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Measurement and spatial statistical analysis of green science and technology innovation efficiency among Chinese Provinces

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Abstract

This paper measured the efficiency of green science and technology (S&T) innovation in 30 Chinese provinces from 2008 to 2017 by constructing a three-stage super-efficiency DEA model that contains undesired output and then analyzed the spatial performance for these provinces. The purpose is to calculate exactly the extent to which S&T innovation in different regions of China has contributed to economic development, excluding negative impacts on the ecological environment and any spatial differences that have emerged in the past decade. The results show that the overall performance of green S&T innovation efficiency in Chinese regions was poor in the past decade, and there is still much room for improvement. In addition, China's investment in S&T innovation and environmental management is inefficient and wasteful. From the temporal perspective, efficiency in green innovation shows a slowly increasing trend. From the spatial perspective, the efficiency shows a strict correlation with economic development, that is, an obvious three-level spatial distribution pattern of "east, middle, and west".

Keywords Chinese provinces · Green science and technology innovation efficiency · Spatial statistical analysis · Three-stage data envelopment analysis model

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1 Introduction

In recent decades, China has been one of the fastest-growing economies in the world. However, China is also one of the most resource-consuming and environmentally destructive countries. How to break the constraints of resources and the environment has become a substantial problem for China's economic development in the next period. In recent years, the Chinese government has made great efforts and introduced many supporting policies to promote the transformation of the economic development pattern toward innovation-driven growth. However, S&T progress does not necessarily mean that pollution will be reduced. S&T can be divided into two types: environmentally friendly and environmentally destructive. Only environmentally friendly and clean emerging technologies can reduce pollution and achieve high-quality economic development, while many traditional technological improvements conversely cause further damage to the ecological environment. Historically, the relationship between technology and the environment has been contradictory in the majority of cases. The extreme destruction of the environment originated from the beginning of the industrial revolution—the development and promotion of modern S&T were realized in industrial production, and the basic characteristics of modern industrialization are high input, high consumption, and high pollution. In other words, the industrial revolution and the rise of modern S&T destroyed the environment. Therefore, in the development of S&T, we should consider not only the economic value but also the ecological value. This study's question is described as follows: in the past 10 years, to what extent has investment in S&T resources in different provinces in China promoted economic growth after eliminating the cost of environmental pollution?

2 Literature review

At present, the international community defines green S&T innovation as any form of innovation aimed at avoiding or reducing environmental pollution, improving ecological carrying capacity, or achieving the more efficient allocation of natural resources (European Commission 2011; Rennings et al. 2016; Rasi and Ester 2016). With the tightening of environmental constraints and the enhancement of S&T productivity, the strength of green innovation ability will undoubtedly become an important aspect to measure a region's competitiveness. Efficiency is the core paradigm of economic research, which shows how to maximize the utility of developing subjects with limited resources at the lowest cost. According to the existing literature, academic research on the innovation efficiency of green S&T is mainly based on input and output and can be divided into three categories. First, research has been conducted on the efficiency of regional green S&T innovation (Yao et al. 2015; Yu et al. 2017; Xiao et al. 2017; Xiao and Zhang 2019; Shen and Zhou 2018; Ren et al. 2014; Cao and Yu 2015; Yi and Cheng 2018; Huang and Wu 2019; Yang et al. 2018). The results show that the efficiency of green S&T innovation in different regions presents an unbalanced development mode with low-efficiency values, and there is still much room for improvement. In addition, due to regional developmental differences, the innovation efficiency of green S&T correspondingly presents an obvious gradient distribution pattern. The industrial structure, technology trading market, and other basic environmental elements are important aspects that affect efficiency. Second, research has been conducted on the efficiency of green S&T innovation in enterprises and industries (Xu et al. 2019; Nie and Qi 2019; Qian et al. 2018; Wang et al. 2016; Liu and Song 2018; Zhu et al. 2018). The study points out that the overall efficiency level of green R&D in Chinese enterprises and industries is low. The losses during the stages of technology R&D and achievement transformation are substantial. The efficiency value is highly correlated with the environmental innovation atmosphere, enterprise and industry scale, government support, and other factors. Third, there are other aspects. For example, Gong et al. (2017) studied how the agglomeration effect of OFDI affects the efficiency of green innovation in industry. They believed that there are three main influencing mechanisms: the lightweight structure effect, scale economy effect, and resource allocation optimization effect. Luo and Liang (2017) empirically analyzed the impact of technology spillover of international R&D capital on green innovation efficiency in China. They believed that international R&D capital not only has a much more apparent promoting effect on green innovation efficiency than domestic R&D capital but also has a crowding-out effect on domestic R&D capital. Peng et al. (2017) studied the impact of formal and informal environmental regulation on green innovation. They found a U-shaped relationship between formal environmental regulation and green innovation efficiency, while there was an inverted U-shaped relationship between informal environmental regulation and green innovation efficiency. Moreover, some scholars have studied the green investment in China (Shen et al. 2021; Li et al. 2020a, b; Khan et al. 2020), and found the cointegration relationship among public-private partnership investment in energy, technological innovation, renewable energy consumption, exports, imports, and consumption-based carbon emissions is proved. Therefore, they think technological innovation for the cleaner production process and public-private partnership investment in renewable energy is needed.

The existing studies provide important references for this paper. However, due to the differences in research objectives, indicator selection, and empirical methods, the conclusions drawn from these studies are inconsistent. Therefore, this paper constructs a three-stage super-efficiency DEA model with unexpected outputs to measure the green S&T innovation efficiency of 30 provinces in China from 2008 to 2017 and studies the spatial performance of these provinces' efficiency values using spatial statistical methods.

3 Measurement of green S&T innovation efficiency

In this study, we define green S&T innovation efficiency as the final result after eliminating the negative impact on the regional environment on the basis of the existing S&T innovation output. The efficiency result should reflect and contain the impact of a region's S&T innovation on the economy and environment.

