicators:

(1) Economic output (expected output): GDP per capita, with relevant data obtained from China's Statistical Yearbook.

(2) Environmental output (unexpected output): CO_2 emissions, exhaust emissions, wastewater discharge, and solid waste emissions. CO_2 emissions are estimated according to the methods developed by the Intergovernmental Panel on Climate Change (IPCC, 2006), with associated parameters determined mainly by reference to results from the relevant research [5,10,14], and environmental output data obtained from China's Statistical Yearbook.

3.2. Spatial Autocorrelation Analysis

3.2.1. Global Spatial Autocorrelation Analysis

The global spatial autocorrelation can be applied to analyze the spatial correlation and cluster patterns regarding energy consumption efficiency in the region as a whole and is generally performed by calculating the global Moran's I index. According to the related literature [5,42–44], the formula used for quantifying the global Moran's I index is:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \left(Y_i - \overline{Y}\right) \left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2} \tag{5}$$

In which I represent the global Moran's I index, n represents the total number of samples, $\overline{Y}$ represents the average value of all samples, Y_i represents the value of the *i*th sample, Y_j represents the value of the *j*th sample, and W_{ij} denotes the spatial weight matrix. A binary adjacency matrix is selected, where spatially adjacent = 1, and non-adjacent = 0. To further determine whether there is a spatial autocorrelation relationship, a significant test of I is required, with the formula as:

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{6}$$

where Z is the test value of the global Moran's I, $E(I)$ is the expectation of I, and $Var(I)$ is the variance of I.

3.2.2. Local Spatial Autocorrelation Analysis

The global spatial autocorrelation only describes the overall spatial distribution patterns. However, since it averages the differences among regions, it does not reflect the spatial dependence of each region. Therefore, it is necessary to conduct a local spatial autocorrelation analysis so that the changing trend of spatial differences regarding energy consumption efficiency can be reflected more comprehensively, and the local spatial distribution characteristics can be better ascertained. According to the related literature [14,42], the formula used for calculating the local Moran's I index is:

$$I_i = \frac{n \left(Y_i - \overline{Y}\right) \sum_{j=1}^{n} W_{ij} \left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)} \tag{7}$$

where I_i represents the local Moran's I index for the *i*th province, n represents the total number of samples, $\overline{Y}$ represents the average value of all samples, Y_i represents the value of the *i*th sample, Y_j represents the value of the *j*th sample, and W_{ij} represents the spatial weight matrix.

In order to further determine whether there is a spatial autocorrelation relationship, a significant test of I_i is required, with the formula as:

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{Var(I_i)}} \tag{8}$$

where $Z(I_i)$ is the test value of the local Moran's I for the ith province, $E(I_i)$ is the expectation of I_i, and $Var(I_i)$ is the variance of I_i.

According to the results from the calculations, four types of spatial correlation can be defined: The types of high-high (H-H), low-high (L-H), high-low (H-L), and low-low (L-L). Among them, H-H and L-L represent a positive spatial autocorrelation, while L-H and H-L represent a negative spatial autocorrelation.

4. Results and Discussion

4.1. The Analysis of the Economic-Environmental Efficiency in Energy Consumption

4.1.1. Economic Efficiency in Energy Consumption

The economic efficiency in energy consumption between 2000 and 2017 was quantified for China's 31 provinces (municipalities and autonomous regions included), with the results shown in Table 1.

Table 1. Economic efficiency in energy consumption between 2000 and 2017 for China's 31 provinces.

Province	Year								
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Beijing	0.955	0.956	0.957	0.959	0.961	0.964	0.966	0.969	0.970
Tianjin	0.822	0.826	0.830	0.833	0.839	0.844	0.845	0.847	0.847
Hebei	0.559	0.557	0.560	0.564	0.589	0.608	0.614	0.628	0.624
Shanxi	0.517	0.526	0.531	0.539	0.562	0.571	0.570	0.581	0.583
Inner Mongolia	0.585	0.583	0.585	0.587	0.589	0.594	0.596	0.597	0.601
Liaoning	0.882	0.886	0.884	0.889	0.891	0.896	0.897	0.896	0.899
Jilin	0.687	0.670	0.675	0.677	0.691	0.721	0.728	0.731	0.739
Heilongjiang	0.721	0.726	0.727	0.735	0.739	0.742	0.751	0.759	0.767
Shanghai	0.962	0.963	0.962	0.964	0.965	0.968	0.970	0.971	0.971
Jiangsu	0.798	0.799	0.802	0.806	0.814	0.819	0.818	0.820	0.821
Zhejiang	0.786	0.788	0.787	0.789	0.801	0.801	0.804	0.811	0.818
Anhui	0.688	0.689	0.692	0.694	0.699	0.702	0.709	0.716	0.721
Fujian	0.793	0.810	0.823	0.836	0.850	0.862	0.871	0.879	0.881
Jiangxi	0.661	0.668	0.673	0.678	0.682	0.684	0.689	0.690	0.698
Shandong	0.643	0.649	0.651	0.657	0.658	0.662	0.667	0.669	0.670
Henan	0.639	0.641	0.649	0.650	0.653	0.654	0.655	0.657	0.657
Hubei	0.628	0.629	0.629	0.631	0.632	0.634	0.636	0.641	0.644
Hunan	0.657	0.657	0.659	0.660	0.662	0.664	0.667	0.668	0.670
Guangdong	0.971	0.974	0.978	0.979	0.981	0.984	0.985	0.987	0.988
Guangxi	0.671	0.672	0.673	0.675	0.674	0.676	0.679	0.680	0.682
Hainan	0.898	0.899	0.901	0.907	0.909	0.913	0.914	0.916	0.919
Chongqing	0.679	0.681	0.680	0.682	0.684	0.685	0.687	0.688	0.690
Sichuan	0.539	0.543	0.549	0.551	0.559	0.563	0.567	0.569	0.572
Guizhou	0.473	0.474	0.476	0.477	0.476	0.479	0.480	0.482	0.483
Yunnan	0.549	0.550	0.553	0.554	0.559	0.560	0.561	0.563	0.564
Tibet	0.301	0.302	0.304	0.305	0.308	0.310	0.311	0.313	0.314
Shanxi	0.481	0.482	0.481	0.483	0.486	0.488	0.489	0.493	0.494
Gansu	0.460	0.461	0.463	0.468	0.469	0.471	0.472	0.475	0.476
Qinghai	0.426	0.427	0.428	0.426	0.428	0.429	0.431	0.432	0.434
Ningxia	0.453	0.457	0.458	0.460	0.461	0.462	0.464	0.467	0.468
Xinjiang	0.438	0.439	0.441	0.442	0.443	0.444	0.447	0.449	0.450
Average	0.6566	65.1928	65.2260	65.262	65.299	0.6583	65.371	65.406	65.441

