Volume 16 • Issue 4 • 2024

sciendo

received: 1 November 2023
accepted: 1 August 2024

pages: 48-68

Evaluation and spatiotemporal evolution of green innovation efficiency in China: a two-stage value chain perspective

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ABSTRACT
As the global problems of environmental pollution and ecological degradation are becoming important obstacles to the realisation of sustainable development, green technological innovation (GTI) has received wide attention in the academic and practical communities worldwide. Commonly, the GTI process can be divided into two stages: green technology R&D and green achievement transformation. The contribution of GTI to economic development and environmental protection depends to a large extent on green innovation efficiency (GIE). Based on the panel data on inputs and outputs of 30 provinces in China from 2007 to 2021, this study applied the super efficiency SBM model considering undesirable outputs to evaluate green technology R&D efficiency (GTRDE) and green achievement transformation efficiency (GATE). Additionally, this study adopted the global and local Moran's I index for spatial autocorrelation analysis. First, GTRDE showed a trend of "eastern > western > central > northeastern", while GATE showed a trend of "eastern > central > western > northeastern". Second, although GATE was higher than GTRDE in most provinces, the differences between provinces were significantly larger for the former than for the latter. Third, global spatial autocorrelation in GIE across provinces was significant only in a few years, while local spatial autocorrelation existed only in a few provinces. Based on the two-stage value chain perspective, the green innovation process is divided into green technology R&D and green achievement transformation. This paper also introduces a super-efficiency SBM model that considers undesirable outputs when calculating GIE. This is in line with the basic laws of GTI and development in reality. Thus, to enhance the efficiency of green innovation, governments and enterprises should raise awareness of GTI, enhance inter-regional exchanges and collaboration, and take a variety of measures to narrow the gap between regions.

KEY WORDS
green innovation efficiency, spatiotemporal evolution, two-stage value chain, green technology R&D, green achievement transformation, super-efficiency SBM model

10.2478/emj-2024-0033

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Introduction

As an integral part of the world's economic system, China's economy has grown by leaps and bounds over the past few decades. According to the World Bank (2023), China's GDP grew at an average annual rate of 6.056 % from 2013–2022 and is now firmly established as the world's second-largest economy, just after the United States. China eliminated absolute poverty and hunger by the end of 2020, a world-renowned achievement that makes it an important representative of developing countries and emerging economies. However, such rapid development is often

Li, M., & Chen, Y. (2024). Evaluation and spatiotemporal evolution of green innovation efficiency in China: a two-stage value chain perspective. *Engineering Management in Production and Services, 16*(4), 48-68. doi: 10.2478/emj-2024-0033

characterised by high inputs, high consumption and high emissions and comes at the expense of the environment and ecology, further leading to environmental pollution and ecosystem degradation (Cao et al., 2021; Fan et al., 2021). For instance, according to the World Resources Institute (2023), China is the world's largest emitter of greenhouse gases. Greenhouse gas emissions have become an important environmental issue in China and worldwide. To change this critical situation and achieve the goal of sustainable development, China proposed the goals of carbon peaking before 2030 and carbon neutrality before 2060 (dual carbon goals) in September 2020, pledging to make every effort to repair the environment and solve ecological problems. Then, the concept of green development has continued to receive extensive attention from the academic and practical communities. In short, green development advocates resource conservation, ecological protection and environmental governance. It seeks to realise the harmonious coexistence between humans and nature and is an important means of achieving the sustainable development goal. At present, the governments at all levels in China have incorporated the concept of low-carbon and green development into policymaking and planning (Zhang et al., 2022).

The realisation of green development cannot be separated from the support of technological innovation. Technology is an important force for human development and social progress, bringing many conveniences to human production and daily life. Specifically, technology helps to free humans from various boring, tedious, and dangerous tasks and move them to other, more important tasks. This way, it accomplishes the social division of labour and collaboration between humans and machines. However, the creation and existence of technology does not always have only positive aspects but also negative impacts, especially for the environment and ecology in the case of non-green parts in technologies. For instance, although the invention of plastics has facilitated people's daily lives, their characteristics of being difficult to degrade and recycle lead to environmental degradation. Some of the discarded plastics have seriously threatened the survival of marine life, such as fish. Additionally, the convenience of technology tends to divert human beings towards extravagant enjoyment, resulting in greater environmental pollution and waste of resources. Therefore, green technologies, as compared with traditional technologies, need to be the focus of attention to realise green development. The active development of green technologies is the key to realising a green and low-carbon transformation of society and resolving the conflict between economic growth, resources, and the environment (Du & Li, 2019; Shan et al., 2021). It has become a consensus to promote economic growth and environmental improvement by raising the level of green technological innovation (GTI) (Faulkner, 2004). GTI can drive rapid economic growth while avoiding negative externalities that innovation activities may bring to the ecology and the environment (Cao et al., 2021; Fang et al., 2022a; Shan et al., 2021; Moskalenko et al., 2022; Fu et al., 2023; Fu & Chang, 2024). Thus, combining green development and technological innovation has become an effective means to achieve sustainable development (Fan et al., 2021; Zeng et al., 2021).

Obviously, the effectiveness of GTI in realising the goal of sustainable development depends largely on the efficiency of green innovation. Normally, efficiency reflects the ratio between the quantities of various inputs and outputs at a specific time (Xu et al., 2020). Under the conditions of a given range of resource inputs and technologies, regions with higher green innovation efficiency (GIE) can produce more desirable outputs (i.e., environmentally friendly outputs) and fewer undesirable outputs (i.e., non-environmentally friendly outputs). According to the National Bureau of Statistics of China (2023), the intramural expenditure on R&D in China grew at an average annual rate of 11.228 % from 2013–2022 and reached 3.087 trillion yuan in 2022. Similarly, the full-time equivalent of R&D personnel in China reached 6.041 million man-years in 2022. However, even with all these inputs, the desirable outputs produced are still relatively insufficient. The low efficiency of green innovation in China may be due to the loss or waste of technology in serving production and life, or it may be due to the management system. In addition, there are differences in GIE between regions due to the differences in geographic location, resource endowment and policy planning. So, measuring the GIE in China's provinces and improving GTI are important issues that China needs to address at present, and they are also the starting point of this study.

The contributions and innovations of this study compared to existing studies are in the following three main aspects. First, the contribution to the research perspective. On the basis of the two-stage value chain perspective, the green innovation process is divided into green technology R&D and green achievement transformation. Besides, considering the time lag effect, this study calculates the green technology R&D efficiency (GTRDE) and the green achievement transformation efficiency (GATE) separately. This is aligned with the reality of the basic laws of GTI and development. Second, the contribution to research methodology. This study introduces a super-efficiency SBM model that considers undesirable outputs when calculating GIE. The efficiency values calculated by this method can be greater than 1.000, avoiding the inability to compare decision-making units (DMUs) when they are simultaneously effective. Meanwhile, this method considers undesirable outputs, such as carbon emissions and energy consumption, and the global frontier-based measure allows for horizontal and vertical comparisons of GIE. Third, the contribution to research content. This study calculates the GIE based on the two-stage value chain perspective. Additionally, this study analyses and visualises the spatial and temporal evolution of GIE in different provinces, as well as the spatial autocorrelation. So it can ensure that the results align with social development's reality.

1. Literature review

1.1. GIE

As an effective means of improving the utilisation efficiency of energy and nature's resources, easing environmental pollution and ecological degradation, and realising sustainable development, the GTI has received extensive attention from academic and practical circles (Cao et al., 2021; Miao et al., 2017; Sun et al., 2017). Among them, much of the existing research provides an in-depth portrayal of the GTI process as a whole (Shan et al., 2021). However, the approach of considering the GTI as a whole is flawed and does not allow for effective differentiation between the subcategories. So, Song and Han (2022) considered categorising GTI into green product innovation and green process innovation. However, such a categorisation still fails to differentiate GTIs from the sequence of processes. In terms of the sequence of processes, based on the innovation value chain perspective, GTI can be categorised into two stages: green innovation of R&D activities and transformation activities of green innovation achievement (Sun et al., 2022; Zhu et al., 2021). Obviously, these two stages are chronologically sequential and can provide a good GTI explanation.

Several research efforts have focused on GTI, measured by using indicators related to green patents (i.e., green invention patents and green utility model patents) applications and grants (Feng et al., 2022; Gao et al., 2022; Zhang & Liu, 2022). For instance, Suki et al. (2022) used green technological patents as the proxy of GTI and evaluated the GTI in the ASEAN region. Wang et al. (2019) also used the patent data to measure the GTI in China. Besides, Xue et al. (2022) used green patents granted to measure the GTI. However, the GTI using green patents as the proxy considers more quantitative performance and neglects the quality and efficiency. Therefore, many research efforts focus on the GIE, e.g., Fang et al. (2022b), Liao and Li (2023), and Miao et al. (2021). In addition, Fan et al. (2021) and Wang et al. (2023) evaluated the GIE of 235 cities and 285 prefecture-level or above cities in China, respectively. Sun et al. (2022) calculated the GIE in tourism in 30 Chinese provinces. So, the existing literature suggests that evaluating the GIE of the study area yields more useful conclusions than evaluating GTIs.

Currently, the research topic of GIE is related to different hierarchies and industries. Specifically, the hierarchies of existing studies include the national level (Dong et al., 2022; Jian & Afshan, 2023; Obobisa et al., 2022; Razzaq et al., 2021; Sharif et al., 2022), the provincial level (Cao et al., 2021; Chen et al., 2023), and the municipal level (Lin & Ma, 2022; Wei et al., 2023). For instance, Song and Han (2022) and Zhao et al. (2023) evaluated the GIE of 30 Chinese provinces. Fan et al. (2021), Huang and Wang (2020), Zeng et al. (2021), and Zhang et al. (2020) also calculated the GIE of 235 cities, 108 cities in the Yangtze River Economic Belt, 26 cities in Yangtze River Delta region, and Xi'an, China, respectively. A careful summary of studies on GIE in China found that most of them were regionally focused, and most of them were at the municipal level. In the industrial sectors, studies were mainly focused on intensive pollution industries (Li & Zeng, 2020; Li et al., 2022b), manufacturing industry (Wang, 2023), industrial enterprises (Miao et al., 2021; Xu et al., 2022b), family enterprises (Zheng et al., in press), and so on. For instance, He et al. (2021) calculated the GIE of listed Chinese papermaking enterprises and showed that the overall GIE of the 12 selected listed paper enterprises was low, as well as significant differences in efficiency between enterprises. In addition, Yin and Wang (2021) measured the GIE of new equipment manufacturing and showed apparent differences in the GIE of different new equipment manufacturing and uneven development. Also, Sun et al. (2022) evaluated the innovation efficiency of China's tourism industry and indicated that all provinces showed some differences in green R&D efficiency and green achievement conversion efficiency.