The methods of efficiency evaluation are mainly divided into parametric and nonparametric methods. The parametric method is dominated by the stochastic frontier approach (SFA), while the nonparametric method is dominated by data envelopment analysis (DEA). Among them, with strong objectivity, DEA is considered the best method for evaluating efficiency. DEA was initially proposed by Charnes et al. in 1978 and was called the CCR model, which is an efficiency evaluation model without considering the change in returns to scale. In 1984, Banker et al. proposed an efficiency evaluation model with variable returns to scale called the BCC model. These two models have become the most classic and common DEA models. However, the BCC and CCR models have two obvious defects. The first is the evaluation method based on radial and angle, which does not take the negative externalities and other unexpected outputs into account. This means that in the case of redundant input or insufficient output (i.e., when there is a nonzero slack in input or output), the efficiency evaluation result will be distorted and may be misevaluated. Tone (2002) proposed a non-radial and non-angular SBM model (slack-based measure) to cover this defect, which can calculate both the amount of slack and redundancy on non-rays. Second, DEA calculations often result in the coexistence of multiple effective DMUs (decision-making units) (that is, the efficiency value of multiple DMUs is 1), which makes it impossible to make further orders. Considering this, Andersen and Petersen (1993) proposed the super-efficiency DEA model to extend the effective value to more than 1. Thus we can further contrast and sort the effective DMUs. To eliminate the influence of environmental and random factors, this paper builds a three-stage super-efficiency SBM model with unexpected outputs to measure green innovation's efficiency in different provinces and cities in China.

3.1 Introduction of three-stage DEA model

Fried and Schmidt (2002) thought the efficiency value under the traditional DEA model is biased because of three influencing factors: managerial inefficiencies, environmental effects, and statistical noise. The most important thing concerning a three-stage DEA is eliminating the three factors' influence in the second stage. The specific steps are described as follows. In the first stage, we use the traditional DEA to measure the initial efficiency results. In the second stage, an SFA model is constructed to adjust each input variable's random error terms to eliminate environmental factor interference and random error interference, ensuring that all decision units are in the same environment. The third stage involves replacing the original input data with the adjusted data and then combining the original output data so the classical DEA model can perform the calculation. The results obtained at this step can objectively reflect the true efficiency values of each DMU due to the elimination of the influence of environmental factors and random errors.

Three-stage DEA has many advantages. The greatest advantage is DEA and SFA's combination to effectively remove disturbances of environmental factors and random errors to make the value more real and effective. In addition, the DEA model has the advantage of simultaneously processing multiple inputs and outputs. Therefore, we use three-stage DEA to take many factors, such as ecological environment constraints, S&T innovation, and economic development, into a discussion framework to obtain a more comprehensive result, which can avoid the partial result calculated by a single indicator. Moreover, the DEA model has no specific functional form, which can avoid parameter estimation and further avert the deviation to make the estimation results more accurate.

3.2 DEA calculation at the first stage—before adjustment

The input of S&T resources has a double impact on the economy, a positive impact on the output of innovation, and a negative impact on the ecological environment. We usually call the former the expected output and the latter the unexpected output. Before evaluation, we first distinguish the expected and the unexpected outputs and then lead them into a specific production equation, the SBM model containing the unexpected output.

To better reflect reality, we select the super-efficiency SBM model with unexpected output to measure the green innovation efficiency of each province and city in China. The formula of the model is derived from Zhang and Pu (2017). Suppose there are n decision-making units (DMUs), denoted as DMU_j $(j = 1, 2, \ldots, n)$, and each DMU has m inputs, denoted as x_i $(i = 1, 2, \ldots, m)$, q_1 expected outputs, denoted as y_r $(r = 1, 2, \ldots, q_1)$, and q_2 unexpected outputs, denoted as b_t $(t = 1, 2, \ldots, q_2)$. For a DMU_k (x_k, y_k, b_k), its production possibility set is

$$P = \left\{ (x_k, y_k, b_k) \middle| x_k \geq \sum_{j=1, j \neq k}^{n} x_{ij}\lambda_j, \quad y_k \leq \sum_{j=1, j \neq k}^{n} y_{rj}\lambda_j, \quad b_k \geq \sum_{j=1, j \neq k}^{n} b_{ij}\lambda_j \right\}$$

The green innovation efficiency, including the unexpected output, is

$$min\ \rho^* = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{tk}}\right)}$$

$$
s.t.\begin{cases}
\sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik}\\
\sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \geq y_{rk}\\
\sum_{j=1,j\neq k}^{n} b_{tj}\lambda_j - s_t^{b-} \geq b_{tk}\\
1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{tk}}\right) > 0\\
\lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0
\end{cases}
$$

In the above formula, s_i^- represents the slack of the ith input; s_r^+ represents the slack of the rth expected output; s_t^{b-} represents the slack of the tth undesired output; and λ is the weight vector.

After introducing the model, the next step is the selection of index variables. To measure green innovation efficiency, it is necessary to clarify the input variables, expected output variables, unexpected output variables, and environmental variables. For the green innovation system, input refers to the cost paid in the innovation process, which includes the economic and human investment and the effort made to improve the ecological environment. The output is divided into expected and unexpected; the former includes the economic benefits generated by innovation, which measures the returns gained by investment in S&T, and the latter includes industrial "three wastes" emissions, which measure to what extent technological innovation and ecological environmental governance investment reduce pollution emissions.

In addition, we set three environmental variables to represent the factors that significantly influence efficiency. In general, many factors can affect the efficiency value. In this paper, the economic development level, industrial structure, and S&T market size are chosen based on existing studies. Detailed indicators are shown in Table 1.

For research objects, 30 provinces (municipalities and autonomous regions) in China are selected. The green innovation efficiency of these provinces are measured from 2008 to 2017 under a total factor analysis framework. Tibet, Hong Kong, Macau, and Taiwan were excluded due to the lack of data. The data are from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China Environmental Statistical Yearbook from 2009 to 2018.

According to econometrics, we use the software MaxDEA pro 6.6 to calculate the efficiency value of green innovation in various regions of China from 2008 to 2017 without removing disturbances, as shown in Table 2.

From Table 2, the average efficiency value of the first stage was 0.518, which is an unsatisfactory result.