Table 1. *Cont.*

Province	Year								
	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.971	0.979	0.980	0.980	0.981	0.983	0.984	0.987	0.988
Tianjin	0.850	0.852	0.857	0.855	0.861	0.869	0.874	0.879	0.882
Hebei	0.687	0.752	0.752	0.761	0.770	0.786	0.793	0.801	0.802
Shanxi	0.594	0.615	0.624	0.629	0.647	0.650	0.662	0.667	0.674
Inner Mongolia	0.614	0.627	0.630	0.638	0.647	0.658	0.663	0.671	0.710
Liaoning	0.904	0.911	0.915	0.918	0.921	0.925	0.928	0.930	0.931
Jilin	0.747	0.753	0.759	0.766	0.770	0.738	0.824	0.828	0.830
Heilongjiang	0.775	0.783	0.791	0.791	0.796	0.805	0.810	0.814	0.816
Shanghai	0.972	0.973	0.976	0.977	0.979	0.982	0.986	0.989	0.991
Jiangsu	0.824	0.825	0.829	0.830	0.835	0.841	0.849	0.850	0.851
Zhejiang	0.826	0.837	0.841	0.848	0.856	0.864	0.872	0.876	0.878
Anhui	0.727	0.731	0.738	0.746	0.749	0.756	0.764	0.768	0.770
Fujian	0.890	0.896	0.896	0.899	0.904	0.909	0.914	0.917	0.918
Jiangxi	0.705	0.709	0.716	0.721	0.725	0.729	0.734	0.736	0.737
Shandong	0.673	0.678	0.680	0.684	0.689	0.711	0.724	0.725	0.728
Henan	0.659	0.663	0.669	0.671	0.675	0.681	0.685	0.688	0.690
Hubei	0.645	0.647	0.648	0.648	0.649	0.651	0.652	0.654	0.658
Hunan	0.672	0.673	0.675	0.676	0.679	0.680	0.682	0.682	0.684
Guangdong	0.990	0.991	0.992	0.994	0.995	0.996	0.997	0.997	0.998
Guangxi	0.683	0.685	0.688	0.689	0.691	0.692	0.695	0.696	0.698
Hainan	0.921	0.924	0.925	0.928	0.930	0.934	0.936	0.937	0.939
Chongqing	0.691	0.692	0.694	0.698	0.710	0.718	0.724	0.732	0.736
Sichuan	0.573	0.574	0.576	0.577	0.579	0.580	0.583	0.585	0.586
Guizhou	0.485	0.486	0.487	0.487	0.489	0.490	0.491	0.493	0.494
Yunnan	0.566	0.569	0.570	0.571	0.572	0.573	0.577	0.579	0.580
Tibet	0.316	0.317	0.318	0.321	0.322	0.325	0.326	0.327	0.329
Shanxi	0.495	0.497	0.498	0.499	0.501	0.504	0.505	0.507	0.508
Gansu	0.478	0.479	0.481	0.484	0.485	0.486	0.488	0.489	0.491
Qinghai	0.435	0.437	0.438	0.440	0.441	0.445	0.447	0.449	0.450
Ningxia	0.469	0.471	0.473	0.476	0.477	0.479	0.480	0.483	0.484
Xinjiang	0.452	0.453	0.455	0.458	0.459	0.461	0.464	0.465	0.467
Average	67.6467	0.66	67.721	0.699	67.795	67.832	0.663	67.908	0.668

(1) The economic efficiency of China's energy consumption displays a rising trend. The average values increased from 0.656 in 2000 to 0.719 in 2017 (an increase of 0.063). In recent years, other scholars also conducted similar studies. For example, Zhang [45] and other scholars concluded that China's regional energy efficiency keeps increasing. Similarly, Tang [46] found that China's economic efficiency in energy consumption is also on the rise, and Zhao [47] suggested that China's overall energy usage efficiency is showing an upward trend. It can be seen, therefore, that since 2000, China has paid more attention to energy consumption, and its economic efficiency in energy consumption is continuously improving.

(2) There is a non-equilibrium situation regarding the economic efficiency in energy consumption across Chinese provinces. In 2000, the Guangdong province had the highest economic efficiency in energy consumption (0.971), whereas the Tibet autonomous region had the lowest economic efficiency in energy consumption (0.301), a difference of 0.67. In 2017, the Guangdong province still had the highest economic efficiency in energy consumption (0.990), and the Tibet autonomous region still had the lowest value (0.316), a difference of 0.674 (Figure 1). The gap is large, and this difference will exist for a relatively long time.
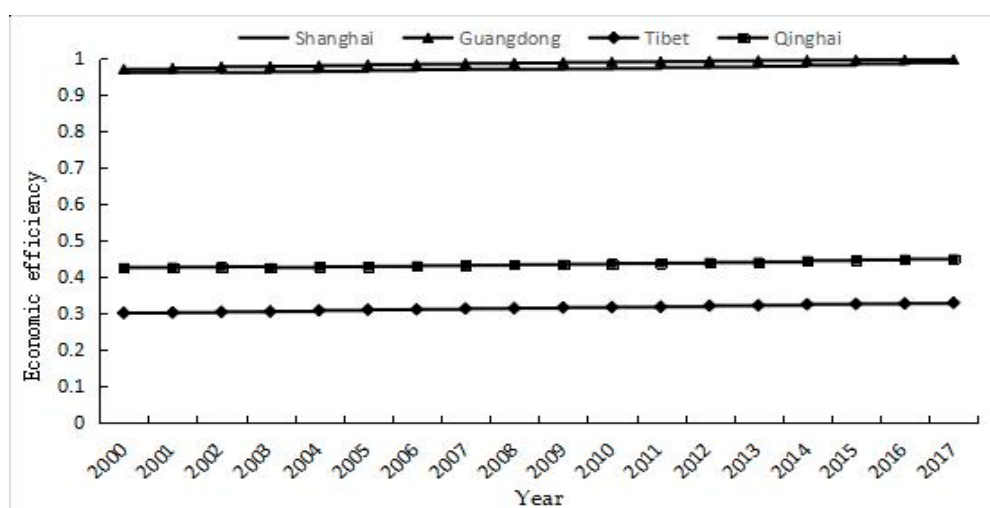
Figure 1. Economic efficiency comparison in Guangdong, Shanghai, Qinghai, and Tibet.