Studies use various methodologies to evaluate GIE. Specifically, the main methods for evaluating GIE are the slacks-based measure of super-efficiency (Super-SBM) model (Xu et al., 2020; Li & Du, 2021; Li & Zeng, 2020; Zhang et al., 2022; Xu et al., 2022a), the super-SBM model considering the undesirable outputs (Li et al., 2022b), and SBM model considering undesirable outputs (Fan et al., 2021). Also, some scholars have adopted the super network SBM model (Liao & Li, 2023), global super epsilon-based measure (EBM) model (Wang et al., 2023), the two-stage SBM model considering undesirable output (Miao et al., 2021), the super EBM-undesirable model (Wang et al., 2022), and the slacks-based measure of directional distance functions (SBM-DDF) model (Zhang et al., 2020). In addition, some scholars focus on the changes in productivity rather than efficiency itself when evaluating the GIE. Therefore, they apply the global Malmquist-Luenberger index to measure GIE (Lv et al., 2021; Long et al., 2020; Zeng et al., 2021). To summarise, the studies show that the super-efficiency SBM model, including undesirable outputs, has become an effective method for evaluating the GIE.

1.2. Application of the super-efficiency SBM model

In 1978, Charnes et al. first introduced the data envelopment analysis (DEA) model to evaluate the effectiveness of decision-making units (DMUs). The DEA model plays an important role in evaluating the effectiveness of multiple inputs and outputs of multiple DMUs. Then, considering the shortcomings of the traditional DEA model, Tone (2001) greatly improved it and named it the slacks-based measure (SBM) model. In addition, when multiple DMUs are effective (i.e., the efficiency value is equal to 1), the traditional DEA model cannot be further compared, which poses a challenge for effectiveness evaluation. So, Tone (2002) introduced the concept of super-efficiency and proposed the super-efficiency SBM model. Then, due to the widespread academic interest in undesirable outputs, Tone (2003) developed the SBM model, which considers undesirable outputs. Thereafter, the super-efficiency SBM model, which considers undesirable outputs, has become one of the most commonly used methods for evaluating the effectiveness of multiple DMUs.

Up to now, the super-efficiency SBM model has been widely used in the evaluation of effectiveness in many fields, such as social, economic and environmental aspects. In the social and economic aspects, this method was used to measure the efficiency of the hotel industry (Ashrafi et al., 2013), urban land use (Zhu et al., 2019), green growth (Razzaq & Yang, 2023), sustainable development (Khan et al., 2021), commercial banks (Shah et al., 2022), green total factor productivity (Wu et al., 2020), and green economic growth (Zhao et al., 2022). Additionally, in the environmental aspect, this method was applied to measure the energy efficiency (Gökgöz & Erkul, 2019; Tran et al., 2019), the environmental efficiency (Dirik et al., 2019; Li et al., 2022a; Taleb et al., 2023), and carbon emission efficiency (Fang et al., 2022a).

2. Materials and methods

2.1. Research process

The following steps were taken to carry out the study described in this paper: the definition of the research topic; the development of a literature review on GIE and application of the super-efficiency SBM model; selection of the study area; the definition and measurement of input and output indicators in the green technology R&D stage and green achievement transformation stage; the data collection; evaluation, spatiotemporal evolution and spatial autocorrelation

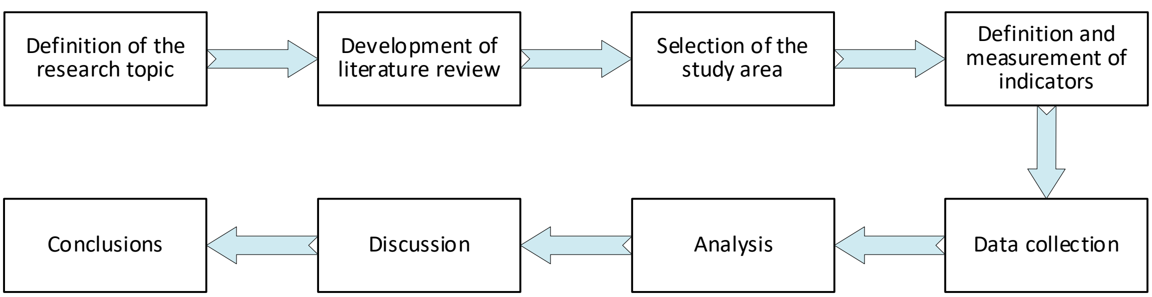

Fig. 1. Research process flow chart

analysis of China's GIE; discussion; and conclusions. The research process flow chart is presented in Fig. 1.

2.2. Study area

The study area in this research, i.e., the administrative division of China, is shown in Fig. 2. According to the definition of the National Bureau of Statistics of China, the country's 34 provincial administrative units can be divided into five regions: Eastern, Central, Western, Northeastern, and Hong Kong, Macao and Taiwan. Also, according to the Codes for the Administrative Divisions of the People's Republic of China (GB/T 2260-2007), a two-letter code for each provincial administrative unit is also labelled in Fig. 2. The eastern region includes ten provinces, the central region includes six provinces, the western region includes twelve provinces, while the northeastern region includes three provinces.

2.3. Definition and measurement of indicators

The study aims to evaluate the efficiency of green innovation; hence, the selected variables are mainly related to input and output indicators. The undesirable outputs, such as carbon dioxide emissions and energy consumption, are fully considered in the output indicators selected. Additionally, as mentioned previously, the green innovation process can be divided into two stages, i.e., green technology R&D and green achievement transformation. Typically, technological innovation has a significant time lag effect, i.e., outputs in a specific year are supposed to result from inputs in previous years. That is, for technological innovation, it is difficult to have a relatively large number of associated outputs within a short period of time for the current year's inputs. Hence, considering that green technologies need to go

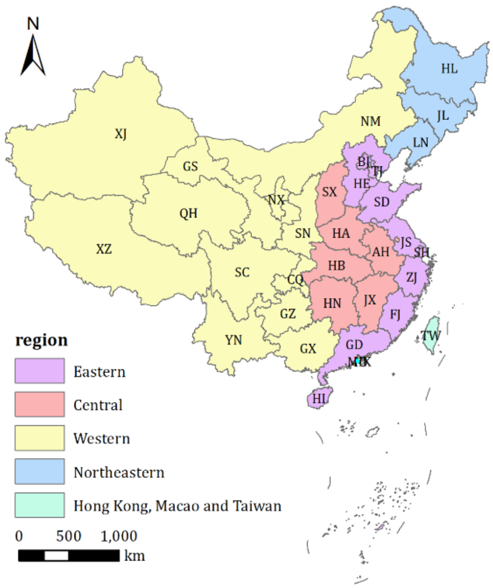

Fig. 2. Division of administrative regions in China

Tab. 1. Definition and measurement of the input and output indicators in the green technology R&D stage

Indicator	Definition and measurement	Unit
Input (4)		
IERD	Intramural expenditure on R&D	billion yuan
GPEST	General public expenditure on S&T	billion yuan
ENPD	Expenditure on new products development	billion yuan
FERDP	Full-time equivalent of R&D personnel	10000 man-years
Output (3)		
NGPA	Number of green patent applications	1000 unit
NGPG	Number of green patent grants	1000 unit
PNPD	Projects for new products development	1000 unit

through a relatively long period of time from R&D to transformation, the input and output indicators for these two stages should be different. When constructing an indicator system to evaluate the efficiency of green innovation, a distinction should be made between the selection of indicators for these two different stages.

The definition and measurement of the input and output indicators in the green technology R&D stage are shown in Table 1. In this stage, the input indicators consist mainly of capital (IERD, GPEST and ENPD) and labour (FERDP).

The output indicators of the green technology R&D stage, which is the antecedent of the green achievement transformation stage, should be considered as part of the input indicators of the green achievement transformation stage. Energy consumption and non-R&D inputs are also input indicators to be considered at this stage. Among them, non-R&D inputs are mainly obtained by adding the expenditure for the acquisition of foreign technology, assimilation, purchase of domestic technology, and technology renovation. The undesirable outputs are mainly considered in the green achievement transformation stage. As one of the undesirable outputs, the comprehensive index of environmental pollution is derived from four indicators (industrial COD discharged, industrial SO2 emission, common industrial solid wastes generated, and CO2 emissions) and is calculated by the entropy weighting method. The evaluation indicators selected for the green achievement transformation stage are shown in Table 2.

2.4. Data sources

In this study, raw data on inputs and outputs of Chinese provinces from 2007 to 2021 were selected to calculate GIE. Four provinces, Hong Kong, Macao, Taiwan and Xizang, were not included in the study area due to the missing data. Hence, only 30 provinces in China were included in the study area, yielding a sample of 450. This study mainly obtained raw data from the National Bureau of Statistics of China, Chinese Research Data Services (CNRDS) Platform, China Statistical Yearbook, China Energy Statistical Yearbook, China Statistical Yearbook on Environment, and China Statistical Yearbook on Science and Technology. Simultaneously, this study filled in the missing data through other official sources (e.g., statistical yearbooks released by the provinces) to ensure the accuracy of the data and the rigour of the study. None of the raw data has been transformed in any way other than that. The data sources of all indicators are shown in Table 3.

Additionally, the descriptive statistics for all indicators are shown in Table 4. In the green technology R&D stage, the time range for the data of IERD, GPEST, ENPD and FERDP is 2007–2019. Correspondingly, the time range of NGPA, NGPG and PNPD is 2008–2020. Similarly, in the green achievement transformation stage, the raw data of TEC and NRDI, besides NGPA, NGPG and PNPD, also range from 2008 to 2020. As output indicators, the raw data of SRNP, TVTM, VAI, CIEP and ECGDP range from 2009 to 2021. That is, considering the time lag effect

Tab. 2. Definition and measurement of the indicators in the green achievement transformation stage

Indicator	Definition and measurement	Unit
Input (5)		
NGPA	Number of green patent applications	1000 unit
NGPG	Number of green patent grants	1000 unit
PNPD	Projects for new products development	1000 unit
TEC	Total energy consumption	million tce
NRDI	Non-R&D inputs	billion yuan
Desirable output (3)		
SRNP	Sales revenue of new products	billion yuan
TVTM	Transaction value in technical markets	billion yuan
VAI	Value-added of industry	billion yuan
Undesirable output (2)		
CIEP	Comprehensive index of environmental pollution	index
ECGDP	Energy consumption per unit of GDP	tce/10000 yuan

Tab. 3. Sources of raw data for all indicators

Indicator	Source
ENPD, PNPD, SRNP, TVTM	The National Bureau of Statistics of China
NGPA, NGPG	Chinese Research Data Services (CNRDS) Platform
GPEST, VAI, ECGDP	China Statistical Yearbook
TEC, CIEP, ECGDP	China Energy Statistical Yearbook
CIEP	China Statistical Yearbook on Environment
IERD, FERDP, NRDI	China Statistical Yearbook on Science and Technology

Tab. 4. Descriptive statistics for all indicators

Indicator	Mean	Min	Median	Max	St. D	Skewness	Kurtosis
IERD	39.560	0.260	17.614	309.849	50.860	2.325	9.068
GPEST	9.573	0.252	4.604	116.879	13.439	3.711	22.585
ENPD	29.936	0.225	12.706	386.498	48.187	3.649	19.768
FERDP	10.963	0.126	6.510	80.321	12.664	2.384	9.599
NGPA	6.296	0.031	2.750	63.361	9.579	3.105	14.364
NGPG	3.420	0.016	1.578	35.825	5.060	3.166	15.660
PNPD	13.128	0.083	6.237	166.140	21.410	3.715	19.832
TEC	144.218	11.350	117.735	421.329	87.645	0.928	3.273
NRDI	15.231	0.152	10.695	111.691	15.071	2.469	11.851
SRNP	538.918	0.857	262.760	4968.490	787.099	2.806	11.940
TVTM	42.908	0.056	10.374	700.565	87.154	4.080	23.503
VAI	850.608	27.370	590.480	4573.070	807.624	1.955	7.318
CIEP	0.284	0.001	0.249	0.866	0.202	0.725	2.830
ECGDP	0.869	0.173	0.670	2.611	0.523	1.186	3.714

of GIE, this study sets the time lag for both inputs and outputs of the green technology R&D stage and the green achievement transformation stage to one year.