3.3 The truncated SFA regression in the second stage

The stochastic frontier approach (SFA) is a parametric method for efficiency evaluation based on the stochastic frontier production function. In general, the SFA

Table 1 Evaluation index system of regional green S&T innovation

Category	Name		Explanation
Input indicators	Labor input in innovation		Full-time equivalent of R&D personnel (person-year)
	Capital input in innovation		R&D expenditure (10,000 yuan)
	Investment in environment governance		Investment completed in pollution treatment projects (10,000 yuan)
Output indicators	Expect output	Innovation patents	Number of valid invention patents (piece)
		Economic benefits of innovation	Sales revenue of new products (10,000 yuan)
	Undesired output	Discharge of "three wastes" from industry	Total effluent discharge (10,000 tons)
			Total exhaust gas pollutants discharge (10,000 tons)
			Total solid waste discharge (10,000 tons)
Environment indicators	Economic development		Gross domestic product (100 million yuan)
	Industrial structure		The proportion of the output value of the secondary industry in GDP (%)
	Scale of technology market		Regional technology market turnover (10,000 yuan)

Table 2 Results of the first stage of green innovation efficiency

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average	Ranking
Beijing	1.657	1.01	1.235	1.308	1.257	1.18	1.131	1.115	1.098	1.657	1.265	1
Tianjin	1.175	1.176	1.152	1.095	1.099	1.153	1.106	1.108	1.119	1.175	1.136	4
Hebei	0.207	0.192	0.206	0.2	0.262	0.262	0.266	0.293	0.327	0.207	0.242	23
Shanxi	0.154	0.148	0.161	0.172	0.18	0.183	0.165	0.202	0.233	0.154	0.175	28
Inner Mongolia	0.157	0.137	0.181	0.133	0.146	0.131	0.111	0.141	0.153	0.157	0.145	30
Liaoning	0.273	0.317	0.274	0.296	0.361	0.37	0.35	0.413	0.404	0.273	0.333	18
Jilin	1.095	1.605	1.041	1.128	1.131	0.238	0.51	0.492	1.084	1.095	0.942	5
Heilongjiang	0.159	0.244	0.203	0.135	0.156	0.133	0.145	0.143	0.139	0.159	0.162	29
Shanghai	1.135	1.280	1.144	1.186	1.199	1.263	1.098	1.064	1.098	1.135	1.16	2
Jiangsu	0.475	0.497	0.571	0.555	0.691	0.611	1.008	1.02	0.783	0.475	0.669	10
Zhejiang	0.648	0.537	0.648	0.64	0.706	1.024	1.025	1.099	1.102	0.648	0.808	8
Anhui	0.403	0.288	0.417	0.385	0.443	0.418	1	1.005	0.712	0.403	0.547	11
Fujian	0.356	0.328	0.322	0.337	0.342	0.305	0.305	0.349	0.383	0.356	0.338	17
Jiangxi	0.223	0.159	0.224	0.21	0.349	0.317	0.339	0.381	0.5	0.223	0.293	19
Shandong	0.37	0.472	0.499	0.416	0.492	0.477	0.449	0.513	0.468	0.37	0.453	12
Henan	0.204	0.238	0.216	0.199	0.228	0.317	0.322	0.423	0.364	0.204	0.272	21
Hubei	0.331	0.298	0.32	0.329	0.386	0.394	0.439	0.614	0.526	0.331	0.397	14
Hunan	0.27	1.326	1.058	0.466	0.554	1.016	0.757	1.002	0.885	0.27	0.76	9
Guangdong	0.717	1.175	1.622	1.437	1.029	1.009	1.14	1.264	1.482	0.717	1.159	3
Guangxi	0.322	0.291	0.36	0.322	0.339	0.408	0.32	0.466	1.007	0.322	0.416	13
Hainan	1.248	0.105	1.234	1.079	0.32	0.382	1.06	1.01	1.095	1.248	0.878	7
Chongqing	0.528	0.561	1.061	1.018	1.003	0.552	1.098	1.288	1.174	0.528	0.881	6
Sichuan	0.288	0.356	0.305	0.416	0.333	0.326	0.413	0.426	0.35	0.288	0.35	16
Guizhou	0.325	0.252	0.277	0.272	0.228	0.239	0.3	0.285	0.276	0.325	0.278	20
Yunnan	0.242	0.268	0.254	0.248	0.227	0.253	0.26	0.252	0.231	0.242	0.248	22
Shaanxi	0.155	0.226	0.228	0.227	0.259	0.234	0.228	0.194	0.22	0.155	0.213	26

Table 2 (continued)

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average	Ranking
Gansu	0.164	0.159	0.23	0.287	0.308	0.291	0.301	0.299	0.15	0.164	0.235	24
Qinghai	1.377	0.237	0.076	0.075	0.118	0.127	0.13	0.154	0.137	1.377	0.381	15
Ningxia	0.123	0.184	0.204	0.17	0.226	0.302	0.187	0.299	0.192	0.123	0.201	27
Xinjiang	0.158	0.166	0.213	0.165	0.194	0.226	0.284	0.299	0.273	0.158	0.214	25
Average	0.498	0.474	0.531	0.497	0.485	0.471	0.541	0.587	0.599	0.498	0.518	–

model can measure the comprehensive technical efficiency of each DMU through the decomposition of error terms. The error terms are usually divided into environmental factors and random variables. The calculation formulas of the model are as follows.

The first step is to establish the relaxation variable:

$$S_{ij} = x_{ij} - X_i\lambda \quad (i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n)$$

In the formula above, S_{ij} represents the relaxation variable of the ith input of the jth DMU, that is, the deviation between the actual and ideal input quantities. Then, we use S_{ij} as the dependent variable to carry out SFA regression for all other relaxation variables. The formula is:

$$S_{ij} = f^i(z_j;\, \beta^i) + v_{ij} + u_{ij}$$

This equation's greatest advantage is that the relaxation variables are clearly decomposed into three categories: environmental impact, random error, and internal management. In the formula, z_j is the jth environmental variable; β^i represents the corresponding estimated value of each environmental variable; and $f^i(z_j;\, \beta^i)$ is the impact of environmental variables on S_{ij}.We usually take $f^i\left(z_j;\beta^i\right) = Z_j\beta^i$; $v_{ij} + u_{ij}$ as the joint error term; v_{ij} is a random error that follows the normal distribution, that is, $v_{ij} \sim N(0,\, \sigma^2_{vi})$; and u_{ij} represents the management inefficiency and presents a truncated normal distribution, that is, $u_{ij} \sim N^+(\mu_i, \sigma^2_{ui})$. Moreover, v_{ij} has no relationship with u_{ij}.

We use Frontier 4.1 software to carry out a regression of the above SFA model.

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$$

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

In the formula, σ_u^2 and σ_v^2 represent the variance of management inefficiency and random error, respectively, and γ represents the ratio of management inefficiency variance to the total variance. If γ is close to 1, the technical efficiency of each DMU is different, and the influence of random factors is small. Then, we use the maximum likelihood method to estimate the equation. If γ is close to 0, the efficiency value of each DMU is not significantly different, and the influence of random factors is great. At this time, we use the least squares method to estimate the equation.