As far as the provinces are concerned, Beijing, Shanghai, and many southeast coastal provinces, such as Guangdong, generally have a high economic efficiency in energy consumption, and they represent high-level development zones. By contrast, Xinjiang, Qinghai, Tibet, and other western provinces generally have low economic efficiency in energy consumption, and they represent low-level development zones. In recent years, other scholars also conducted similar studies. For example, Yang [39] concluded that China's eastern provinces generally have a high energy consumption efficiency, whereas western provinces generally have a low energy consumption efficiency, with a large gap existing among provinces regarding energy consumption efficiency. Sun [48] also found out that, in China, there are significant regional differences in energy consumption efficiency, and the current energy allocation is not practical. Wang [49] concluded that China's economic efficiency in energy consumption differs regionally, and China's eastern coastal areas are superior to other regions in this regard. Zhao [50] also found that industrial districts in eastern China are more energy efficient than other regions. It can be seen that, in China, the overall economic efficiency in energy consumption shows obvious regional differences. Geographically speaking, there is a decreasing pattern from the east toward the west, or from the southeast toward the northwest, which is mainly related to the geographical location and industrial structure. There is a good level of economic growth in the eastern region of China, as this region has a geographical advantage and full access to financial, technical and information-related support. As a result, the processes of sustainable energy transformation and development can be accelerated, and economic efficiency in energy consumption can be improved. By contrast, the opposite situation is found in the western region. A relatively greater industrial structure is found in the eastern region of China, which takes the lead in the implementation of sustainable energy transformation and development strategy, and the strengthening of the input and consumption efficiency of available energy, so that the economic efficiency in energy consumption can be ultimately improved. Again, the opposite situation is found in the western region.

4.1.2. Environmental Efficiency in Energy Consumption

The environmental efficiency in energy consumption between 2000 and 2017 was quantified for China's 31 provinces (municipalities and autonomous regions included), with the results shown in Table 2.

Table 2. Environmental efficiency between 2000 and 2017 for China's 31 provinces.

Province	Year								
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Beijing	0.821	0.829	0.837	0.848	0.857	0.869	0.867	0.872	0.880
Tianjin	0.721	0.732	0.739	0.743	0.756	0.763	0.769	0.776	0.781
Hebei	0.498	0.503	0.506	0.509	0.511	0.514	0.522	0.529	0.531
Shanxi	0.421	0.428	0.433	0.438	0.441	0.448	0.453	0.460	0.466
Inner Mongolia	0.563	0.570	0.576	0.581	0.587	0.594	0.599	0.563	0.568
Liaoning	0.671	0.678	0.682	0.689	0.697	0.709	0.715	0.720	0.727
Jilin	0.642	0.649	0.657	0.660	0.668	0.674	0.679	0.686	0.691
Heilongjiang	0.710	0.716	0.720	0.728	0.731	0.738	0.742	0.749	0.752
Shanghai	0.913	0.917	0.924	0.928	0.932	0.938	0.943	0.949	0.953
Jiangsu	0.791	0.794	0.796	0.799	0.804	0.808	0.811	0.813	0.816
Zhejiang	0.698	0.699	0.672	0.675	0.679	0.682	0.687	0.691	0.694
Anhui	0.613	0.618	0.621	0.624	0.629	0.634	0.638	0.640	0.645
Fujian	0.784	0.787	0.789	0.790	0.792	0.796	0.798	0.801	0.803
Jiangxi	0.642	0.647	0.650	0.654	0.657	0.661	0.664	0.669	0.672
Shandong	0.629	0.632	0.633	0.635	0.639	0.641	0.643	0.644	0.648
Henan	0.625	0.628	0.629	0.631	0.635	0.638	0.640	0.643	0.644
Hubei	0.619	0.621	0.622	0.624	0.626	0.627	0.629	0.629	0.631
Hunan	0.648	0.649	0.651	0.652	0.654	0.657	0.658	0.660	0.661
Guangdong	0.908	0.911	0.913	0.914	0.916	0.919	0.921	0.923	0.924
Guangxi	0.664	0.665	0.668	0.669	0.671	0.672	0.674	0.675	0.678
Hainan	0.886	0.889	0.891	0.892	0.892	0.894	0.895	0.897	0.899
Chongqing	0.583	0.585	0.586	0.588	0.591	0.596	0.597	0.599	0.602
Sichuan	0.527	0.529	0.532	0.533	0.535	0.536	0.538	0.541	0.542
Guizhou	0.432	0.433	0.435	0.437	0.440	0.443	0.445	0.448	0.449
Yunnan	0.537	0.539	0.542	0.546	0.548	0.549	0.551	0.552	0.554
Tibet	0.288	0.289	0.291	0.293	0.294	0.295	0.297	0.298	0.301
Shanxi	0.478	0.479	0.482	0.483	0.484	0.486	0.489	0.491	0.491
Gansu	0.376	0.378	0.379	0.381	0.383	0.384	0.386	0.389	0.390
Qinghai	0.424	0.425	0.427	0.428	0.429	0.431	0.433	0.434	0.437
Ningxia	0.469	0.470	0.472	0.473	0.475	0.477	0.478	0.481	0.482
Xinjiang	0.456	0.457	0.459	0.461	0.462	0.464	0.465	0.467	0.469
Average	65.116	65.151	65.1860	65.221	65.2576	65.293	65.328	65.362	65.397

Province	Year								
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Beijing	0.886	0.910	0.918	0.927	0.931	0.938	0.943	0.947	0.949
Tianjin	0.786	0.792	0.791	0.794	0.796	0.802	0.811	0.816	0.820
Hebei	0.539	0.547	0.551	0.558	0.567	0.573	0.582	0.589	0.594
Shanxi	0.471	0.479	0.482	0.487	0.490	0.496	0.501	0.508	0.513
Inner Mongolia	0.579	0.586	0.592	0.598	0.606	0.611	0.619	0.624	0.637
Liaoning	0.734	0.742	0.749	0.758	0.763	0.771	0.778	0.781	0.788
Jilin	0.695	0.713	0.719	0.726	0.732	0.739	0.744	0.749	0.756
Heilongjiang	0.760	0.768	0.776	0.781	0.785	0.788	0.792	0.799	0.807
Shanghai	0.958	0.961	0.964	0.965	0.968	0.970	0.972	0.973	0.975
Jiangsu	0.821	0.827	0.829	0.831	0.834	0.835	0.837	0.838	0.840
Zhejiang	0.698	0.701	0.705	0.709	0.714	0.716	0.719	0.723	0.725
Anhui	0.649	0.652	0.658	0.663	0.666	0.671	0.676	0.681	0.689
Fujian	0.804	0.806	0.809	0.810	0.812	0.813	0.816	0.817	0.819
Jiangxi	0.673	0.674	0.678	0.680	0.682	0.685	0.687	0.689	0.692
Shandong	0.652	0.655	0.657	0.658	0.657	0.659	0.661	0.664	0.669
Henan	0.645	0.647	0.648	0.650	0.652	0.654	0.657	0.658	0.660
Hebei	0.633	0.636	0.638	0.639	0.642	0.644	0.648	0.649	0.651
Hunan	0.664	0.665	0.666	0.669	0.671	0.672	0.672	0.675	0.678
Guangdong	0.927	0.929	0.932	0.934	0.935	0.937	0.938	0.941	0.943
Guangxi	0.679	0.681	0.683	0.685	0.686	0.688	0.689	0.691	0.693
Hainan	0.902	0.908	0.909	0.911	0.913	0.917	0.919	0.921	0.922
Chongqing	0.605	0.609	0.612	0.614	0.618	0.621	0.625	0.627	0.629