2.5. Methods

The Super-efficiency SBM Model. In this study, the super efficiency SBM model considering undesirable outputs is applied to calculate the GTRDE and the GATE in 30 provinces in China. Specifically, this model combines the advantages of both the SBM model and the super-efficiency model, i.e., it considers undesirable outputs and allows for further differentiation of relatively efficient DMUs. This model assumes n DMUs, and each DMU involves input, desirable output, and undesirable output indicators. Then, referring to Xu et al. (2020), this model can be constructed as in Eq. (1).

$$\min \rho = \frac{1+\frac{1}{m}\sum_{m=1}^{M}\frac{s_m^x}{x_{jm}^t}}{1-\frac{1}{l+h}\left(\sum_{l=1}^{L}\frac{s_l^y}{y_{jl}^t}+\sum_{h=1}^{H}\frac{s_h^b}{b_{jh}^t}\right)}$$

$$s.t.\begin{cases} x_{jm}^t \geq \sum_{j=1,j\neq 0}^{n} \lambda_j^t x_{jm}^t + s_m^x \\ y_{jl}^t \geq \sum_{j=1,j\neq k}^{n} \lambda_j^t y_{jl}^t - s_l^y \\ b_{jh}^t \geq \sum_{j=1,j\neq k}^{n} \lambda_j^t b_{jh}^t + s_h^b \\ \lambda_j^t \geq 0,\, s_m^x \geq 0,\, s_l^y \geq 0,\, j=1,\cdots,n \end{cases} \tag{1}$$

where ρ denotes the GIE of provinces, and the larger the value, the higher the GIE of the specific province. λ represents the constant vector of the j-th DMU. Moreover, x_j^t, y_j^t and b_j^t denote the input, desirable output, and undesirable output indicator of the j-th DMU in the t-th year, respectively. m, l and h denote the number of the input, desirable output, and undesirable output indicator, while s_m^x, s_l^y and s_h^b are the slack vector of the input, desirable output, and undesirable output indicator, respectively.

Global and Local Moran's I Index. In this study, the global Moran's I index is adopted to investigate the global spatial autocorrelation, i.e., the overall distribution of the GIE, and to judge whether there is a spatial clustering characteristic and the degree of clustering of all provinces. The value range of the global Moran's I index is [-1,1]. Also, a global Moran's I index greater than 0 means that provinces with higher (or lower) values of GIE are spatially clustered, i.e., the contiguous provinces have very similar GIE. Conversely, a global Moran's I index of less than 0 implies the existence of negative spatial autocorrelation, i.e., strong variability in GIE among contiguous provinces. When the global Moran's I index is equal to 0, it indicates that there is no spatial autocorrelation, i.e., the GIE of each province is spatially randomly distributed. Referring to Li et al. (2023) and Mei et al. (2023), the global Moran's I index can be calculated as in Eq. (2).

$$Global\ Moran's\ I = \frac{n \times \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \times \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (2)$$

where n represents the number of provinces. Also, x_i denotes the GIE of the i-th province. $\bar{x}$ is the average of the green innovation efficiencies of all provinces. Moreover, w_{ij} is the spatial weight matrix that indicates the adjacency relationship between the i-th province and j-th province. When the i-th province and j-th province are adjacent, $w_{ij} = 1$; otherwise, $w_{ij} = 0$. In addition, a specific province is not adjacent to itself, i.e., it is specified that $w_{ii} = 0$.

The local Moran's I index is used to measure the local spatial autocorrelation and spatial distribution of the GIE of each province in relation to adjacent provinces. Thus, referring to Li et al. (2023) and Mei et al. (2023), the local Moran's I index can be calculated as in Eq. (3).

$$Local\ Moran's\ I = \frac{n \times \left(x_i - \bar{x}\right) \times \sum_{j=1}^{n} w_{ij}\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \quad (3)$$

3. Results and discussion

3.1. Evaluation of GIE

The evaluation of GTRDE in each province is shown in Table 5. Due to layout constraints, Table 5 only shows the evaluated efficiencies for even-numbered years. Among all the GTRDEs, the highest value appeared in Hainan in 2008, with an efficiency of 1.406, while the lowest value appeared in Inner Mongolia in 2012, with an efficiency of 0.185. That is, the highest value was 7.6 times the lowest value. Inner Mongolia ranked in the top ten lowest GTRDEs in seven years; hence, it became the province with the lowest average GTRDE, with a value of only 0.314. Other provinces with low GTRDE included Jilin, Shanxi, Shanghai, and Liaoning, with average values below 0.5. On the contrary, the province with the highest GTRDE was Zhejiang, followed by Hainan, Beijing, Sichuan, Chongqing, and Ningxia, with average values above 0.7. Additionally, with the exception of Guangdong and Inner Mongolia, persistent fluctuation was a distinctive characteristic of the GTRDE exhibited by the vast majority of provinces. The GTRDE of Guangdong and Inner Mongolia generally showed a steady upward trend during the examined time period.

The evaluation of GATE in each province is shown in Table 6. Due to layout constraints, Table 6 only shows the efficiencies for odd-numbered years. GATE in Hainan in 2014 was 1.835, which was the highest of all efficiencies. In comparison, Guangxi had the lowest efficiency in 2015, at 0.054. The top 26 lowest-ranked of all efficiencies were from some selected years in Guangxi, Guizhou, Xinjiang, and Ningxia. In consequence, Ningxia, Guizhou, and Guangxi became the three provinces with the lowest average GATE, with an average efficiency of 0.142, 0.247, and 0.259, respectively. On the contrary, Xinjiang was ranked 14th with an efficiency of 0.650. This is mainly due to the very large fluctuations in the GATE in Xinjiang in different years, spanning from 0.079 (in 2016) to 1.101 (in 2011), a difference of nearly 14 times. Furthermore, Hainan, Guangdong, and Henan had GATE higher than 1, followed closely by Qinghai, Jiangxi and Beijing, which had efficiencies higher than 0.9. Overall, compared with the GTRDE, the disparity in the GATE in different provinces was more apparent.

3.2. Temporal evolution of GIE

The temporal evolution of GTRDE in each divided region in China is shown in Fig. 3. As shown in Fig. 3, the temporal evolution of GTRDE is highly consistent across regions. Nationwide, while the GTRDE has remained on the rise amidst fluctuations, it has only increased from 0.651 in 2008 to 0.757 in

Tab. 5. Evaluation of GTRDE

Province	Code	2008	2010	2012	2014	2016	2018	2020	Average
Zhejiang	ZJ	1.066	0.469	0.660	0.620	0.825	1.181	1.072	0.863
Hainan	HI	1.406	1.054	0.598	0.571	0.686	1.073	1.132	0.845
Beijing	BJ	1.160	0.439	0.573	0.781	1.010	1.099	0.611	0.798
Sichuan	SC	0.769	0.524	0.678	0.620	0.828	1.063	0.657	0.748
Chongqing	CQ	1.039	0.593	0.685	0.665	0.767	0.717	0.607	0.743
Ningxia	NX	1.047	0.384	0.607	0.550	0.731	1.035	0.778	0.724
Guizhou	GZ	1.051	0.438	0.516	0.589	0.659	1.065	0.650	0.690
Tianjin	TJ	1.022	0.405	0.483	0.491	0.583	1.033	1.005	0.681
Anhui	AH	0.625	0.411	0.585	0.591	0.829	1.072	0.636	0.677
Jiangsu	JS	0.559	0.434	0.557	0.537	0.649	1.064	1.073	0.677
Guangxi	GX	1.006	0.304	0.366	0.499	1.011	0.774	0.627	0.632
Shaanxi	SN	1.069	0.484	0.602	0.553	0.443	0.559	0.650	0.620
Guangdong	GD	0.392	0.419	0.435	0.410	0.553	1.154	1.092	0.609
Shandong	SD	0.508	0.460	0.460	0.452	0.589	0.638	1.011	0.597
Yunnan	YN	0.518	0.390	0.454	0.528	0.728	1.007	0.641	0.594
Fujian	FJ	0.361	0.411	0.470	0.441	0.743	1.046	0.659	0.575
Hebei	HE	0.414	0.399	0.481	0.436	0.637	0.773	1.005	0.552
Heilongjiang	HL	0.561	0.419	0.436	0.506	0.563	0.711	0.754	0.550
Qinghai	QH	1.079	0.286	0.411	0.205	0.344	0.675	1.084	0.545
Jiangxi	JX	0.435	0.344	0.381	0.407	0.672	1.039	0.535	0.526
Hubei	HB	0.775	0.453	0.435	0.422	0.443	0.565	0.470	0.519
Hunan	HN	0.683	0.412	0.482	0.485	0.492	0.603	0.528	0.516
Henan	HA	0.525	0.437	0.413	0.442	0.535	0.723	0.582	0.515
Gansu	GS	0.533	0.386	0.478	0.435	0.443	1.031	0.703	0.512
Xinjiang	XJ	0.450	0.365	0.328	0.375	0.545	1.007	1.037	0.510
Liaoning	LN	0.391	0.347	0.357	0.311	0.486	0.742	0.649	0.453
Shanghai	SH	0.418	0.341	0.402	0.394	0.430	0.484	0.496	0.426
Shanxi	SX	0.277	0.313	0.318	0.295	0.446	0.615	0.663	0.405
Jilin	JL	0.359	0.276	0.319	0.292	0.320	0.457	0.488	0.402
Inner Mongolia	NM	0.217	0.186	0.185	0.228	0.296	0.460	0.818	0.314
Average	/	0.691	0.419	0.472	0.471	0.610	0.849	0.757	0.594