We used Frontier 4.1 software to calculate the estimated results of each parameter ($\hat{\beta}_i$, $\hat{\sigma}^2_{vi}$, $\hat{\mu}_i$, $\hat{\sigma}^2_{ui}$) and adjusted the input value by the estimated results to eliminate the impact of random error on the model calculation so that all DMUs were under the same environmental conditions to obtain more realistic, scientific, and reasonable efficiency values. Theoretically, there are generally two adjustment methods: increase the DMU input in a good environment or reduce the DMU input in a poor environment. Undoubtedly, the first method is more reasonable and realistic. Therefore, we selected the first method to adjust the input of all other DMUs based on the most effective DMUs as the standard:

$$x_{ij}^{A} = x_{ij} + (max_j(z_j, \hat{\beta}^i) - z_j\hat{\beta}^i) + (max\{\hat{v}_{ik}\} - \hat{v}_{ik})$$

According to the above equation, we need to separate the random error from the mixed error term in the SFA regression model. The separation and estimation formula of the random error $\hat{v}_{ik}$ is

$$\hat{E}(v_{ij}\Big|v_{ij} + u_{ij}) = s_{ij} - z_j\hat{\beta} - \hat{E}(u_{ij}\Big|v_{ij} + u_{ij})$$

The estimation formula for the separation of environmental factors $\hat{\mu}_{ij}$ is

$$\hat{E}(u_{ij}\Big|v_{ij} + u_{ij}) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi(\varepsilon_i\lambda/\sigma)}{\phi(\varepsilon_i\lambda/\sigma)} + \frac{\varepsilon_i\lambda}{\sigma}\right]$$

From the equation above,$\lambda = (\sigma_u/\sigma_v)$ and $\varepsilon_i = v_{ij} + u_{ij}$ are the joint error terms, and φ and ϕ represent the density and distribution functions of the standard normal distribution, respectively.

Here, we take the relaxation variables calculated at the first DEA stage as the explained variables and the environmental variables as the explanatory variables to construct the stochastic frontier model for further regression analysis. The software used here is Frontier Version 4.1, and the results are shown in Table 3.

As can be seen from Table 3 demonstrates that the coefficients of the three environmental variables on the input relaxation variables all passed the significance test,

Table 3 The second stage SFA regression analysis results

Name	Slack in labor input for technological innovation	Slack in capital input for technological innovation	Slack in ecological & environment investment management
Intercept term	− 37,959.347	− 1,140,785.3***	− 261,142.6***
	(− 71.974)	(− 1,131,045.8)	(− 260,931.56)
Economic development	− 0.069***	− 29.945 ***	1.848***
	(− 3.77)	(− 16.99)	(5.03)
Industrial structure	67,847.437***	976,142.5**	349,795.49*
	(281.63)	(974,230.73)	(349,734.46)
Technology market scale	− 0.001***	− 0.006***	0.002***
	(− 23.103)	(− 0.928)	(1.606)
Sigma^2 (σ^2)	780,588,430***	703,659,800,000***	54,001,370,000***
	(780,566,700)	(703,659,800,000)	(54,001,370,000)
Gamma (γ)	0.995***	0.803***	0.982***
	(433.769)	(23.941)	(79.119)
log likelihood function	− 3357.175	− 4412.477	− 3966.203
LR test of the one-sided error	77.561***	36.723***	72.873***

***, ** and * indicate significance at 1%, 5% and 10%, respectively; in parentheses is the t statistic and the values representing the ratio of managerial inefficiency variance to total variance also all passed the significance test at the 1% level. This result shows that the external environmental variables significantly impact the relaxation of investment in green innovation in China. Further analysis shows that the values of the input slack of labor, capital, and environmental governance are all close to 1 (0.995, 0.803, and 0.982), indicating that slack is affected more by management factors than random errors. Therefore, it is necessary to use the SFA model to eliminate the environmental factors and the influence of random errors on green technology's innovation efficiency.

3.4 DEA analysis after adjustment in the third stage

After analyzing the above two steps, we successfully decomposed the loss of efficiency into the redundancy rate of input and undesired output and the deficiency rate of expected output. The input redundancy rate is $IEx = (1/m)\sum_{i=1}^{m} s_i^-/x_i$, where the redundancy rate of each input i is $IE_{xi} = (s_i^-/x_i)$. The deficiency rate of the expected output is $IE_y = (1/q_1)\sum_{r=1}^{q_1} (s_r^+/y_r)$, and the deficiency rate of each expected output is $IE_{gr} = (s_r^+/y_r)$. The redundancy rate of the unexpected output is $IE_b = (1/q_2)\sum_{t=1}^{q_2} (s_t^{b-}/b_t)$, and the deficiency rate of each unexpected output is $IE_{bt} = (s_t^{b-}/b_t)$.

The third stage's method takes the value after adjusting environmental factors and random error terms in the second step as the new input value. It then calculates again with the super-efficiency SBM model that contains the unexpected output. This time, we can obtain a more realistic efficiency value.

We used MaxDEA Pro 6.6 again to calculate the value of green S&T innovation efficiency in all regions of China from 2008 to 2017 after removing the disturbance term, as shown in Table 4.

From Table 4 shows that the comprehensive average efficiency values of the third stage of green S&T innovation in Chinese provinces from 2008 to 2017 is 0.23. This result is a very bad. Before adjustment, the value of China's green S&T innovation efficiency was unsatisfactory (0.518) in the first stage, and the adjusted value dropped by more than half. This finding shows that China's performance in green technology innovation is highly unsatisfactory.

4 Spatial statistical analysis of green S&T innovation efficiency

4.1 Introduction of spatial statistical theory

Exploratory spatial data analysis (ESDA) is a method that studies how to describe and simulate spatial phenomena and processes with mathematical and statistical models.