Table 2. *Cont.*

Province	Year								
	2009	2010	2011	2012	2013	2014	2015	2016	2017
Sichuan	0.544	0.545	0.548	0.551	0.552	0.554	0.557	0.559	0.561
Guizhou	0.451	0.452	0.454	0.457	0.458	0.461	0.463	0.464	0.466
Yunnan	0.557	0.559	0.562	0.563	0.565	0.566	0.568	0.570	0.571
Tibet	0.304	0.309	0.310	0.312	0.313	0.315	0.316	0.317	0.318
Shanxi	0.493	0.495	0.496	0.498	0.499	0.502	0.504	0.505	0.507
Gansu	0.392	0.393	0.395	0.396	0.398	0.401	0.402	0.403	0.405
Qinghai	0.439	0.440	0.441	0.443	0.445	0.446	0.447	0.449	0.451
Ningxia	0.484	0.485	0.487	0.488	0.489	0.491	0.493	0.494	0.496
Xinjiang	0.470	0.471	0.473	0.474	0.476	0.479	0.481	0.484	0.485
Average	67.598	67.636	67.672	67.709	67.745	67.782	67.818	67.854	67.891

(1) The environmental efficiency of China's energy consumption displays a rising trend. The average values increase from 0.614 in 2000 to 0.668 in 2017 (an increase of 0.054). However, compared to the economic efficiency in energy consumption, its growth rate is smaller. In recent years, other scholars also conducted similar studies. For example, Chen [40] found that China's environmental efficiency has increased, although the growth rate remains low. Huang [15] concluded that China's environmental efficiency in energy consumption is generally fluctuating and rising, although the growth rate is limited. Yang [51] suggested that China's environmental efficiency has generally improved. It can be seen that since 2000, China has paid a great deal of attention to environmental protection, with environmental awareness continuously enhanced and investment in environmental protection continuously accelerated. Nonetheless, while the environmental efficiency of China's energy consumption keeps increasing, it is still lower than its economic efficiency.

(2) There is a non-equilibrium situation regarding the environmental efficiency in energy consumption across Chinese provinces. In 2000, Shanghai had the highest environmental efficiency in energy consumption (0.913), whereas the Tibet autonomous region had the lowest environmental efficiency in energy consumption (0.288), a difference of 0.657. In 2017, Shanghai still had the highest economic efficiency in energy consumption (0.975), and the Tibet autonomous region still had the lowest value (0.318), a difference of 0.657 (Figure 2). Clearly, this gap is large and could continue to grow.
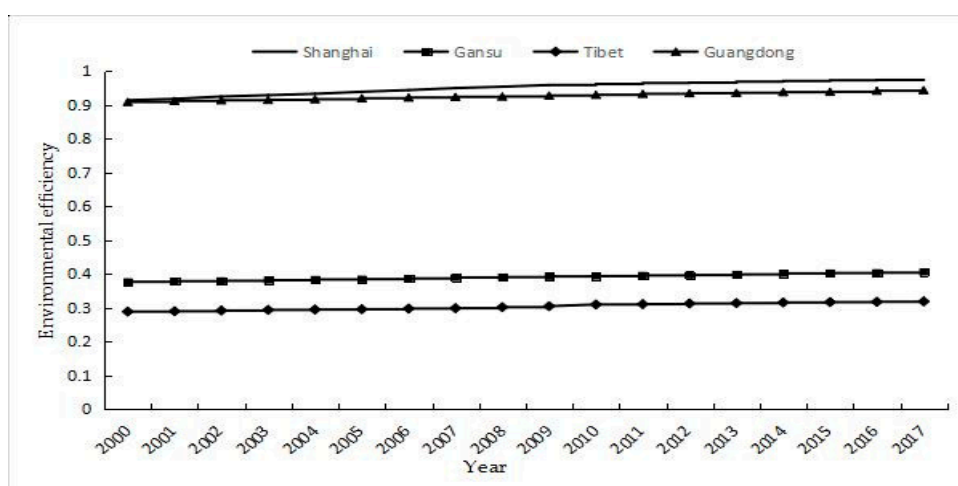

Figure 2. Efficiency comparison of energy consumption in Guangdong, Shanghai, Qinghai, and Tibet.

As far as the provinces are concerned, Beijing, Shanghai, and many southeast coastal provinces, such as Guangdong, generally have a high environmental efficiency in energy consumption, and they represent high-level development zones. By contrast, Qinghai, Tibet, Gansu, and other western provinces

generally have a low environmental efficiency in energy consumption, and they represent low-level development zones. In recent years, other scholars also conducted similar studies. For example, Song [52] found that China's eastern provinces generally have a high environmental efficiency. Chen [40] pointed out that significant differences exist regarding the environmental efficiency across Chinese provinces. Wang [49] concluded that as far as environmental efficiency in energy consumption is concerned, the overall development in China is unbalanced, with a decreasing trend from the east towards the west. It can be seen that, in China, the overall environmental efficiency in energy consumption shows obvious regional differences. Geographically speaking, there is a decreasing pattern from the east towards the west, or from the southeast towards the northwest, which is consistent with the spatial pattern of economic efficiency in energy consumption. Therefore, environmental efficiency is mainly affected by economic efficiency. In other words, regions with high economic efficiency in energy consumption should also have a high environmental efficiency, and vice versa.