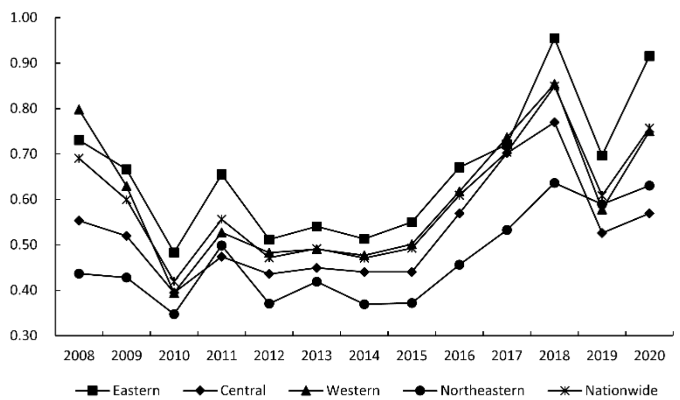

Fig. 3. Temporal evolution of GTRDE by region

Tab. 6. Evaluation of GATE

Province	Code	2009	2011	2013	2015	2017	2019	2021	Average
Hainan	HI	1.529	1.119	1.016	1.033	1.035	1.136	1.041	1.173
Guangdong	GD	1.013	1.045	1.016	1.040	1.020	1.113	1.111	1.050
Henan	HA	1.016	1.030	1.014	0.867	1.023	1.011	1.028	1.006
Qinghai	QH	1.236	1.073	1.066	1.101	1.140	1.049	0.410	0.971
Jiangxi	JX	1.014	1.050	1.044	1.001	0.762	0.469	1.072	0.952
Beijing	BJ	1.027	1.035	1.020	0.590	0.651	1.191	1.217	0.946
Fujian	FJ	0.620	1.024	0.606	1.012	1.002	1.021	1.048	0.886
Hubei	HB	0.262	0.640	0.890	1.023	1.047	1.059	1.069	0.868
Jiangsu	JS	1.033	1.015	0.627	0.576	0.641	1.001	1.080	0.866
Chongqing	CQ	0.524	1.004	0.562	0.645	1.005	1.015	1.047	0.815
Shanghai	SH	0.584	0.703	0.611	0.635	1.015	1.011	0.737	0.811
Inner Mongolia	NM	1.038	1.017	1.002	0.338	0.477	0.434	1.047	0.774
Shaanxi	SN	0.222	0.341	0.604	0.498	1.012	1.044	1.067	0.734
Hunan	HN	1.210	0.380	0.403	0.470	1.007	0.622	1.032	0.720
Shandong	SD	1.014	1.003	0.489	0.474	0.462	0.519	1.033	0.673
Tianjin	TJ	0.468	0.524	0.513	0.641	0.701	0.577	0.826	0.661
Xinjiang	XJ	0.172	1.101	1.007	0.093	0.089	1.018	1.029	0.650
Shanxi	SX	0.371	1.019	0.431	0.224	0.658	0.413	0.597	0.541
Jilin	JL	0.419	0.831	0.264	0.302	0.652	0.870	0.458	0.516
Zhejiang	ZJ	0.321	0.348	0.179	0.308	0.320	0.491	1.039	0.492
Hebei	HE	0.486	1.016	0.337	0.276	0.261	0.428	0.648	0.472
Anhui	AH	0.474	0.486	0.367	0.344	0.301	0.346	0.889	0.449
Gansu	GS	0.445	0.499	0.350	0.242	0.249	0.438	0.539	0.445
Sichuan	SC	0.326	0.348	0.366	0.405	0.466	0.577	0.666	0.445
Liaoning	LN	0.317	0.386	0.411	0.344	0.410	0.400	0.482	0.394
Yunnan	YN	0.225	1.012	0.443	0.344	0.320	0.251	0.298	0.360
Heilongjiang	HL	0.178	0.221	0.256	0.233	0.365	0.297	0.477	0.294
Guangxi	GX	0.121	0.296	0.128	0.054	0.172	0.300	1.016	0.259
Guizhou	GZ	0.078	0.219	0.122	0.149	0.227	0.405	0.490	0.247
Ningxia	NX	0.122	0.299	0.080	0.106	0.115	0.124	0.185	0.142
Average	/	0.596	0.736	0.574	0.512	0.620	0.688	0.823	0.654

2020 over the examined period, with an average annual growth rate of only 1.265 %. Moreover, only in 2017, 2018, and 2020 was the national average GTRDE higher than in 2008. Only in 2018 and 2020, with an efficiency of 0.954 and 0.916, respectively, was the GTRDE in the eastern region higher than in 2008 (with an efficiency of 0.731). The GTRDE in the central region was higher in 2016, 2017, 2018, and 2020 than in 2008. In contrast, in the western region, only 2018 (with an efficiency of 0.854) has a higher GTRDE than 2008. Also, the temporal evolution of GTRDE in the northeastern region is more unique than in other regions, with higher efficiency in 2011 and the years after 2016 than in 2008. It should be noted that regardless of region, the highest value of GTRDE occurred in 2018, while the lowest value occurred in 2010. Besides, Fig. 3 also shows that the temporal evolution of GTRDE showed the basic characteristic of "eastern>western>central>northeastern".

Overall, the temporal evolution of GTRDE in each region can be divided into four stages: 2008–2010, 2010–2015, 2015–2018, and 2018–2020. In the first stage (2008–2010), GTRDE was characterised by a continuous decline, even reaching its lowest value in 2010 for the entire examined period. In 2008, several global events (e.g., the Beijing 2008 Summer Olympics) were held in China, promoting GTI in industries such as information technology, construction, transportation, tourism and services. This has resulted in increased investment in green technology research and development in the relevant industries, leading to many green technology patents and new products. Due to the Asian Financial Crisis that erupted in 2008, many firms had to cut back on unnecessary expenditures, including R&D, in the following year or two, which seriously affected the output of products and services produced via green technology. As China gradually recovered from the recession in the second stage (2010–2015), green technology R&D inputs and outputs began stabilising, and the efficiency remained on a relatively flat trend. In the third stage (2015–2018), the GTRDE increased rapidly and reached its highest value in 2018 for the examined period. This may be attributed to the fact that the government had introduced a number of policies to promote GTI, such as supporting financial subsidies and tax incentives to the firms that actively research and develop green technologies and opening up green channels to support the introduction of advanced talents. In addition, the GTRDE fluctuated and was characterised by a clear V-shaped pattern in the fourth stage (2018–2020). In summary, the GTRDE of each region shows an upward trend in the long term.

The temporal evolution of GATE in China is shown in Fig. 4. In similarity to the temporal evolution of GTRDE, while GATE maintains a long-term growth pattern over the period examined, the growth amplitude is relatively small and varies considerably across regions. The difference is that the temporal evolution of GATE generally shows the characteristic of "eastern>central>western>northeastern". Also, all regions, except the northeastern, reached their highest values for the period examined in 2014 in terms of GATE. Specifically, in the northeastern region, the highest value occurred in 2019 at 0.522. Due to a good economic foundation and a well-developed infrastructure and business environment, the GATE is significantly higher in the eastern and central regions compared to others. The GTRDE and GATE in the northeastern region are the lowest among all regions, and the efficiency gap with other regions tends to widen. One possible explanation is that it is difficult to adjust the long-standing national economic system of the northeastern region based on heavy industry to environmental and ecological constraints. Also, owing to its geographical location and natural environment, the region is less likely to attract advanced technical talents.

Generally, the temporal evolution of GATE can be divided into three stages: 2009–2013, 2013–2015, and 2015–2021. In the first stage (2009–2013), the GATE experienced the first significant fluctuation in the period examined, with the turning point occurring in 2011. This year, China's science and technology authorities issued a number of documents related to the "Twelfth Five-Year Plan", as well as the National Medium- and Long-Term Plan for the Development of S&T Talents (2010–2020). The second significant fluctuation occurred in the second stage (2013–2015), with the turning point occurring in 2014, and was characterised by an obvious reverse V-shape. In the third stage (2015–2021), beginning in 2015, the GATE entered a period of steady growth. In 2015, China amended the Law of the PRC on Promoting the Transformation of S&T Achievements to further provide policy support for promoting the transformation of green achievements. The trend in efficiency during this stage remained upward, although there were occasional slight fluctuations. In addition, the similarity in the temporal evolution of GTRDE and

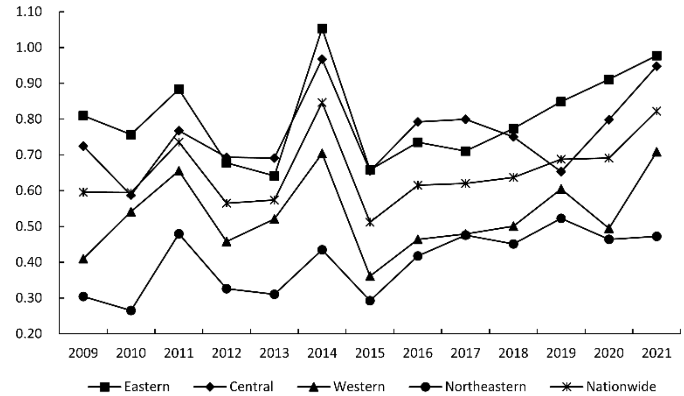

Fig. 4. Temporal evolution of GATE by region

GATE suggests, to some extent, a correlation between the two. This further justifies this study's consideration of the time lag effect of technology in calculating the GIE. However, there are also differences in the temporal evolution of the two, indicating that green technologies need to go through many complex processes, from R&D to the translation of achievements. Management systems, technology preferences, and corporate mission and vision may all influence the effectiveness of green technology transformation. In fact, the low efficiency of technology transformation has always been an urgent and critical issue in China's technology sector. Many green technologies are often shelved after being invented, and difficult to commercialise.