The most important part of spatial statistical analysis is to combine the research object with a geographical location. Generally, scholars use the spatial weight matrix to sample the distance of research objects. The establishment of the spatial weight matrix

Table 4 Results of the third stage of green innovation efficiency

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average	Ranking
Beijing	0.244	0.184	0.243	0.291	0.274	0.3	0.34	0.298	0.34	1.003	0.352	7
Tianjin	0.362	0.317	0.368	0.371	0.398	0.476	0.441	0.429	0.445	0.362	0.397	6
Hebei	0.109	0.101	0.12	0.146	0.178	0.188	0.195	0.2	0.233	0.274	0.174	17
Shanxi	0.07	0.059	0.063	0.088	0.091	0.094	0.081	0.074	0.095	0.136	0.085	21
Inner Mongolia	0.05	0.044	0.072	0.066	0.07	0.066	0.056	0.065	0.074	0.106	0.067	22
Liaoning	0.161	0.193	0.184	0.241	0.248	0.283	0.261	0.247	0.243	0.268	0.233	13
Jilin	0.164	0.424	0.206	0.311	0.255	0.085	0.19	0.205	0.3	0.326	0.247	12
Heilongjiang	0.05	0.051	0.059	0.054	0.054	0.052	0.045	0.044	0.049	0.063	0.052	25
Shanghai	1.001	0.39	0.659	1.001	0.495	0.509	0.507	0.43	0.504	1.03	0.653	1
Jiangsu	0.338	0.334	0.418	0.511	0.547	0.539	0.603	0.604	0.717	1.034	0.564	4
Zhejiang	0.347	0.296	0.39	0.485	0.491	0.571	0.593	0.762	1.021	0.805	0.576	3
Anhui	0.093	0.123	0.199	0.258	0.267	0.272	0.311	0.336	0.404	0.507	0.277	10
Fujian	0.156	0.142	0.176	0.23	0.219	0.213	0.214	0.216	0.263	0.29	0.212	15
Jiangxi	0.077	0.057	0.097	0.109	0.149	0.172	0.18	0.197	0.285	0.327	0.165	18
Shandong	0.283	0.332	0.413	0.412	0.431	0.437	0.418	0.415	0.455	0.505	0.41	5
Henan	0.118	0.123	0.14	0.162	0.16	0.243	0.245	0.282	0.295	0.351	0.212	14
Hubei	0.148	0.134	0.187	0.226	0.253	0.292	0.314	0.351	0.386	0.466	0.276	11
Hunan	0.114	0.161	0.205	0.284	0.32	0.361	0.396	0.421	0.539	0.583	0.338	8
Guangdong	0.32	0.337	0.454	0.539	0.471	0.518	0.587	0.669	1.05	1.161	0.61	2
Guangxi	0.071	0.095	0.119	0.139	0.137	0.171	0.141	0.177	0.218	0.253	0.152	19
Hainan	0.008	0.001	0.012	0.018	0.017	0.021	0.018	0.02	0.024	0.024	0.016	29
Chongqing	0.176	0.201	0.307	0.341	0.257	0.267	0.322	0.398	0.468	0.432	0.317	9
Sichuan	0.128	0.156	0.139	0.192	0.174	0.187	0.19	0.211	0.216	0.253	0.185	16
Guizhou	0.024	0.022	0.039	0.053	0.045	0.041	0.046	0.056	0.074	0.089	0.049	26
Yunnan	0.039	0.031	0.032	0.047	0.053	0.052	0.059	0.059	0.075	0.081	0.053	24
Shaanxi	0.057	0.068	0.094	0.104	0.088	0.093	0.097	0.091	0.125	0.162	0.098	20

Table 4 (continued)

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Average	Ranking
Gansu	0.032	0.03	0.05	0.071	0.078	0.079	0.086	0.067	0.035	0.041	0.057	23
Qinghai	0.011	0.011	0.004	0.002	0.004	0.005	0.006	0.006	0.009	0.017	0.008	30
Ningxia	0.014	0.016	0.018	0.024	0.032	0.046	0.03	0.044	0.031	0.05	0.03	28
Xinjiang	0.026	0.014	0.039	0.039	0.04	0.049	0.063	0.062	0.059	0.051	0.044	27
Average	0.16	0.148	0.183	0.227	0.21	0.223	0.234	0.248	0.301	0.368	0.23	–

must meet the requirements of the first law of geography; that is, the spatial correlation of different subjects must decrease with increasing distance. The assumption of spatial correlation makes the research subject's performance highly correlated with its geographical position, thus making the research more scientific and reasonable in its application.

In this paper, based on the efficiency calculation result at the third stage, we analyze spatial autocorrelation. Then, we also described the spatial cluster status of efficiency and the forming reason.

4.2 Global spatial autocorrelation analysis

Global spatial autocorrelation analysis mainly studies the spatial distribution of things through their position and performance in the overall space. It is often represented by the global Moran's I index, whose value range is [− 1,1]. Generally, if Moran's I value is higher than 0, it indicates that units with similar efficiency show spatial clustering characteristics. The higher the value is, the higher the degree of clustering. If Moran's I value is less than 0, it indicates that units show the feature of spatial dispersion, and the smaller the value is, the higher the degree of dispersion. If Moran's I value is 0, it indicates that the units have a uniform distribution and no spatial correlation, which only exists in the theoretical hypothesis. The closer Moran's I is to 0, the more uniform the distribution of each subject and the weaker the spatial correlation.

The calculation formula of the global Moran's I value (Yang et al. 2018) is:

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

In the formula, $S^2 = (1/n)\sum_{i=1}^{n}(x_i - \overline{x})^2$, $\overline{x} = (1/n)\sum_{i=1}^{n} x_i$,$n$ represent the number of space units,x_i and x_j represent the observed value of the ith or jth space unit, and w_{ij} is the binary adjacency matrix; if the space elements are adjacent,$w_{ij} = 1$, and if the spatial units are not adjacent,$w_{ij} = 0$.

In this paper, based on the third stage results in 30 provinces and cities from 2008 to 2017, we use Geoda software for analysis and then obtain the standardized Moran's I value. The results are shown in Table 5.

From Table 5, we can find that Moran's I values from 2008 to 2017 are all greater than 0. This indicates that the efficiency values in all provinces of China are positively correlated globally. However, the correlation number is small, indicating that the positive correlation is not strong. From the time trend, the correlation value presents an

Table 5 Moran's I value of green innovation efficiency from 2008 to 2017

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Moran's I value	0.113	0.114	0.152	0.128	0.211	0.219	0.207	0.197	0.192	0.157

inverted U-shaped parabola, reaches a peak in 2013 (0.219), and then decreases. As ecological S&T innovation activities are highly correlated with economic development, we speculate that the decline in the spatial correlation coefficient after 2013 may be related to the slowdown of China's economic growth.

