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Research Article

Green Innovation Efficiency Measurement Based on Sensor Data: Evidence from China

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Based on the theoretical knowledge of technological innovation, this paper designs a sensor data value incubation model and a sensor data collection model to collect the original data on green innovation efficiency. In order to explore the spatial and temporal differentiation characteristics of China's provincial green innovation efficiency and the spatial spillover effect of China's provincial green innovation efficiency, the entropy weight TOPSIS model is adopted to measure the green innovation efficiency of China's 30 provinces (cities) from 2005 to 2021 and analyze its temporal and spatial evolution characteristics. This paper uses an exploratory spatial data analysis method to prove the agglomeration phenomenon of China's provincial green innovation efficiency in the ground space. Finally, a spatial econometric model is introduced to study the impact of government R&D investment, green supervision, and green innovation efficiency on spatial spillover effects. The study found the following three conclusions: First, the efficiency of green innovation in China's provinces has been fluctuating in stages, and the overall trend has been increasing year by year. The overall efficiency of green innovation in China's provinces is low, and the overall development is uneven and uncoordinated. Second, from the results of the spatial autocorrelation test, there is a clear and positive spatial correlation between China's provincial green innovation efficiency and agglomeration in the geospatial space. Third, government R&D inputs and different types of green regulations have a significant impact on green innovation efficiency and have significant spatial spillover effects. Along from the eastern region to the central region, then to the northeast and western regions, the degree of effect on green innovation efficiency and the intensity of spatial spillover effects have gradually weakened. It is believed that the government should reduce R&D investment in the eastern region and increase green sewage charges. Instead, the government should raise R&D investment in the central, northeast, and western regions and offer enterprises green innovation subsidies.

1. Introduction

1.1. The Relationship between Green Innovation and Economic Growth. Since human beings entered the 21st century, the depletion of energy and increasingly severe green pollution have made green development new kinetic energy for the high-quality growth of all countries [1]. Green innovation is a concrete manifestation of the deep integration of green development concepts and technological innovation and is an effective focus for breaking the traditional extensive economic development model [2]. In order to seize the opportunities, the developed countries have deployed the national strategy of green innovation. Both the United States' sustainable performance strategic plan and the EU's 2020 strategy have brought innovation and innovation into the national strategic position.

Since the reform and opening up, China's economic growth has achieved world-renowned achievements. However, the economic development model of "GDP" has led to problems such as green pollution and energy shortage in various regions of China [3]. The rapid growth of China's economy comes at the expense of green sacrifice and energy waste, which is unsustainable development [4]. China is in a stage of rapid industrialization and urbanization, and it is a period when the contradictions between economic development, resource utilization, and green protection are most acute [5]. On the other hand, the Chinese government has invested more in green pollution and energy shortages year by year. The 19th National Congress and the 13th Five-Year Plan emphasize the promotion of green development and the emphasis on ecological civilization. Green innovation has become a vital method for China to break through the constraints of resources and the environment. Besides, it could also guide overall sustainable development. Its role in China's development is more important than ever.

Through the above analysis, Chinese scholars and the Chinese government have reached an agreement that China's economic growth cannot be at the expense of the environment, and a balance should be sought between economic growth and green pollution. In October 2017, General Secretary Xi Jinping clearly stated in the report to the 19th National Congress of the Communist Party that China's economy has shifted from a stage of rapid growth to a stage of high-quality development. Green development is a part of high-quality economic development. The two have a dialectical and unified relationship, and green innovation is an important source of green development. To achieve the strategic goal of high-quality economic development, we cannot simply pursue GDP growth. We need to fully consider resource endowments and green-carrying capacity.

We believe that green innovation is an important means to balance the ecological environment and high-quality economic growth, and it is also the only way for high-quality economic development:

① Green innovation is essentially the innovation of green technology, which is to follow the principles of ecology and the laws of ecological economy, save resources and energy, avoid, eliminate, or reduce pollution and damage of the ecological environment, and minimize the ecological negative effects of "no pollution" or "less pollution." It is a general term for technologies, processes, and products. Green technological innovation is a new modern technological system coordinated with the ecological environment system.