4.2. Spatial Autocorrelation Analysis

4.2.1. Economic Efficiency in Energy Consumption

(1) Global spatial autocorrelation

The Global Moran's I index, as shown in Table 3, was statistically significant. In general, China's economic efficiency in energy consumption across the provinces displays a positive spatial correlation, with the characteristics of a cluster found at the provincial level. In other words, the economic efficiency in energy consumption is not distributed randomly; conversely, it shows a spatial cluster of high/low values. Provinces with higher economic efficiency in energy consumption tend to be adjacent to each other, whereas provinces with lower economic efficiency in energy consumption tend to be closer to one another. As time goes by, the degree of clustering keeps increasing, indicating that the spatial dependence of economic efficiency in energy consumption is becoming increasingly stronger.
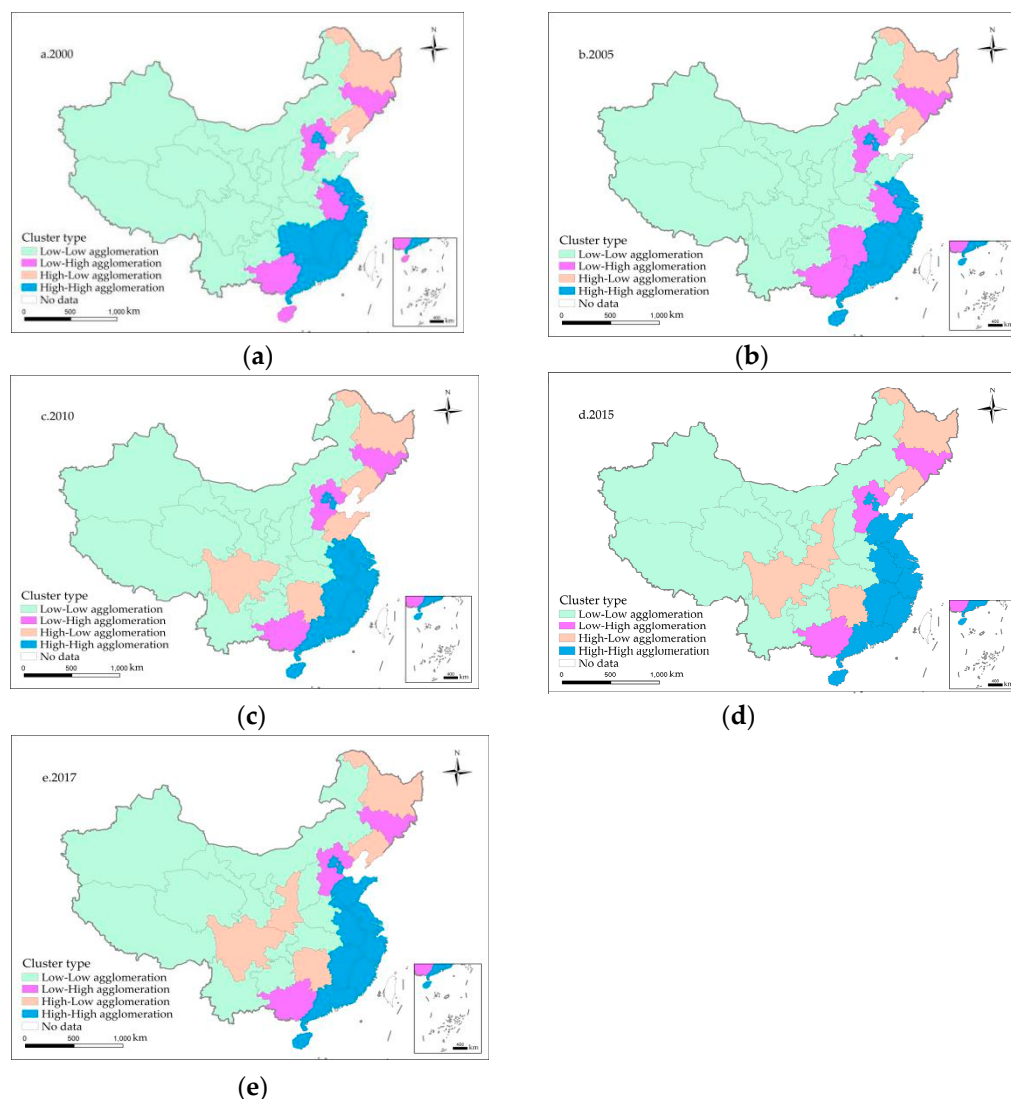
Table 3. Global Moran's I index of economic efficiency in energy consumption between 2000 and 2017.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008
I	0.234	0.248	0.262	0.281	0.294	0.334	0.329	0.332	0.389
Z	1.981	2.071	2.043	2.004	1.612	1.803	1.642	1.797	2.074
Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
I	0.393	0.399	0.422	0.392	0.339	0.347	0.411	0.424	0.453
Z	2.095	2.124	2.239	2.092	1.642	1.742	2.134	2.142	2.144

(2) Local spatial autocorrelation

In this study, we chose 2000, 2005, 2010, 2015, and 2017 as five representative years, and conducted a local spatial autocorrelation analysis. The Local Moran's I index was statistically significant. It can be seen from Figure 3 that the economic efficiency in energy consumption across Chinese provinces displays visible spatial cluster characteristics, accompanied by a strong spatial dependence and heterogeneity. Moreover, there are significant regional differences regarding economic efficiency in energy consumption. Shanghai, Guangdong, Zhejiang, and many other southeast coastal provinces generally maintain a high level of economic growth, representing a spatial cluster of high values. By contrast, Xinjiang, Qinghai, Tibet, and many other western provinces generally maintain a low level of economic growth, representing a spatial cluster of low values. As time goes by, the extent of clustering could become more prominent, accompanied by an increasing spatial cluster of high values and a decreasing spatial cluster of low values. For example, the number of spatial clusters of high values increased from nine in 2000 to 11 in 2017, while the number of spatial clusters of low values decreased from 15 in 2000 to 12 in 2017. In recent years, other scholars have also conducted similar studies, providing more evidence that there is a decrease in the number of spatial clusters of low values. For example, Zhang [45] found that China's regional energy efficiency displayed a significant spatial

autocorrelation and noticeable spatial effects, with a decreasing trend from coastal areas towards inland areas. Tang [46] concluded that China's economic efficiency in energy consumption is spatially dependent with high heterogeneity. All provinces with a high efficiency belong to eastern zones with high levels of economic growth, whereas midwestern inland areas of China have intermediate or low levels of economic efficiency. It can be seen that China's economic efficiency in energy consumption displays some visible spatial cluster characteristics. In other words, there is a gradual transition from the east towards the west, or from the southeast towards the northwest, where high-value clusters have transitioned to low-value clusters. Therefore, the location factor plays a critical role in affecting the economic efficiency in energy consumption.

(**a**)　　　　　　　　　　(**b**)

(**c**)　　　　　　　　　　(**d**)

(**e**)

Figure 3. Correlation of economic efficiency in energy consumption in China.

4.2.2. Environmental Efficiency in Energy Consumption

(1) Global spatial autocorrelation

The Global Moran's I index, as shown in Table 4, was statistically significant. In general, China's environmental efficiency in energy consumption across the provinces displays a positive spatial correlation, with the characteristics of a cluster found at the provincial level. In other words, the environmental efficiency in energy consumption is not distributed randomly. Conversely, it shows a spatial cluster of high/low values. Provinces with higher environmental efficiency in energy

consumption tend to be adjacent to each other, whereas provinces with lower environmental efficiency in energy consumption tend to be closer to one another.