4.3 Local spatial autocorrelation analysis

The global spatial autocorrelation value reveals the overall agglomeration and dispersion of green innovation efficiency across the whole country. However, the value cannot further reveal the spatial performance of different regions in more detail. Local spatial autocorrelation is the global version's improvement, which can analyze the various situations of different subjects in space more effectively by refining each space unit's correlation. Local spatial autocorrelation analysis is generally studied by local Moran's I, and the calculation formula is

$$I_i = Z_i \sum_{j=1}^{n} w_{ij} Z_{ij}$$

where Z_i and Z_j represent the standardized observation values of spatial units i and j, respectively, and w_{ij} represents the spatial weight matrix.

Usually, we take Moran's local scatter plot to represent local spatial autocorrelation. The horizontal axis represents the observed value of each province's efficiency, and the vertical axis represents the spatial lag value. According to these two indicators' values, we divide the 30 provinces into four types, represented by four quadrants, as shown in Table 6.

To clearly illustrate the evolution tendency of efficiency agglomeration, this paper described the Moran scatter plot by dividing the 30 provinces and cities into four groups to classify these provinces based on their local space relationships with adjacent provinces. See Fig. 1 for details.

From Fig. 1, we know that most provinces are concentrated in the first, second, and third quadrants, indicating that China's provinces are generally geographically characterized by the spatial correlation of H–H, L–H, and L–L.

Table 6 Spatial properties of Moran scatter plots

Quadrant	The local spatial relationship
I	The value of provinces and surrounding provinces are both high (High–High agglomeration, H–H)
II	The value of the province is low, but the surrounding level is high (Low–High agglomeration, L–H)
III	The value of provinces and surrounding provinces are both low (Low–Low agglomeration, L–L)
IV	The value of the province is high, but the surrounding level is low (High–Low agglomeration, H–L)

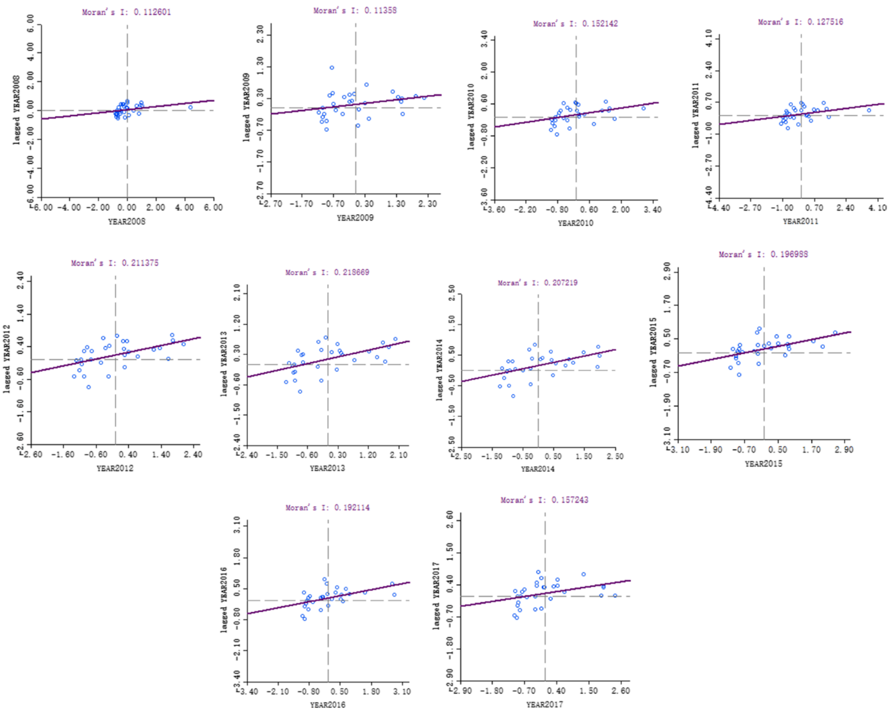

Fig 1. Moran scatter chart of green innovation efficiency in Chinese provinces from 2008 to 2017

4.4 LISA analysis

Local indicators of spatial association analysis (LISA), one of the most common spatial analysis methods, is a supplement to local spatial correlation analysis. Its main function is studying the spatial connection type between each research subject.

To further identify the local spatial clustering situation of green innovation efficiency levels in 30 provinces of China during the study period, a LISA analysis was conducted. However, we first need to conduct the Z-value test of the LISA significance level; the results are shown in Table 7.

The provinces listed in the above table show significant local clustering. From 2008 to 2017, an increasing number of provinces passed the Z-value test of the LISA significance level. This means that there are an increasing amount of provinces and cities connected in the spatial statistical meaning. The local agglomeration of green S&T innovation efficiency in different regions of China is becoming increasingly obvious.

By filtrating the four quadrants of Moran's I scatter diagram and deleting insignificant provinces, we can obtain the regional clusters of China's green S&T innovation efficiency in the study year, as shown in Table 8 and Fig. 2.

From Table 8 and Fig. 2 show that among these significant provinces and cities, all H–H regions are located in the Yangtze River Delta, meaning that the Yangtze River Delta's high-level development has a certain radiation effect on the

Table 7 Test results of LISA's significance Z-value

Year	Provinces that pass the significance test
2008	Jiangsu, Shanghai, Xinjiang, Gansu, Sichuan
2009	Jiangsu, Xinjiang, Gansu, Sichuan
2010	Jiangsu, Shanghai, Xinjiang, Gansu, Inner Mongolia
2011	Jiangsu, Shanghai, Zhejiang, Xinjiang, Gansu, Inner Mongolia
2012	Jiangsu, Shanghai, Zhejiang, Anhui, Jiangxi, Xinjiang, Gansu, Sichuan
2013	Jiangsu,Shanghai,Anhui,Fujian,Jiangxi,Xinjiang,Gansu,Sichuan,Inner Mongolia
2014	Jiangsu, Shanghai, Zhejiang, Anhui, Fujian, Jiangxi, Gansu, Inner Mongolia, Sichuan
2015	Jiangsu,Shanghai,Anhui,Fujian,Jiangxi,Xinjiang,Gansu,Sichuan,Inner Mongolia
2016	Jiangsu,Shanghai,Anhui,Fujian,Jiangxi,Xinjiang,Gansu,Sichuan,Inner Mongolia
2017	Jiangsu,Shanghai,Anhui,Zhejiang,Fujian,Jiangxi,Xinjiang,Gansu,Sichuan,Inner Mongolia

Table 8 Local concentration of green technology innovation efficiency in China from 2008 to 2017