② Green innovation is an important part of green development. Green development is a way of economic growth and social development that aims at efficiency, harmony, and sustainability. Green development and sustainable development are ideologically inherited. They are not only the inheritance of sustainable development but also the theoretical innovation of sustainable development in China.

③ Green innovation is an important way to protect the ecological environment. On the one hand, if the ecological environment is good and the living environment is good, the quality of human health is guaranteed. If ecological green protection is good, natural resource regeneration ability is strong, economic development is sustainable, the development space is broader, and stamina is more sufficient. On the other hand, economic development can provide a solid material guarantee for ecological compensation and ecological restoration.

1.2. Green Innovation Efficiency. Green innovation efficiency (GIE) is a basic indicator for measuring the innovation efficiency of regional green innovation activities, which is also a comprehensive innovation capability that takes energy scarcity and green costs into full consideration [6]. Green innovation mainly aims at energy conservation and green improvement from the two paths of product innovation and process innovation [7]. China's vast territory, regional resource endowments, and economic development levels are varied, leading to obvious heterogeneity of regional green innovation, which not only affects the balanced development of the interregional economy but also the coordinated development of the interregional ecological environment. Therefore, the green transformation of China's economic growth mode is imminent [8]. Among the process, government R&D investment and green regulations are the two main players. On the one hand, resources and environment are public goods, so many problems in the field of green pollution and ecological destruction cannot be solved completely through market mechanisms. Green control policy work must be supplemented in addition to market mechanisms. On the other hand, since China entered the new normal, the factor endowment structure dependent on economic growth has changed. In the past, extensive economic growth driven by factors such as demographic dividend, land dividend, resource dividend, and investment dividend was unsustainable. The important content of this paper includes how to systematically analyze and comprehensively evaluate regional green innovation performance and how to accurately grasp the evolutionary law of green innovation. Besides, the paper also discusses the importance of green innovation performance theories for China's exploration of green development models to achieve sustainable green, economic development, and practical significance.

This paper sorts out recent related research and summarizes the main research work and main views of experts and scholars on green innovation efficiency, as shown in Table 1.

1.3. The Implication and Innovation of This Paper

① It explores the relationship between green innovation and high-quality economic growth, taking China's economic growth as a case.

② It integrates the entropy weight TOPSIS model and the spatial measurement model to explain the regional differences between green innovation and economic growth.

③ Taking a developing country such as China as an example, the conclusions obtained can provide reference for developing countries in the world.

④ It constructed an green innovation evaluation index system and took China as an example. This evaluation index system can provide a reference for measuring the efficiency of green innovation in other countries.

Table 1: Summarization of the recent works.

Authors	Main work and contributions
Ghisetti and Rennings	The depletion of energy and increasingly severe green pollution have made green development new kinetic energy for the high-quality growth of all countries
Yang and Chai	A development model at the expense of greenness and energy waste is unsustainable development
Song, Zhu, Wang et al.	The period when the contradiction between China's economic development, resource utilization, and green protection is the most prominent
Albort-Morant, Leal-Millán et al.	Green innovation efficiency is a comprehensive innovation capability that comprehensively considers energy scarcity and green cost
Yuan and Xiang	Green innovation mainly aims at energy conservation and green improvement from the two paths of product innovation and process innovation
Dong, Wang, Jin et al.	The green transformation of China's economic growth mode is imminent

⑤ The policy recommendations and enlightenment in this paper have practical guiding significance for the government to formulate policies.

2. Literature Review

So far, the academic community has achieved more research results in green innovation research, mainly from three levels: concept analysis, influencing factors, and evaluation models. There is no consensus on the academic concept of green innovation. Case studies and cross-case comparative analysis show that green innovation is equivalent to green technology [9]. Discussing the biofuel innovation system in the United States and Brazil suggests that eco-innovation is a development model that can solve energy shortages and green pollution problems [10]. We find sustainable innovation based on sustainable energy technologies for consumable resources (natural gas, oil, and coal). Some people believe that green innovation is the same as sustainable innovation [11]. The main reason why scholars have a different understanding of green innovation is that they varied in their research perspectives, but all of their understandings reflect the unified relationship between resources, environment, and innovation.