Table 4. Global Moran's I index of environmental efficiency in energy consumption between 2000 and 2017.

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008
I	0.279	0.312	0.356	0.298	0.402	0.456	0.411	0.435	0.324
Z	2.085	2.135	2.056	1.988	2.901	3.125	2.856	2.963	2.657
Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
I	0.419	0.431	0.368	0.345	0.439	0.402	0.325	0.420	0.311
Z	3.411	3.103	2.132	2.429	3.162	3.125	2.198	3.022	2.731

(2) Local spatial autocorrelation

In this study, we chose 2000, 2005, 2010, 2015, and 2017 as five representative years, and conducted a local spatial autocorrelation analysis. The Local Moran's I index was statistically significant. It can be seen from Figure 4 that China's environmental efficiency in energy consumption across the provinces generally displays a robust spatial autocorrelation and visible spatial cluster characteristics. Shanghai, Guangdong, Fujian, and many other southeast coastal provinces generally display a high environmental efficiency in energy consumption, representing spatial clusters of high values. By contrast, Xinjiang, Qinghai, Gansu and many other western provinces generally display a low environmental efficiency in energy consumption, representing spatial clusters of low values. As time goes by, the extent of clustering could become more prominent, accompanied by an increasing spatial cluster of high values and a decreasing spatial cluster of low values. For example, the number of spatial clusters of high values increased from seven in 2000 to 11 in 2017, while the number of spatial clusters of low values decreased from 13 in 2000 to 10 in 2017. In recent years, other scholars have also conducted similar studies, providing more evidence that there is a decrease in the number of spatial clusters of low values. For example, Huang [15] found that China's regional environmental efficiency in energy consumption displayed significant spatial differences, with a decreasing trend from the east towards the west; furthermore, there were obvious spatial non-equilibrium features. Wu [53] also concluded that China's environmental efficiency in energy consumption displayed significant regional differences and spatial correlations, showing a gradual reduction in development patterns along the east-central-northwest-west geographic gradient. It can be seen that China's environmental efficiency in energy consumption displays some obvious spatial cluster characteristics. In other words, there is a gradual transition from the east towards the west, or from the southeast towards the northwest, where high-value clusters have transitioned to low-value clusters. Such spatial distribution characteristics of environmental efficiency are similar to that of economic efficiency, as the location factor plays a critical role in affecting the environmental efficiency in energy consumption.

(**a**)

(**b**)

(**c**)

(**d**)

(**e**)
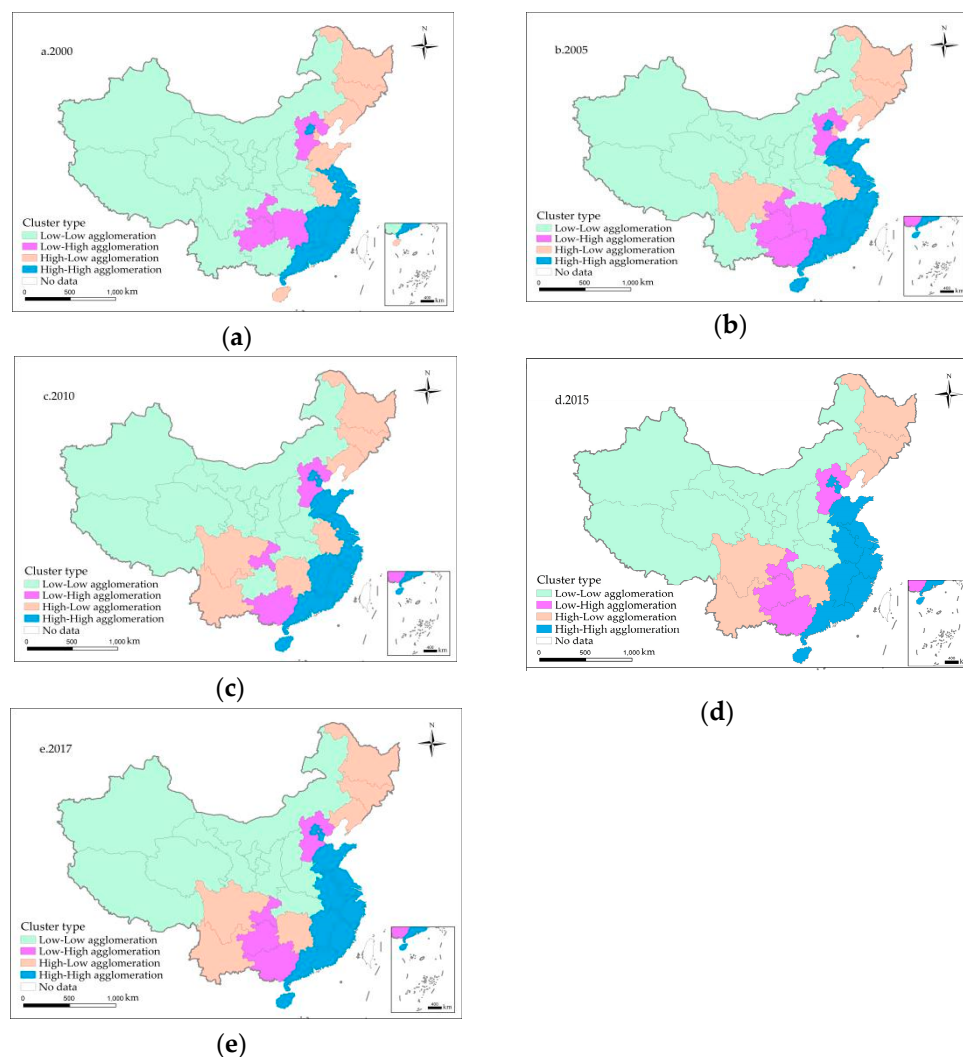
Figure 4. Correlation of environmental efficiency in energy consumption in China.

5. Conclusions

The economic-environmental efficiency in energy consumption displays a positive correlation, which is manifested as a parallel and synchronizing relationship. On the one hand, when the economic efficiency in energy consumption is high, the corresponding environmental efficiency is also high, and vice versa. On the other hand, as the economic efficiency in energy consumption increases, so does the corresponding environmental efficiency and vice versa.

At a national level, China's economic and environmental efficiency in energy consumption is generally on the rise, but the rate of economic efficiency, environmental efficiency, and the overall development level show some discrepancies. For example, economic efficiency is higher than environmental efficiency, which is consistent with China's actual development. At the provincial level, there are obvious regional differences regarding economic and environmental efficiency in energy consumption across the provinces, with a descending pattern from the east towards the west, or from the southeast towards the northwest.