Year	H–H	L–H	L–L	H–L
2008	Jiangsu, Shanghai	–	Xinjiang, Gansu, Sichuan	–
2009	Jiangsu	–	Xinjiang, Gansu	Sichuan
2010	Jiangsu, Shanghai	–	Xinjiang, Gansu, Inner Mongolia	–
2011	Jiangsu, Shanghai, Zhejiang	–	Xinjiang, Gansu, Inner Mongolia	–
2012	Jiangsu, Shanghai, Zhejiang, Anhui	Jiangxi	Xinjiang, Gansu, Sichuan	–
2013	Jiangsu, Shanghai, Anhui	Fujian, Jiangxi	Xinjiang, Gansu, Inner Mongolia, Sichuan	–
2014	Jiangsu, Shanghai, Zhejiang, Anhui	Fujian, Jiangxi	Gansu, Inner Mongolia, Sichuan	–
2015	Jiangsu, Shanghai, Anhui	Fujian, Jiangxi	Xinjiang, Gansu, Inner Mongolia, Sichuan	–
2016	Jiangsu, Shanghai, Anhui	Fujian, Jiangxi	Xinjiang, Gansu, Inner Mongolia, Sichuan	–
2017	Jiangsu, Shanghai, Zhejiang, Anhui	Fujian, Jiangxi	Xinjiang, Gansu, Inner Mongolia, Sichuan	

surrounding areas, but the effect is limited. The L–H zone was empty in 2008, Jiangxi joined in 2012, and Fujian joined a year later, thus, this zone has comprised these two provinces since. The H–L region had the fewest provinces, with only Sichuan being included in 2009. The L–L region is dominated by Xinjiang, Gansu, Inner Mongolia, and Sichuan, all of which are located in the west and are very stable. Therefore, the spatial clustering of green innovation efficiency in these Chinese provinces over the past 10 years is very stable, and it is difficult for a province to break away from its original cluster.

The results of the LISA analysis conforms to the real status of China's development. The provinces that performed well are all located in the eastern region because the eastern region has a relatively high economic development level,

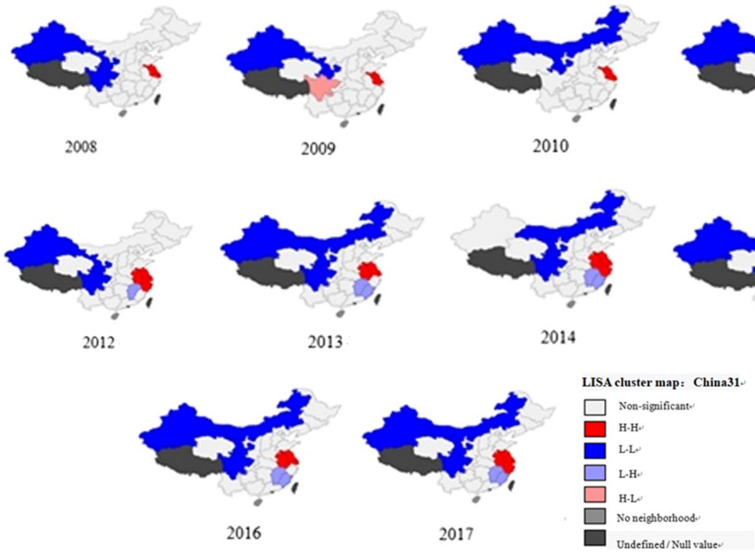

Fig 2. Moran aggregation chart of green innovation efficiency in Chinese provinces from 2008 to 2017

relatively strong scientific and technological strengths, and is moving toward innovation-driven development. Comparatively, the western region is rich in energy and resources but has a low economic development level and a dated industrial structure. The development of these regions has caused certain damage to the ecological environment. For the Jiangxi and Fujian provinces, which have always been in the L–H region, their space manifests as low efficiency for themselves and high efficiency for the surrounding provinces. This is largely due to the special geographical location of the two provinces. On the map, the two provinces are sandwiched between the Yangtze River Delta and the Pearl River Delta, two of China's most important economic centers, both of which are highly efficient, excellent-performing provinces. By contrast, Jiangxi and Fujian's efficiency performance is not sufficient, forming an "efficiency lowland" and thus always in the "L–H" region. This result also indicates that the eco-technological innovation in the Yangtze River Delta and the Pearl River Delta has limited ability regarding spillover into the surrounding areas.

The results of the LISA analysis show that there is a strong spatial similarity in the development of green S&T innovation efficiency among neighboring provinces and cities in China geographically, which is specifically reflected in the fact that provinces and cities with higher and lower efficiency values tend to be relatively close to each other and are relatively concentrated geographically. Therefore, China's strategy to improve the efficiency of green innovation should use the driving effect between different regions and form growth poles by cultivating efficiency heights to drive ecological civilization's development and progress in larger regions and even the whole country.

5 Conclusions

Under the concept of ecological civilization and innovation-driven development, the effective improvement of the green innovation efficiency in different provinces of China and fully understanding the effects of innovation on ecological and environmental constraints are very important for improving the quality of China's economic development. Based on the perspective of green innovation, this paper calculated the green S&T innovation efficiency of China over the past ten years by building three stages of ultra-efficient SBM models that contain unexpected outputs. Then, we use the efficiency value results as the analysis objects and investigate the spatial correlation and heterogeneity of Chinese provincial green technological innovation efficiency by the exploratory spatial data analysis (ESDA) method. The results show that the efficiency value of green technology innovation in Chinese provinces is highly unsatisfactory in the whole research period, and there is still much room for improvement. In addition, after eliminating slacks, such as variable redundancy and management inefficiency, the efficiency value of China's green S&T innovation declines significantly. This result means that China's investment in S&T innovation and environmental management suffers from serious waste and low utilization efficiency.

In addition, the Chinese provincial efficiency value showed significant spatial autocorrelation in both global and local conditions. The spatial distribution presented an obviously nonrandom geographical agglomeration pattern. Different provinces and cities have shown spatial heterogeneity and correlation, the spillover effect is obvious, and the space network structure is stable. The LISA test results show that an increasing number of provinces are effective, indicating an increasing number of provinces are involved in the waves of "ecological civilization" and are "innovation-driven." The correlation between provinces is strengthening. The bad news is that the provinces with the "High-High" model did not expand significantly in the study period (10 years), indicating that the strength of space overflow is limited and the overall correlation strength is low, which needs to be further reinforced.