3.3. Spatial evolution of GIE

Fig. 5 shows the spatial evolution of GTRDE in each province in 2008, 2012, 2016, and 2020. As shown in Fig. 5(a), the highest GTRDE in 2008 was in Hainan (1.406), and the lowest was in Inner Mongolia (0.216), with the former being 6.5 times higher than the latter. Besides, the GTRDE was higher in the western region than in the east, followed by the central and northeastern regions, and there was a very large gap between the former two and the latter. The efficiency in the western region encompassed all five levels, with no clear pattern in the spatial distribution of the different levels. But, except Qinghai, the provinces in the western region with high GTRDE showed a clear spatial concentration characteristic, i.e., the vertical type. These provinces were better geographically and resource-wise than other provinces in the western region. Also, they were in a better economic condition to provide financial support for R&D in green basic technologies. In contrast, the spatial distribution of GTRDE in the central region was complex, contained in four different levels, and the distribution of each level was generally concentrated. GTRDE was included in three levels in the eastern region while in two levels in the northeast region. Provinces in the eastern region with higher GTRDE appeared in Beijing, Tianjin and Zhejiang, all of which were more economically developed regions. However, GTRDE in Shanghai, Guangdong and Fujian, which also had good economic development, was relatively low in 2008. A possible explanation is that although Guangdong and Fujian had high levels of economic development in 2008, there was a wide

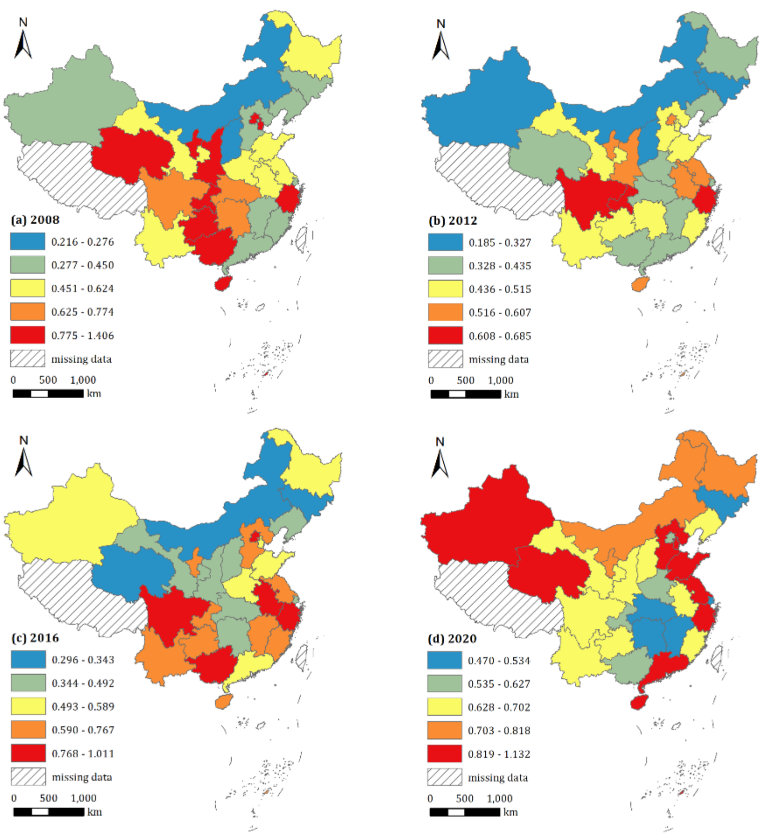

Fig. 5. GTRDE in 2008, 2012, 2016 and 2020 by province

gap in economic development among cities within the provinces. Some cities were still at the stage of having a relatively weak economic base and did not have sufficient funds to invest in technology R&D.

In 2012, the GTRDE was lower in almost every province than in 2008. As seen in Fig. 5(b), the spatial distribution of GTRDE became more dispersed and irregular. Overall, provinces with high GTRDE showed relatively isolated points. In 2012, the province with the highest GTRDE was Chongqing (0.685), while the lowest remained Inner Mongolia (0.185), and the majority of the efficiencies ranged from 0.3 to 0.6. Moreover, the efficiency in the western region included all five levels, and only two provinces (i.e., Chongqing and Sichuan) were at the highest level, falling from six in 2008. Both the eastern region and the central region contained four levels, of which the former had no provinces at the lowest level, and the latter had no provinces at the highest level. Specifically, in the eastern region, only Zhejiang was at the highest level, while Shanxi in the central region was at the lowest. Compared with the previous period, the GTRDE of the three provinces in the northeast region had continued to decline, with Jilin's GTRDE being only 0.319.

As shown in Fig. 5(c), the spatial concentration distribution characteristics of GTRDE in 2016 in each province were relatively evident. In 2016, the highest GTRDE in Guangxi (1.011) was 3.4 times higher than the lowest in Inner Mongolia (0.296). In the eastern region, Zhejiang and Beijing were at the highest level of GTRDE. All other eastern provinces except Guangdong and Shandong were in the second-highest level. Hence, areas with high GTRDE in the eastern region were mainly concentrated in the Beijing-Tianjin-Hebei region and the Yangtze River Delta region, which were almost the most important economic zones and urban clusters in China. Actually, green technology R&D in these two areas benefited from good location advantages, policy favouritism, and the introduction of technological talents. In the western region, the spatial concentration of GTRDE was characterised by a very significant and clear demarcation line. Among them, the provinces with higher efficiency were mainly concentrated in the southwestern area, especially in Sichuan and Guangxi. The central region had a spatial correlation between the provinces with high GTRDE. Also, the provinces in the central region, which were spatially neighbouring to the eastern region, were relatively more efficient in green technology R&D than other provinces in the central region. This evidence confirmed that the eastern region had a strong but limited radiation effect on green technology R&D in the central region. Generally, nationwide, the provinces with high GTRDE were mainly concentrated in the southwestern area and the eastern region, and the concentration characteristic was very significant.

In 2020, in 21 provinces, the GTRDE was higher than the efficiency in 2016. Of the nine remaining provinces, two (Beijing and Fujian) were from the eastern region, two were from the central region (Jiangxi and Anhui), and the others were from the western region. As seen in Fig. 5(d), the spatial concentration characteristic of the GTRDE was most significant in 2020 compared with the previous years. Nationwide, in 2020, the areas with high GTRDE were mainly concentrated in the eastern region, Qinghai and Xinjiang in the northwestern area, and Heilongjiang and Inner Mongolia in the northern area. Similarly, the spatial correlation of regions with low GTRDE was also very clear, mainly concentrated in certain provinces in the central and western regions. Normally, the eastern region attracted more technical talents by virtue of its good economic foundation and continuously increased its investment in technological research and development to improve efficiency. The sudden outbreak of the new crown epidemic that swept the world in 2020 posed a serious challenge to some of the less economically developed provinces. Regardless, the GTRDE in most provinces may be increasing in the long run.

Fig. 6 shows the spatial evolution of GATE by province in 2009, 2013, 2017, and 2021. In 2009, the province with the highest GATE was Hainan, with an efficiency of 1.529, and the province with the lowest was Guizhou, with only 0.078. The former was 19.6 times more efficient than the latter, which was a huge gap. As seen in Fig. 6(a), GATE in the eastern provinces included four levels, among which Zhejiang was alone in the second-lowest level. The spatial distribution of GATE of the provinces in the other three regions was relatively decentralised, and there was generally no obvious spatial correlation. Moreover, with the exception of Heilongjiang, Liaoning, Zhejiang, Shanxi, and Hubei, most of the provinces within the lowest and second-lowest levels belonged to the western region. This indicates that in 2009, the spatial distribution of GATE was still relatively loose. There was no unified system for green achievement transformation, resulting in huge differences between regions. Meanwhile, the spatial radiation effect of the provinces with high GATE on the neighbouring areas was not well-reflected. In terms of geographical dis-

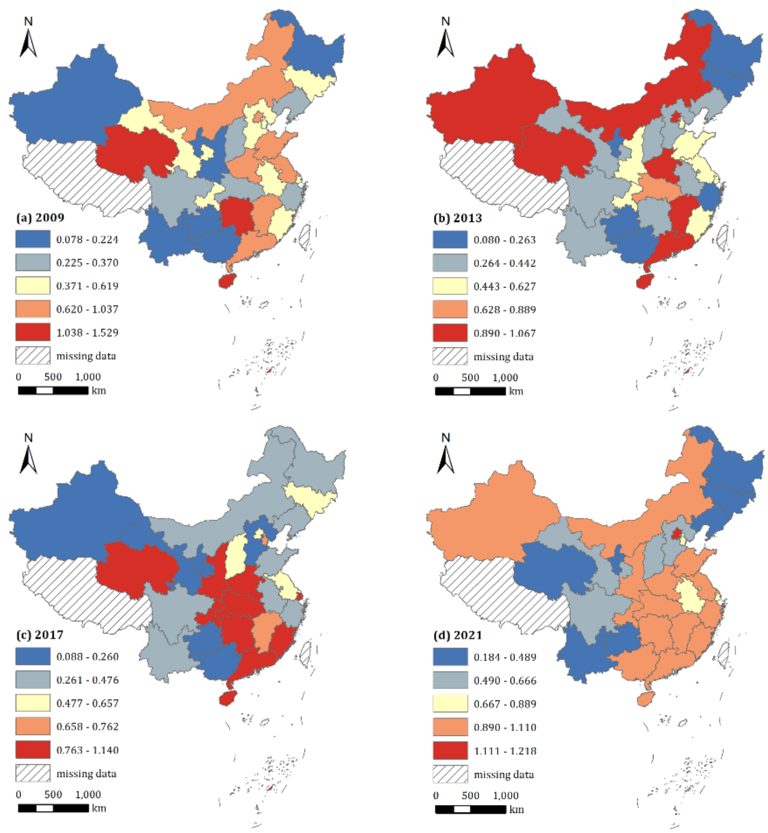

Fig. 6. GATE in 2009, 2013, 2017, and 2021 by province

tribution, GATE was characterised by "high in the east and low in the west". This result was at variance with that presented in Fig. 5(a) (in 2008); thus, most of the provinces with high GTRDE, especially in the southwest area, had low GATE. This is a further indication that the gap between green technology R&D and transformation needs to be narrowed.

The province which had the highest GATE in 2013 was Qinghai (1.067), while the lowest was Ningxia (0.080), with the former 13.3 times higher than the latter. As shown in Fig. 6(b), the spatial distribution of the GATE in 2013 was relatively concentrated compared to that of 2009. Both provinces with high and low GATE showed pronounced concentration characteristics. Hence, it means that some provinces with high GATE were gradually having a radiation effect on neighbouring areas. In addition, the GATE of the eastern and western regions contained four levels. Similarly, the central region contained three levels, and the northeastern region contained two levels. The GATE across several levels was a powerful indication that the differences between provinces were significant. Besides, in the eastern region, only Beijing, Guangdong, and Hainan were at the highest level of GATE, and in the central region, they were Henan and Jiangxi. In the western region, there were three provinces ranked at the highest level, namely Xinjiang, Qinghai, and Inner Mongolia. Similar to 2009, the GATE in the northeastern region was low, which may be related to the economic system based on heavy industry.

Fig. 6(c) depicts the spatial distribution of GATE in each province in 2017. In 2017, the province with the highest GATE was Qinghai (1.140), and it was higher than the efficiency in 2013 (1.067). The province with the lowest efficiency was Xinjiang, with an efficiency of 0.088. As can be seen in Fig. 6(c), nationwide, except Qinghai, the provinces with high GATE were concentrated and had a general north-south direction. Additionally, in the eastern region, Shanghai, Fujian, Guangdong, and Hainan were located at the highest level. Namely, the spatial distribution of GATE in the provinces in the eastern region had both concentrated features and isolated points. The provinces in the central region had a higher average value of GATE than other regions, which could be verified by Fig. 6(c). This indicated that the provinces in the central region had a relatively strong radiation effect on the neighbouring regions. Furthermore, in the western region, only Qinghai, Shaanxi, and Chongqing were located at the highest level, while all other provinces were located at the lowest and second-lowest levels. This might be connected to the less-than-perfect business environment for hi-tech companies. In contrast, the spatial distribution of GATE in the northeast had not changed much from the previous years, and its efficiency had always stabilised at a low level.