For China's various provinces, the economic efficiency and environmental efficiency in energy consumption display a positive spatial correlation, as well as a robust spatial dependence and heterogeneity. The economic and environmental efficiency in energy consumption is not distributed randomly; conversely, it shows a spatial cluster of high/low values. The eastern coastal area of China represents a spatial cluster of high values, whereas the midwestern inland area of China represents

a spatial cluster of low values. China's economic efficiency and environmental efficiency in energy consumption display some visible spatial cluster characteristics as far as a spatial distribution pattern is concerned, with a spatial cluster of high values transitioning to a spatial cluster of low values from the east towards the west, or from the southeast towards the northwest. As time goes by, the extent of clustering could become more prominent, accompanied by an increasing spatial cluster of high values and a decreasing spatial cluster of low values.

China needs to improve its energy consumption efficiency further and promote sustainable energy transformations. First, regional cooperation needs to be strengthened in order to enhance the diffusion capacity of the eastern coastal area of China with a higher energy consumption efficiency. Consequently, the energy consumption efficiency in surrounding areas could be guided and improved, spatial differences could be narrowed, and an overall improvement in multiple areas could be achieved simultaneously. Second, certain 'tilt' policies designed for the central and western regions of China with a lower energy consumption efficiency could help accelerate industrial restructuring, strengthen investments in capital and technology, and enhance environmental protection. As a result, their energy consumption efficiency could be improved effectively, and the overall level of China's energy consumption efficiency could be enhanced dramatically. Third, China's energy structure needs to be further optimized and adjusted, and the proportion of "green" components in energy consumption and economic growth needs to be increased, thereby improving the energy consumption efficiency and promoting the coordinated development of economic and environmental efficiency in energy consumption.

References

1. Zhao, X.Y.; Zhao, H.L.; Jiang, L.; Lu, C.Y.; Xue, B. The Influence of Farmers' Livelihood Strategies on Household Energy Consumption in the Eastern Qinghai–Tibet Plateau, China. *Sustainability* **2018**, *10*, 1780. [CrossRef]
2. Lu, C.Y.; Li, W.L.; Pang, M.; Xue, B.; Miao, H. Quantifying the Economy-Environment Interactions in Tourism: Case of Gansu Province, China. *Sustainability* **2018**, *10*, 711. [CrossRef]
3. Zhang, Z.L.; Wang, K.Y.; Chen, X.P. The relationship between Ecological Efficiency Evolution and Environmental Regulation in China-based on SBM Model and Interprovincial Panel data estimation. *Econ. Weky.* **2015**, *32*, 126–131. (In Chinese)
4. Sheng, C.H.; Cao, Y.; Xue, B. Residential Energy Sustainability in China and Germany: The Impact of National Energy Policy System. *Sustainability* **2018**, *10*, 4535. [CrossRef]
5. Xu, S.T. Spatiotemporal Evolution and Influencing Factors of Energy Ecological Efficiency in China. Ph.D. Thesis, Liaoning Normal University, Dalian, China, 2016. (In Chinese)
6. Jimenez, R.; Mercado, J. Energy Intensity: A Decomposition and Counterfactual Exercise for Latin American Countries. *Energy Econ* **2014**, *42*, 161–171. [CrossRef]
7. Filippini, M.; Hunt, L.C. *'Underlying Energy Efficiency' in the US*; CER-ETH Economics Working Paper Series; 2013; Volume 10, p. 2139.
8. Proskuryakova, L.; Kovalev, A. Measuring energy efficiency: Is energy intensity a good evidence base? *Appl. Energy* **2015**, *138*, 450–459. [CrossRef]

9. Gökgöz, F.; Güvercin, M.T. Energy security and renewable energy efficiency in EU. *Renew. Sustain. Energy Rev.* **2018**, *96*, 226–239. [CrossRef]

10. Simsek, N. Energy Efficiency with Undesirable Output at the Economy-Wide level: Cross Country Comparison in OECD sample. *Am. J. Energy Res.* **2014**, *2*, 9–17. [CrossRef]

11. Borozan, D. Technical and total factor energy efficiency of European regions: A two-stage approach. *Energy* **2018**, *152*, 521–532. [CrossRef]

12. Wrigley, K.; Crawford, R.H. Identifying policy solutions for improving the energy efficiency of rental properties. *Energy Policy* **2017**, *108*, 369–378. [CrossRef]

13. Huang, J.B.; Du, D.; Hao, Y. The driving forces of the change in China's energy intensity: An empirical research using DEA-Malmquist and spatial panel estimations. *Econ. Model.* **2017**, *65*, 41–50. [CrossRef]

14. Guan, W.; Xu, S.T. Spatial pattern and spatial effect of China's energy ecological efficiency. *J. Geogr.* **2015**, *70*, 980–992. (In Chinese)

15. Huang, J. Spatial correlation network structure of energy and environmental efficiency in China and its influencing factors. *Resour. Sci.* **2018**, *40*, 759–772. (In Chinese)

16. Suzuki, S.; Nijkamp, P. An evaluation of energy-environment-economic efficiency for EU, APEC and ASEAN countries: Design of a Target-Oriented DFM model with fixed factors in Data Envelopment Analysis. *Energy Policy* **2016**, *88*, 100–112. [CrossRef]

17. Jebali, E.; Hédi, E.; Khraief, N. The analysis of energy efficiency of the Mediterranean countries: A two-stage double bootstrap DEA approach. *Energy* **2017**, *134*, 991–1000. [CrossRef]

18. Wang, T.; Yan, L.; Yi, M. Evaluation of energy ecological efficiency in China. *Macroecon. Res.* **2017**, *7*, 149–157. (In Chinese)

19. Bhat, J.A.; Haider, S.; Kamaiah, B. Interstate energy efficiency of Indian paper industry: A slack-based non-parametric approach. *Energy* **2018**, *161*, 284–298. [CrossRef]

20. Ghiyasi, M. Industrial sector environmental planning and energy efficiency of Iranian provinces. *J. Clean. Prod.* **2017**, *142*, 2328–2339. [CrossRef]

21. Ruizfuensanta, M.J. The region matters: A comparative analysis of regional energy efficiency in Spain. *Energy* **2016**, *101*, 325–331. [CrossRef]

22. Martínez, C.I.; William, H.; Piña, A. Regional analysis across Colombian departments: A non-parametric study of energy use. *J. Clean. Prod.* **2016**, *115*, 130–138. [CrossRef]

23. Xu, H.; Bai, X.Y.; Cheng, S.Q.; Ma, G.Q. Comparative study on total factor energy efficiency of silk road economic belt. *Ecol. Econ.* **2018**, *34*, 44–49. (In Chinese)