This paper suggests that Chinese central government endow local governments with greater autonomy in development, and that local governments implement development policies according to local conditions. To help develop the eastern region, the local governments should provide more preferential treatment, help, support and guidance for modern service industries and high-tech industries with little pollution and high value, and give rewards to enterprises with mature technologies and considerable benefits. To help develop the central region, the local governments should further improve the degree of concentration, extend the industrial chain, and implement the strategy of diversified development. And more time and energy should be put in resource recycling, product quality improvement, technology improvement, and market development, thus actively carrying out environmental rectification work and promoting the transformation and upgrading of traditional industries. In the western region, local governments should selectively undertake industrial transfer from the eastern and central regions, make the development of green innovation a priority of government investment, and support the development of green and technological enterprises through investment, subsidies, or interest discounts.

Due to the large differences in area and development, different regions in China should adopt different development strategies. Local governments should have more development initiatives to make decisions. However, it should be noted that more power for local governments may lead to chaos in competition. To a large extent, the deterioration of China's environment is caused by previous local governments lowering environmental protection standards and implementing extensive development mode in order to win the race in the fierce regional economic competition. Now, with the environment increasingly deteriorated, this wrong concept of development has shown huge side effects, seriously affecting the economic sustainability. Therefore, in order to standardize the development behavior of local governments, the central government needs to perfect and strictly implement the environmental assessment mechanism of local government.

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References

Andersen P, Petersen NC (1993) A procedure for ranking efficient units in data envelopment analysis. Manage Sci 39:1261–1264

Cao X, Yu J (2015) Regional innovation efficiency in China from the green low-carbon perspective, China population. Resour Environ 25:10–19

Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2:429–444

European Commission (2011) Environmental Technology Action Plan (Eco AP), http://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0899:FIN:EN:PDF

Fried L, Schmidt Y (2002) Accounting for environmental effects and statistical noise in data envelopment analysis. J Prod Anal 17:121–136

Gong XS, Li MJ, Zhang HZ (2017) Has OFDI promoted the industrial enterprises' green innovation efficiency in China—evidence based on agglomeration economic effect. J Int Trade 11:127–137

Huang L, Wu CQ (2019) Research on the efficiency and synergetic effect of industry's green development and innovative development in the Yangtze River economic belt. J Chongqing Univ (Soc Sci Ed) 3:1–13

Khan Z, Ali M, Kirikkaleli D, Wahab S, Jiao Z (2020) The impact of technological innovation and public-private partnership investment on sustainable environment in China: consumption-based carbon emissions analysis. Sustain Dev 1–14

Liu J, Song QY (2018) Space Network structure and formation mechanism of green innovation efficiency of tourism industry in China. China Popul Resour Environ 28:127–137

Li JW, Zhang XY, Ali Shahid, Khan Zeeshan (2020) Eco-innovation and energy productivity: new determinants of renewable energy consumption. J Environ Manage 271:111028

Li ZZ, Li YM, Malik MY, Murshed M, Khan Z, Umar M (2020) Determinants of carbon emission in China: how good is green investment? Sustain Prod Consump Sustain Prod Consump 27:392–401

Luo LW, Liang SR (2017) The Spatial Effect Of International R&D capital technology spillovers on the efficiency of China's green technology innovation. Bus Manage J 39:21–33

Nie MH, Qi H (2019) Can OFDI improve China' s industrial green innovation efficiency?: based on the perspective of innovation value chain and spatial correlation effect. World Econ Stud 2:111–122+137.
Peng WB, Cheng FF, Lu JL (2017) A study on the threshold effect of environmental regulation to provincial green innovation efficiency. South China J Econ 9:73–84
Qian L, Wang WP, Xiao RQ (2018) Research on the regional disparities of China's industrial enterprises green innovation efficiency from the perspective of shared inputs. China Popul Resour Environ 28:27–39
Rasi K, Ester MR (2016) Towards green growth: how does green innovation affect employment. Res Policy 45:1218–1232
Ren Y, Niu CH, Niu T, Yao XL (2014) Theoretical model and empirical research on green innovation efficiency. Manage World 7:176–177
Rennings K, Markewitz P, Vegele S (2016) How clean is clean incremental versus radical technological change in coal-fired power plants. J Evol Econ 2:331–355
Shen N, Zhou JJ (2018) A study on China's green innovation efficiency evaluation and functional mechanism based on hybrid DEA and SEM model. J Ind Eng Eng Manage 32:46–53
Shen YJ, Su ZW, Malik MY, Umar M, Khan Z, Khan M (2021) Does green investment, financial development and natural resources rent limit carbon emissions? A provincial panel analysis of China. Sci Tot Environ 755:142538
Tone K (2002) A slacks–based measure of super—efficiency in data envelopment analysis. Eur J Oper Res 143:32–41
Wang H, Wang SQ, Miao Z, Li XC (2016) Heterogeneity threshold effect of R&D investment on green innovation efficiency based on chinese high–tech industries. Sci Res Manage 37:63–71
Xiao LM, Gao JF, Liu S (2017) Trend of green technology innovation efficiency in China based on spatial gradient—empirical analysis of inter-provincial panel data. Soft Sci 31:63–68
Xiao LM, Zhang XP (2019) Spatio-temporal characteristics of coupling coordination between green innovation efficiency and ecological welfare performance under the concept of strong sustainability. J Nat Resour 34:312–324
Xu JZ, Wang MM, Guan J (2019) Research on mechanism of carbon emission from energy consumption and green innovation efficiency in dynamic endogenous perspective based on chinese equipment manufacturing industries. Manage Rev 31:81–93
Yang SW, Wu T, Li ZB (2018) Spatial and temporal differentiation of green innovation efficiency in cities of Yangtze River economic belt and its influencing factors. Urban Probl 6:107–117+132
Yao XL, Niu CH, Liu J (2015) Innovation driven, green growth and industrial economic efficiency. Forum Sci Technol China 57-62
Yi M, Cheng XM (2018) Spatial and temporal differentiation of green innovation efficiency in cities of Yangtze River economic belt and its influencing factors. Urban Probl 31–39
Yu SJ, Li XS, Peng ZY (2017) Research on environmental regulation model and green innovation efficiency of Yangtze River economic belt—an empirical analysis based on 38 cities. Jianghai Acad J 209-214
Zhang JQ, Pu SD (2017) Measuring allocation efficiency of regional green S&T resource based on three-stage SBM-DEA—taking guilin city as an example. Resour Dev Market 33:1–7
Zhu CL, Liu RM, Wang HW (2018) Green innovation performance evaluation and promotion path of patent intensive industries. J Quant Techn Econ 35:61–79

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