As shown in Fig. 6(d), in 2021, Beijing was the province which had the highest GATE, with an efficiency of 1.218. The lowest was Ningxia (0.184). The former was 6.6 times higher than the latter. In the eastern region, except the Beijing-Tianjin-Hebei region and Shanghai, all the other provinces were located in the second-highest level. Similarly, in the central region, all provinces except Shanxi and Anhui were in the second-highest level of efficiency. And, the three provinces in the northeastern region were located at the lowest level. That is, in the eastern, central and northeastern regions, the gaps in efficiency between provinces within the specific region had narrowed. However, the spatial distribution of GATE in the western region was more complicated. In the western region, there were distinct spatial concentration characteristics in the provinces with high and low efficiency, respectively. Compared with 2017, the GATE in Xinjiang and Inner Mongolia was improved to a large extent, while the situation in Qinghai was completely opposite. Specifically, in 2009, 2013 and 2017, Qinghai's GATE was consistently at the highest level, but in 2021, its efficiency fell to the lowest level. In addition, Fig. 6(d) also showed that there were significant differences in efficiency within major city clusters, especially in the Beijing-Tianjin-Hebei region. This further suggests that further synergies are needed in the transformation of green technology achievements among the provinces.

3.4. Spatial autocorrelation analysis

Table 7 shows the global Moran's I index of GIE (i.e., GTRDE and GATE). As the table shows, the spatial autocorrelation of GTRDE was not significantly manifested overall. Of all the years, the largest global Moran's I index was 0.2032 in 2018 (P-value of 0.037), while the smallest was -0.0205 in 2019 (P-value of 0.441). Furthermore, the global Moran's I index of GTRDE did not show a significant upward or downward trend during the period examined. In individual years, i.e., 2012, 2014–2016, and 2018, GTRDE exhibited a significant positive spatial autocorrelation. The significance level is 10 % for 2012 and 2014–2016 and 5 % for 2018. This means that, excluding 2013 and 2017, GTRDE exhibited a positive spatial autocorrelation only during 2012–2018.

As shown in Table 7, in terms of GATE, the global Moran's I index exhibited more complex irregularities during 2009–2021. The highest global Moran's I index occurred in 2020 (0.3247), while the lowest occurred in 2011 (-0.1171). However, the global Moran's I index exhibited significant positive spatial autocorrelation only in 2015, 2020, and 2021. The significance level is 10 % for 2015 and 2021 and 1 % for 2020. Thus, this suggests a lack of strong evidence for the existence of spatial autocorrelation overall, although

Tab. 7. Global Moran's I index of GIE

Year	GTRDE			GATE		
	Moran's I	*Z*-score	*P*-value	Moran's I	*Z*-score	*P*-value
2008	0.1256	1.2308	0.125			
2009	0.0132	0.3496	0.338	-0.0797	-0.4158	0.353
2010	0.0015	0.4204	0.331	0.0612	0.7388	0.226
2011	0.0902	0.9712	0.171	-0.1171	-0.7220	0.242
2012	0.1627	1.5182	0.074	-0.0577	-0.2158	0.426
2013	0.0997	0.9828	0.163	-0.0479	-0.1508	0.463
2014	0.1920	1.7478	0.054	0.0611	0.7736	0.218
2015	0.1519	1.5733	0.067	0.1309	1.3965	0.095
2016	0.1702	1.7111	0.056	0.0934	1.0422	0.157
2017	0.0844	0.9939	0.166	0.0351	0.5669	0.276
2018	0.2032	1.8642	0.037	0.1165	1.2513	0.114
2019	-0.0205	0.1211	0.441	0.0181	0.4184	0.327
2020	0.0639	0.8464	0.191	0.3247	2.9109	0.004
2021				0.1581	1.4469	0.099

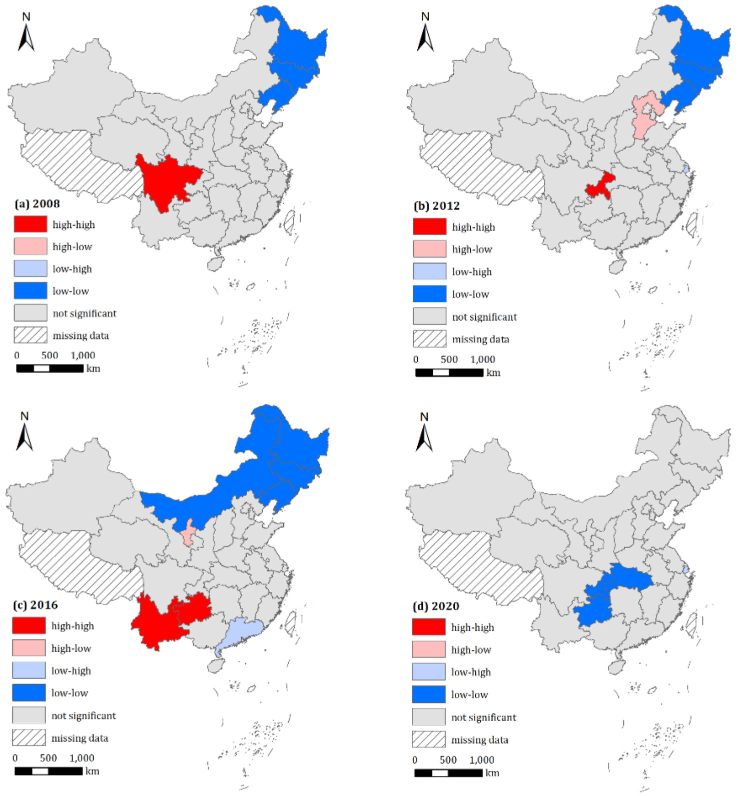

Fig. 7. Local spatial autocorrelation of GTRDE in 2008, 2012, 2016, and 2020 by province

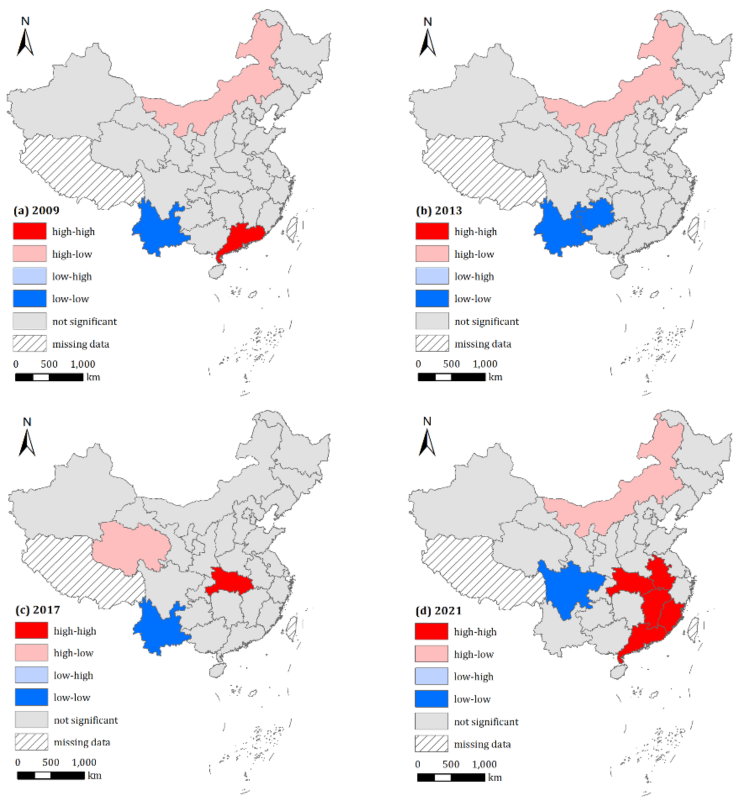

Fig. 8. Local spatial autocorrelation of GATE in 2009, 2013, 2017, and 2021 by province

the global Moran's I index of GATE shifts from negative to positive during 2009–2021. This further validates the results obtained mentioned above when analysing the spatial distribution of GIE.

The results of the local Moran's I index can be shown by the local indicators of spatial association (LISA) clustering map, as seen in Figs. 7 and 8. Specifically, Fig. 7 is the LISA clustering map of GTRDE, and Fig. 8 shows the LISA clustering map of GATE. Besides, in the LISA clustering map, the local spatial aggregation can be grouped into five categories: high-high, high-low, low-high, low-low, and not significant. Hence, in this study, the LISA clustering map can be easily adopted to show the local spatial aggregations of provinces with high and low GIE.

As seen in Fig. 7, the GTRDE exhibited different local spatial aggregation characteristics in the specific years. In 2008, Sichuan was the only province in the high-high region, while the northeastern region was in the low-low region. In 2012, the northeastern region remained in the low-low region. Meanwhile, Chongqing, Hebei and Shanghai belonged to the high-high, high-low, and low-high regions, respectively. In 2016, there had been an increase in the number of provinces belonged to the high-high and low-low regions. Yunnan and Guizhou were in the high-high region, and Inner Mongolia and the northeastern region belonged to the low-low region. Ningxia and Guangdong were in the high-low and low-high regions, respectively. In 2020, there were three provinces belonging to the low-low region, namely, Guizhou, Chongqing, and Hubei. Additionally, Shanghai was the only province in the low-high region.

Fig. 8 shows the local spatial aggregation of GATE. In 2009, Guangdong belonged to the high-high region. Inner Mongolia and Yunnan were in the high-low and low-low regions, respectively. In 2013, provinces in the low-low region were Yunnan and Guizhou. Also, Inner Mongolia still remained in the high-low region. In 2017, Hubei, Qinghai and Yunnan belonged to the high-high, high-low and low-low regions, respectively. In addition, the local spatial aggregation of GATE in 2021 changed significantly when compared to the previous years, especially in the high-high region. Five provinces belonged to the high-high region, namely, Fujian, Guangdong, Jiangxi, Hubei, and Anhui. Inner Mongolia belonged to the low-high region, while Sichuan belonged to the low-low region. Except for the provinces mentioned above, the other provinces shown in Figs. 7 and 8 belonged to the non-significant region.

4. Discussion

As indicated in Figs. 3 and 4, the GTRDE and GATE exhibit significant temporal heterogeneity in China across years and a general trend of increasing volatility. This fully demonstrates the key role played by internal and external factors, such as science and technology policies and the innovation environment, in GIE, as well as the fact that GIE is susceptible to the synergistic interaction of multiple factors. The national and local governments have continued to adopt various policies and measures to enhance the GIE, and although some of these policies and measures have led to large fluctuations in the GIE, the overall trend remains positive and favourable. It should be noted that regardless of GTRDE or GATE, the magnitude of recovery and enhancement of GIE is relatively small compared to the earlier stages, so there is still much room for China's overall GIE to be enhanced. Particularly, in formulating science, technology and innovation policies, the national and local governments should ensure that the policies are relatively forward-thinking and cutting-edge.