24. Zhang, N.; Fang, Z.G. Study on regional differences in total factor energy efficiency and its influencing factors in Xinjiang. *Sci. Technol. Manag. Res.* **2015**, *9*, 90–93. (In Chinese)

25. Sağlam, U. A two-stage data envelopment analysis model for efficiency assessments of 39 state's wind power in the United States. *Energy Convers. Manag.* **2017**, *146*, 52–67. [CrossRef]

26. Wu, C.Q.; Dong, X. Study on total factor energy efficiency of the Yangtze river economic belt under environmental constraints. *China Soft Sci.* **2016**, *3*, 73–83. (In Chinese)

27. Qin, Q.D.; Li, X.; Chen, X.D.; Li, L. Study on energy efficiency in China's eastern coastal areas considering unexpected output. *Sci. Technol. Manag. Stud.* **2016**, *36*, 54–58. (In Chinese)

28. Poggi, F.; Firmino, A.; Amado, M. Assessing energy performances: A step toward energy efficiency at the municipal level. *Sustain. Cities Soc.* **2017**, *33*, 57–69. [CrossRef]

29. Mohseni, P.; Borghei, A.M.; Khanali, M. Coupled life cycle assessment and data envelopment analysis for mitigation of environmental impacts and enhancement of energy efficiency in grape production. *J. Clean. Prod.* **2018**, *197*, 937–947. [CrossRef]

30. Raheli, H.; Rezaei, R.M.; Jadidi, M.R. A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. *Inf. Process. Agric.* **2017**, *4*, 342–350. [CrossRef]

31. Goto, M.; Otsuka, A.; Sueyoshi, T. DEA (Data Envelopment Analysis) assessment of operational and environmental efficiencies on Japanese regional industries. *Energy* **2014**, *66*, 535–549. [CrossRef]

32. Zhang, Q.; Song, H.; Wang, Y.L. Total factor energy efficiency analysis of jiangsu province based on DEA model. *Land Nat. Resour. Res.* **2018**, *1*, 59–61. (In Chinese)

33. Jiang, C. Research on Energy Efficiency Measurement of Resource-Based Cities Based on Full Factor Framework. Ph.D. Thesis, China University of Geosciences, Beijing, China, 2017. (In Chinese)

34. Imran, M.; Özçatalbaş, O.; Bashir, M.K. Estimation of energy efficiency and greenhouse gas emission of cotton crop in South Punjab, Pakistan. *J. Saudi Soc. Agric. Sci.* **2018**, in press. [CrossRef]

35. Sun, X.M.; Wang, G.; Dong, H.Z.; Zhang, H. Study on carbon Emission efficiency and influencing factors of Resource-Based cities based on DEA and SE-SBM Model. *Res. Sci. Technol. Manag.* **2016**, *36*, 78–84. (In Chinese)

36. Huang, H.F.; Ge, L.; Wang, M.C. An Analysis of the Energy efficiency of Urban Total element in China. *Urban Issues* **2015**, *8*, 53–60. (In Chinese)

37. Ewertowska, A.; Galán-Martín, A.; Guillén-Gosálbez, G.; Gavaldá, J.; Jiménez, L. Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis. *J. Clean. Prod.* **2016**, *116*, 13–22. [CrossRef]

38. Fang, J.C.; Liu, L.X.; Wan, Q. Regional differences in total factor energy efficiency in China. *China Mark.* **2015**, *34*, 10–14. (In Chinese)

39. Yang, T.; Chen, W.; Zhou, K.L.; Ren, M.L. Regional energy efficiency evaluation in China: A super efficiency slack-based measure model with undesirable outputs. *J. Clean. Prod.* **2018**, *198*, 859–866. [CrossRef]

40. Chen, L.; Jia, G.Z. Environmental efficiency analysis of China's regional industry: A data envelopment analysis (DEA) based approach. *J. Clean. Prod.* **2017**, *142*, 846–853. [CrossRef]

41. Zhu, D.M.; Zhao, H.B. Regional difference analysis of China's energy environmental efficiency under environmental constraints. *Nanjing Soc. Sci.* **2016**, *4*, 15–23. (In Chinese)

42. Cao, Q.; Fan, M.T. Study on interprovincial energy efficiency rating in China-empirical analysis based on multi-ordered Probit model. *Shanghai Econ. Res.* **2016**, *2*, 72–81. (In Chinese)

43. Huang, Y.Y.; Yan, Q.W.; Zhang, C.R. Spatial–Temporal Distribution Characteristics of $PM_{2.5}$ in China in 2016. *J. Geovis. Spat. Anal.* **2018**, *2*. [CrossRef]

44. Ghosh, K.G. Analysis of Rainfall Trends and its Spatial Patterns During the Last Century over the Gangetic West Bengal, Eastern India. *J. Geovis. Spat. Anal.* **2018**, *2*. [CrossRef]

45. Zhang, W.; Pan, X.F.; Yan, Y.B.; Pan, X.Y. Convergence analysis of regional energy efficiency in china based on large-dimensional panel data model. *J. Clean. Prod.* **2017**, *142*, 801–808. [CrossRef]

46. Tang, H.B. Study on Spatial Measurement of Regional Energy Economic Efficiency Association and Its Influencing Factors in China. Master's Thesis, Chongqing Normal University, Chongqing, China, 2017. (In Chinese)

47. Zhao, N.; Wang, X.R.; Zhu, W.J. Study on convergence of China's inter-provincial energy efficiency. *Stat. Stud.* **2015**, *32*, 29–35. (In Chinese)

48. Sun, J.S.; Li, G.; Wang, Z.H. Optimizing China's energy consumption structure under energy and carbon constraints. *Struct. Chang. Econ. Dyn.* **2018**, in press. [CrossRef]

49. Wang, K.; Yu, S.W.; Zhang, W. China's regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation. *Math. Comput. Model.* **2018**, *58*, 1117–1127. [CrossRef]

50. Zhao, X.L.; Yang, R.; Ma, Q. China's total factor energy efficiency of provincial industrial sectors. *Energy* **2014**, *65*, 52–61.

51. Yang, L.; Ouyang, H.; Fang, K.N.; Ye, L.L.; Zhang, J. Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA. *Ecol. Indic.* **2018**, *51*, 13–19. [CrossRef]

52. Song, M.L.; Peng, J.; Wang, J.L.; Zhao, J.J. Environmental efficiency and economic growth of China: A Ray slack-based model analysis. *Eur. J. Oper. Res.* **2018**, *269*, 51–63. [CrossRef]

53. Wu, X.X. Regional differences in energy and environmental efficiency under the pressure of energy conservation and emission reduction and their influencing mechanism. *Ecol. Econ.* **2018**, *34*, 49–56. (In Chinese)