In terms of factors affecting green innovation, the famous "Porter hypothesis" believes that green regulations will stimulate green innovation and reduce or offset the cost of green regulations [12]. Regulation is a positive alternative to green innovation by replacing markets, especially in developing countries, where regulation is an important component of competition. Technology, market demand, and green policy are the key influencing factors of green innovation, and corporate green innovation activities mainly come from the interaction of three important factors [13]. From a technical point of view, some studies have found that the introduction of foreign green technologies and the improvement of enterprises' green technology capabilities have actively promoted enterprises' independent innovation, which is also an important factor affecting green innovation. Using the stochastic frontier analysis method to study the pros and cons of green innovation, it is found that improving green innovation is conducive to improving the efficiency of natural resource utilization [14]. Competitive advantage is directly proportional to corporate green innovation, and government green regulation has a certain impact on green innovation. From the perspective of industrial organization [15], Peattie [16] compared and analyzed the factors affecting green innovation in various markets and believes that market demand has a significant impact on corporate green product development. It is believed that foreign direct investment can play an active role in green innovation by reducing the cost of green innovation in the host country [17]. On the other hand, government R&D investment can promote the efficiency of green innovation and has a leverage effect [18]. Broekel [19] believes that government R&D investment is not conducive to the improvement of green innovation efficiency and has a "crowding effect."

In addition, the academic research on sensors mainly includes five aspects: visual sensors, industrial robots, automobile manufacturing, medical and health monitoring, and food processing and packaging. First, in terms of visual sensors, in the production line of electronic manufacturing, both robot assembly and electronic component detection are inseparable from the application of visual sensor equipment. As one of the focuses of machine vision, image sensors are widely used in consumer electronics, medical electronics, avionics, and other fields [20]. Second, in the aspect of industrial robots, in order to improve the adaptability of the robot and detect the working environment in time, a large number of sensing devices are applied to the robot. These sensors improve the working condition of the robot and enable it to complete complex work more fully. The application of sensors in the robot industry has attracted the attention of most countries, mainly the United States and Japan. Driven by these advanced countries, the world has set off a boom in the development of "intelligent sensors" [21]. Robots provide a good landing scene and higher requirements for the development of sensors. Third, in terms of bicycle manufacturing, sensors are the information source of the vehicle electronic control system and the basic key components of the vehicle electronic control system. Traditional automobile sensors feed back information in the control process of each system to realize automatic control. They are the "neurons" of automobiles and are mainly used in powertrain systems, body control systems, and chassis systems [22]. In these systems, automobile sensors are responsible for the collection and transmission of information. After information collected is processed by the electronic control unit, instructions sent to the actuator are formed to complete the electronic control. Fourth, in terms of medical treatment and health monitoring, sensors can enable medical devices to present more accurate images, helping doctors correctly diagnose diseases and effectively treat patients; High precision sensors can obtain accurate monitoring data, making medical staff's diagnosis and equipment monitoring patient's body data more accurate [23]. Fifth, in terms of food processing and packaging, through the network function of wireless sensors, consumers can better understand the whole process of food production, storage and transportation in food processing plants, make food processing more intuitive and transparent, and effectively eliminate consumers' concerns about food safety [24]. At the same time, in case of problems, wireless sensor technology can also facilitate the regulatory authorities to find problems in a timely manner and can be well documented to curb food safety problems from the source.

Therefore, this paper uses the existing research at home and abroad for reference, applies sensor technology to the process of green innovation, and further studies the space-time characteristics of innovation efficiency on the basis of measuring China's provincial green innovation efficiency. Based on the provincial data of China, the spatial structure characteristics and spatial overlap effect of provincial green innovation efficiency are analyzed. Compared with previous studies, this paper has the following incremental contributions: First, it establishes a sensor data value incubation mechanism. Second, the multisource data acquisition model of sensor technology is constructed. Third, it objectively and systematically measures the efficiency of green innovation in China's provinces. The fourth is to use a spatial econometric model to study the spatial spillover effect of green innovation efficiency.