With regard to spatial distribution, as indicated in Figs. 5 and 6, the GTRDE and GATE exhibit significant spatial heterogeneity across provinces in China. By and large, this heterogeneity is closely related to the political, economic, social, cultural, environmental, and resource endowments of a region. Among them, the role of economic development is the most powerful because it can provide sufficient financial and human resources and technological support for green innovation. Hence, driven by the nature of chasing profits, enterprises and other science and technology innovation subjects are more willing to promote green innovation. However, in individual provinces, the GIE shows results that mismatch the level of economic development. For instance, Shanghai's average GTRDE is ranked 27th in China, a total mismatch with its level of economic development as reflected in its 2nd-ranked GDP per capita. This may be related to the province's industrial planning, development orientation, urban resilience and development bottlenecks.

With the deepening geospatial correlation of economic development, as well as the deepening communication and cooperation between different spatial units, the green innovation development of individual provinces is not isolated and is susceptible to positive or negative influences from surrounding provinces. Hence, GIE usually exhibits significant spatial autocorrelation and obvious spatial clustering characteristics. Nevertheless, the findings obtained from Tab. 7, Figs. 7 and 8 are relatively different from such an inference; that is, the spatial autocorrelation of China's interprovincial GIE is significant only in a few years, and its spatial clustering characteristics appear only in a few provinces. This fully demonstrates that there is still no favourable exchange and cooperation mechanism between provinces in China in terms of economic development, technological progress, green innovation, and talent mobility and that the in-depth integration between different geospatial units needs to be strengthened. Hence, the local governments need to take a macro-global perspective when formulating policies to enhance GIE.

Conclusions

Based on the original panel data of 30 provinces in China from 2007 to 2021, this study adopts the super efficiency SBM model considering undesirable outputs to evaluate the GTRDE and GATE and applies the global and local Moran's I index for spatial autocorrelation analysis. The GTRDE showed the basic characteristic of "eastern>western>central>northeastern", while that of GATE was "eastern>central>western>northeastern". Although the GATE was higher than that of the GTRDE in most provinces, the gap between provinces was significantly larger for the former than for the latter, i.e., the distribution of the former was more discrete while the latter was more concentrated. Also, significant global spatial autocorrelation in GIE across provinces existed only in a few years, and local spatial autocorrelation existed only in a few provinces.

According to the conclusions, a number of practical and targeted policy recommendations were proposed. First, the governments at all levels in China should implement the concepts of green development and technological innovation and closely integrate the two, emphasising that GTI is an important means of achieving environmental protection and ecological sustainability. Second, governments should actively guide the enterprises to strengthen GTI and support green technological research and development and the transformation of achievements through financial policies, tax incentives, and the introduction of talents so as to improve the GIE continuously. Third, the governments should avoid carrying out GTI only in a small area and should prefer to strengthen the exchanges and collaboration with neighbouring regions to continuously narrow the gap between regions to maximise the radiation and spatial spillover effects of green technology.

This paper evaluated GTRDE and GATE in China's 30 provinces, but some limitations still exist. Due to the constraints of data availability, the selection of input and output indicators for the two stages of GTI was only limited to a few of the most prominent ones. This may affect the results of the efficiency evaluation. Besides, due to missing data, this study had to exclude four provinces and select only 30 provinces in China. Since the evaluation of efficiency based on data envelopment analysis is a relative efficiency, this issue of missing samples may affect the relative effectiveness between regions. Also, although this study divided the GTI process into two stages, it did not provide a more in-depth comparison and analysis of GIEs of these two stages, e.g., regional differences in GIEs.

Future research could focus on the following three main areas. First, based on a comprehensive and complete indicator system and samples, future research can adopt some cutting-edge evaluation methods to scientifically and rationally evaluate GIE in China and the rest of the world. Also, future research can analyse the evaluation results of GIE in depth to enrich the research content. For instance, future research can adopt kernel density estimation to analyse the dynamic evolution of GIE, apply the Dagum Gini coefficient to explore differences between regions and use the convergence model to examine the convergence of GIE. Moreover, future research could analyse in depth the influencing factors of GIE, e.g., with the help of geographically and temporally weighted regression, to explore the impact of different variables on GIE in the temporal and spatial dimensions. Alternatively, in the future, a dynamic qualitative comparative analysis approach can be used to analyse the synergies and configuration effects among the influencing factors and to explore the multivariate configuration paths to enhance the GIE in China's provinces.

Acknowledgments

This research was funded by the Innovation Strategy Research Project of Fujian Province, China, grant number 2023R0075.

Literature

Ashrafi, A., Seow, H.-V., Lee, L. S., & Lee, C. G. (2013). The efficiency of the hotel industry in Singapore. *Tourism Management*, *37*, 31-34. doi: 10.1016/j.tourman.2012.12.003

Cao, S., Nie, L., Sun, H., Sun, W., & Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *Journal of Cleaner Production*, *327*, 129458. doi: 10.1016/j.jclepro.2021.129458

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444. doi: 10.1016/0377-2217(78)90138-8

Chen, J., Abbas, J., Najam, H., Liu, J., & Abbas, J. (2023). Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *Journal of Cleaner Production*, *382*, 135131. doi: 10.1016/j.jclepro.2022.135131

Dirik, C., Şahin, S., & Engin, P. (2019). Environmental efficiency evaluation of Turkish cement industry: An application of data envelopment analysis. *Energy Efficiency*, *12*(8), 2079-2098. doi: 10.1007/s12053-018-9764-z

Dong, F., Zhu, J., Li, Y., Chen, Y., Gao, Y., Hu, M., Qin, C., & Sun, J. (2022). How green technology innovation affects carbon emission efficiency: Evidence from developed countries proposing carbon neutrality targets. *Environmental Science and Pollution Research*, *29*(24), 35780-35799. doi: 10.1007/s11356-022-18581-9

Du, K., & Li, J. (2019). Towards a green world: How do green technology innovations affect total-factor carbon productivity. *Energy Policy*, 131, 240-250. doi: 10.1016/j.enpol.2019.04.033

Fan, F., Lian, H., Liu, X., & Wang, X. (2021). Can environmental regulation promote urban green innovation Efficiency? An empirical study based on Chinese cities. *Journal of Cleaner Production*, *287*, 125060. doi: 10.1016/j.jclepro.2020.125060

Fang, T., Fang, D., & Yu, B. (2022a). Carbon emission efficiency of thermal power generation in China: Empirical evidence from the micro-perspective of power plants. *Energy Policy*, *165*, 112955. doi: 10.1016/j.enpol.2022.112955

Fang, Z., Razzaq, A., Mohsin, M., & Irfan, M. (2022b). Spatial spillovers and threshold effects of internet development and entrepreneurship on green innovation efficiency in China. *Technology in Society*, *68*, 101844. doi: 10.1016/j.techsoc.2021.101844

Faulkner, S. (2004). Urbanization impacts on the structure and function of forested wetlands. *Urban Ecosystems*, *7*(2), 89-106. doi: 10.1023/B:UECO.0000036269.56249.66

Feng, S., Zhang, R., & Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Structural Change and Economic Dynamics*, *61*, 70-83. doi: 10.1016/j.strueco.2022.02.008

Fu, Q., & Chang, C.-P. (2024). Cross-national sanctions and green innovation: Worldwide investigation. *Oeconomia Copernicana*, *15*(2), 435-469. doi: 10.24136/oc.2712

Fu, Q., Zhao, X., & Chang, C.-P. (2023). Does ESG performance bring to enterprises' green innovation? Yes, evidence from 118 countries. *Oeconomia Copernicana*, *14*(3), 795-832. doi: 10.24136/oc.2023.024

Gao, P., Wang, Y., Zou, Y., Su, X., Che, X., & Yang, X. (2022). Green technology innovation and carbon emissions nexus in China: Does industrial structure upgrading matter? *Frontiers in Psychology*, *13*, 951172. doi: 10.3389/fpsyg.2022.951172

Gökgöz, F., & Erkul, E. (2019). Investigating the energy efficiencies of European countries with super efficiency model and super SBM approaches. *Energy Efficiency*, *12*(3), 601-618. doi: 10.1007/s12053-018-9652-6

He, Z., Lu, W., Hua, G., & Wang, J. (2021). Factors affecting enterprise level green innovation efficiency in the digital economy era - Evidence from listed paper enterprises in China. *BioResources*, *16*(4), 7648-7670. doi: 10.15376/biores.16.4.7648-7670

Huang, Y., & Wang, Y. (2020). How does high-speed railway affect green innovation efficiency? A perspective of innovation factor mobility. *Journal of Cleaner Production*, *265*, 121623. doi: 10.1016/j.jclepro.2020.121623

Jian, X., & Afshan, S. (2023). Dynamic effect of green financing and green technology innovation on carbon neutrality in G10 countries: Fresh insights from CS-ARDL approach. *Economic Research-Ekonomska Istraživanja*, *36*(2), 2130389. doi: 10.1080/1331677X.2022.2130389

Khan, S. U., Cui, Y., Khan, A. A., Ali, M. A. S., Khan, A., Xia, X., Liu, G., & Zhao, M. (2021). Tracking sustainable development efficiency with human-environmental system relationship: An application of DPSIR and super efficiency SBM model. *Science of The Total Environment*, *783*, 146959. doi: 10.1016/j.scitotenv.2021.146959

Li, B., Han, Y., Wang, C., & Sun, W. (2022a). Did civilized city policy improve energy efficiency of resource-based cities? Prefecture-level evidence from China. *Energy Policy*, *167*, 113081. doi: 10.1016/j.enpol.2022.113081

Li, D., & Zeng, T. (2020). Are China's intensive pollution industries greening? An analysis based on green innovation efficiency. *Journal of Cleaner Production*, *259*, 120901. doi: 10.1016/j.jclepro.2020.120901

Li, G., Li, X., & Huo, L. (2023). Digital economy, spatial spillover and industrial green innovation efficiency: Empirical evidence from China. *Heliyon*, *9*(1), e12875. doi: 10.1016/j.heliyon.2023.e12875

Li, J., & Du, Y. (2021). Spatial effect of environmental regulation on green innovation efficiency: Evidence from prefectural-level cities in China. *Journal of Cleaner Production*, *286*, 125032. doi: 10.1016/j.jclepro.2020.125032

Li, S., Zhang, W., & Zhao, J. (2022b). Does green credit policy promote the green innovation efficiency of heavy polluting industries? - Empirical evidence from China's industries. *Environmental Science and Pollution Research*, *29*(31), 46721-46736. doi: 10.1007/s11356-022-19055-8

Liao, B., & Li, L. (2023). Urban green innovation efficiency and its influential factors: The Chinese evidence. *Environment, Development and Sustainability*, *25*(7), 6551-6573. doi: 10.1007/s10668-022-02316-4

Lin, B., & Ma, R. (2022). How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective. *Journal* *of Environmental Management*, *320*, 115833. doi: 10.1016/j.jenvman.2022.115833

Long, X., Sun, C., Wu, C., Chen, B., & Boateng, K. A. (2020). Green innovation efficiency across China's 30 provinces: Estimate, comparison, and convergence. *Mitigation and Adaptation Strategies for Global Change*, *25*(7), 1243-1260. doi: 10.1007/s11027-019-09903-3

Lv, C., Shao, C., & Lee, C.-C. (2021). Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Economics*, *98*, 105237. doi: 10.1016/j.eneco.2021.105237

Mei, K., Kou, R., Bi, Y., Liu, Y., Huang, J., & Li, W. (2023). A study of primary health care service efficiency and its spatial correlation in China. *BMC Health Services Research*, *23*, 247. doi: 10.1186/s12913-023-09197-x

Miao, C., Duan, M., Zuo, Y., & Wu, X. (2021). Spatial heterogeneity and evolution trend of regional green innovation efficiency - An empirical study based on panel data of industrial enterprises in China's provinces. *Energy Policy*, *156*, 112370. doi: 10.1016/j.enpol.2021.112370

Miao, C., Fang, D., Sun, L., & Luo, Q. (2017). Natural resources utilization efficiency under the influence of green technological innovation. *Resources, Conservation and Recycling*, 126, 153-161. doi: 10.1016/j.resconrec.2017.07.019

Moskalenko, B. ., Lyulyov, O. ., & Pimonenko, T. . (2022). The investment attractiveness of countries: coupling between core dimensions. *Forum Scientiae Oeconomia*, *10*(2), 153-172. doi: 10.23762/FSO_VOL10_NO2_8

Suki, M. N., Suki, M. N., Afshan, S., Sharif, A., Kasim, A. M., & Hanafi, R. M. S. (2022). How does green technology innovation affect green growth in ASEAN-6 countries? Evidence from advance panel estimations. *Gondwana Research*, *111*, 165-173. doi: 10.1016/j.gr.2022.06.019

National Bureau of Statistics of China. (2023). *National Statistical Data of China*. Retrieved from https://data.stats.gov.cn/english/easyquery.htm?cn=C01

Obobisa, E. S., Chen, H., & Mensah, I. A. (2022). The impact of green technological innovation and institutional quality on CO_2 emissions in African countries. *Technological Forecasting and Social Change*, *180*, 121670. doi: 10.1016/j.techfore.2022.121670

Razzaq, A., Wang, Y., Chupradit, S., Suksatan, W., & Shahzad, F. (2021). Asymmetric inter-linkages between green technology innovation and consumption-based carbon emissions in BRICS countries using quantile-on-quantile framework. *Technology in Society*, *66*, 101656. doi: 10.1016/j.techsoc.2021.101656

Razzaq, A., & Yang, X. (2023). Digital finance and green growth in China: Appraising inclusive digital finance using web crawler technology and big data. *Technological Forecasting and Social Change*, *188*, 122262. doi: 10.1016/j.techfore.2022.122262

Shah, W. U. H., Hao, G., Yan, H., & Yasmeen, R. (2022). Efficiency evaluation of commercial banks in Pakistan: A slacks-based measure Super-SBM approach with bad output (Non-performing loans). *PLOS ONE*, *17*(7), e0270406. doi: 10.1371/journal.pone.0270406

Shan, S., Genç, S. Y., Kamran, H. W., & Dinca, G. (2021). Role of green technology innovation and renewable energy in carbon neutrality: A sustainable investigation from Turkey. *Journal of Environmental Management*, *294*, 113004. doi: 10.1016/j.jenvman.2021.113004

Sharif, A., Saqib, N., Dong, K., & Khan, S. A. R. (2022). Nexus between green technology innovation, green financing, and CO_2 emissions in the G7 countries: The moderating role of social globalisation. *Sustainable Development*, *30*(6), 1934-1946. doi: 10.1002/sd.2360

Song, W., & Han, X. (2022). The bilateral effects of foreign direct investment on green innovation efficiency: Evidence from 30 Chinese provinces. *Energy*, *261*, 125332. doi: 10.1016/j.energy.2022.125332

Sun, L., Miao, C., & Yang, L. (2017). Ecological-economic efficiency evaluation of green technology innovation in strategic emerging industries based on entropy weighted TOPSIS method. *Ecological Indicators*, *73*, 554-558. doi: 10.1016/j.ecolind.2016.10.018

Sun, Y., Ding, W., & Yang, G. (2022). Green innovation efficiency of China's tourism industry from the perspective of shared inputs: Dynamic evolution and combination improvement paths. *Ecological Indicators*, *138*, 108824. doi: 10.1016/j.ecolind.2022.108824

Taleb, M., Khalid, R., Emrouznejad, A., & Ramli, R. (2023). Environmental efficiency under weak disposability: An improved super efficiency data envelopment analysis model with application for assessment of port operations considering NetZero. *Environment, Development and Sustainability*, *25*(7), 6627-6656. doi: 10.1007/s10668-022-02320-8

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498-509. doi: 10.1016/S0377-2217(99)00407-5

Tone, K. (2002). A slacks-based measure of super-efficiency in data envelopment analysis. *European Journal of Operational Research*, *143*(1), 32-41. doi: 10.1016/S0377-2217(01)00324-1

Tone, K. (2003). *Dealing with undesirable outputs in DEA: a Slacks-Based Measure (SBM) approach*. Tokyo: GRIPS Research Report Series.

Tran, T. H., Mao, Y., Nathanail, P., Siebers, P.-O., & Robinson, D. (2019). Integrating slacks-based measure of efficiency and super-efficiency in data envelopment analysis. *Omega*, *85*, 156-165. doi: 10.1016/j.omega.2018.06.008

Wang, K.-L., Sun, T.-T., Xu, R.-Y., Miao, Z., & Cheng, Y.-H. (2022). How does internet development promote urban green innovation efficiency? Evidence from China. *Technological Forecasting and Social Change*, *184*, 122017. doi: 10.1016/j.techfore.2022.122017

Wang, K.-L., Zhang, F.-Q., Xu, R.-Y., Miao, Z., Cheng, Y.-H., & Sun, H.-P. (2023). Spatiotemporal pattern evolution and influencing factors of green innovation efficiency: A China's city level analysis. *Ecological Indicators*, *146*, 109901. doi: 10.1016/j.ecolind.2023.109901

Wang, M. L. (2023). Effects of the green finance policy on the green innovation efficiency of the manufacturing industry: A difference-in-difference model. *Technological Forecasting and Social Change*, *189*, 122333. doi: 10.1016/j.techfore.2023.122333

Wang, Q., Qu, J., Wang, B., Wang, P., & Yang, T. (2019). Green technology innovation development in China in 1990-2015. *Science of The Total Environment*, *696*, 134008. doi: 10.1016/j.scitotenv.2019.134008

Wei, L., Lin, B., Zheng, Z., Wu, W., & Zhou, Y. (2023). Does fiscal expenditure promote green technological innovation in China? Evidence from Chinese cities. *Environmental Impact Assessment Review*, *98*, 106945. doi: 10.1016/j.eiar.2022.106945

World Bank. (2023). *GDP (constant 2015 US$) released in World Bank Open Data*. Retrieved from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD?locations=CN

World Resources Institute. (2023). *Global Historical GHG Emissions released by Climate Watch*. Retrieved from https://www.climatewatchdata.org/ghg-emissions?regions=TOP

Wu, H., Li, Y., Hao, Y., Ren, S., & Zhang, P. (2020). Environmental decentralization, local government competition, and regional green development: Evidence from China. *Science of The Total Environment*, *708*, 135085. doi: 10.1016/j.scitotenv.2019.135085

Xu, S., Wu, T., & Zhang, Y. (2020). The spatial-temporal variation and convergence of green innovation efficiency in the Yangtze River Economic Belt in China. *Environmental Science and Pollution Research*, *27*(21), 26868-26881. doi: 10.1007/s11356-020-08865-3

Xu, Y., Liu, S., & Wang, J. (2022a). Impact of environmental regulation intensity on green innovation efficiency in the Yellow River Basin, China. *Journal of Cleaner Production*, *373*, 133789. doi: 10.1016/j.jclepro.2022.133789

Xu, Y., Zhang, Y., Lu, Y., & Chen, J. (2022b). The evolution rule of green innovation efficiency and its convergence of industrial enterprises in China. *Environmental Science and Pollution Research*, *29*(2), 2894-2910. doi: 10.1007/s11356-021-15885-0

Xue, Q., Bai, C., & Xiao, W. (2022). Fintech and corporate green technology innovation: Impacts and mechanisms. *Managerial and Decision Economics*, *43*(8), 3898-3914. doi: 10.1002/mde.3636

Yin, J., & Wang, D. (2021). Dynamic evaluation of green innovation efficiency of patent-intensive industries: Evidence from the new equipment manufacturing. *Technology Analysis & Strategic Management*, 1-14. doi: 10.1080/09537325.2021.1963428

Zeng, J., Škare, M., & Lafont, J. (2021). The co-integration identification of green innovation efficiency in Yangtze River Delta region. *Journal of Business Research*, *134*, 252-262. doi: 10.1016/j.jbusres.2021.04.023

Zhang, J., Kang, L., Li, H., Ballesteros-Pérez, P., Skitmore, M., & Zuo, J. (2020). The impact of environmental regulations on urban green innovation efficiency: The case of Xi'an. *Sustainable Cities and Society*, *57*, 102123. doi: 10.1016/j.scs.2020.102123

Zhang, M., Hong, Y., Wang, P., & Zhu, B. (2022). Impacts of environmental constraint target on green innovation efficiency: Evidence from China. *Sustainable Cities and Society*, *83*, 103973. doi: 10.1016/j.scs.2022.103973

Zhang, M., & Liu, Y. (2022). Influence of digital finance and green technology innovation on China's carbon emission efficiency: Empirical analysis based on spatial metrology. *Science of The Total Environment*, *838*, 156463. doi: 10.1016/j.scitotenv.2022.156463

Zhao, P., Lu, Z., Kou, J., & Du, J. (2023). Regional differences and convergence of green innovation efficiency in China. *Journal of Environmental Management*, *325*, 116618. doi: 10.1016/j.jenvman.2022.116618

Zhao, X., Ma, X., Shang, Y., Yang, Z., & Shahzad, U. (2022). Green economic growth and its inherent driving factors in Chinese cities: Based on the Metafrontier-global-SBM super-efficiency DEA model. *Gondwana Research*, *106*, 315-328. doi: 10.1016/j.gr.2022.01.013

Zheng, Z., Xu, Y., & Chen, J. (2023). Digital economy, industrial structure upgrading and green innovation efficiency of family enterprises. *International Entrepreneurship and Management Journal*, in press. doi: 10.1007/s11365-023-00854-5

Zhu, L., Luo, J., Dong, Q., Zhao, Y., Wang, Y., & Wang, Y. (2021). Green technology innovation efficiency of energy-intensive industries in China from the perspective of shared resources: Dynamic change and improvement path. *Technological Forecasting and Social Change*, *170*, 120890. doi: 10.1016/j.techfore.2021.120890

Zhu, X., Li, Y., Zhang, P., Wei, Y., Zheng, X., & Xie, L. (2019). Temporal-spatial characteristics of urban land use efficiency of China's 35mega cities based on DEA: Decomposing technology and scale efficiency. *Land Use Policy*, *88*, 104083. doi: 10.1016/j.landusepol.2019.104083