3. Indicator System and Research Model

The construction of the index system and the selection of research models are crucial to the research results. Figure 1 shows the logical relationship between the index system and various research models. First, an innovation and innovation indicator system and green regulation indicators are built, and the advance detailed analysis of indicators is carried out. Second, the entropy weight TOPSIS model is used to measure the efficiency of green innovation in China's provinces and test its autocorrelation. Finally, on the basis of the first two steps, the spatial measurement model is used to make spatial spillover recommendations and draw conclusions and policy recommendations.

3.1. Indicator System Design

3.1.1. Variable Selection and Description. At present, there is no separate indicator system for the green innovation evaluation system. The common practice in the academic community is to use the input-output method as an idea to include green and energy indicators that reflect green in the innovation evaluation system. According to the OECD's description of green innovation evaluation indicators, the green innovation evaluation indicators are mainly evaluated from the two aspects of green product innovation and green process innovation.

This paper measures the efficiency of provincial green innovation as a whole and therefore selects the input and output indicators of the R&D and economic transformation stages of the innovation process. The OECD evaluation system is adopted to comprehensively consider the redundancy and availability of China's provincial green innovation indicators and reshape the green innovation evaluation index system. The specific indicators have the following meanings:

① Innovative inputs are divided into capital investment and labor input. According to their research [25], capital stock (K) and R&D personnel full-time equivalent (TSI) are used as indicators to measure capital input and labor input. The capital stock is still estimated by the perpetual inventory method proposed by the study (current capital stock = current capital stock $*$ (1–9.6%) + current fixed assets), and the estimated results are based on the figures for the year 2000. Both capital investment and labor input are positive indicators.

② Innovative outputs are divided into expected output and non-expected output. Through their methods [26] and [27], product innovation (GPTI) is used to measure expected output and high-tech new products are used to sell revenue and energy consumption. The ratio is measured by the ratio. The emissions of three industrial wastes (waste water, exhaust gas, solid waste, and THW) are used as a measure of poor output. In order to eliminate the influence of different sizes, a three-waste weighted value calculation was performed. Product innovation is a positive indicator, while the three industrial wastes are a negative indicator.

③ Green regulation is a comprehensive consideration of China's green protection system, especially in the field of green innovation, which is controlled by the government and the market and public participation. It is not easy to generalize green regulations with certain types of indicators. In [28], the green regulation is divided into the command-based green regulation (F), incentive green regulation (I), and public participation green regulation (P). The command-based environment uses the SO_2 removal rate (SOO) as a measure. The incentive-type environment uses the unit GDP's sewage charge (USD) as a measure. The public-participating environment uses the total number of green letters and visits (EP) in each region as a measure.

This paper covers 30 provinces (including autonomous regions and municipalities) in China as the object of investigation and measures the efficiency of China's provincial green innovation from 2005 to 2021, but the investigation

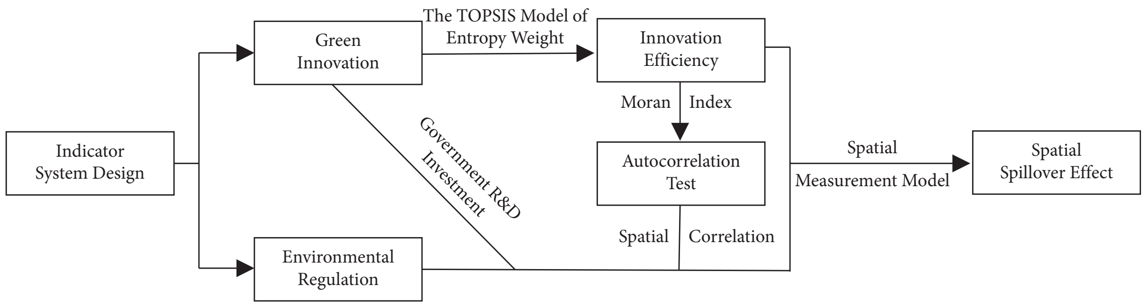

Figure 1: The logical route of this article.

does not include Tibet, Hong Kong, Macao, and Taiwan. In addition, according to the statistics revealed by the National Bureau of Statistics division in 2011, 30 provinces (autonomous regions and municipalities) are divided into four major economic zones: the eastern, central, western, and northeastern regions. The indicators of innovation input and innovation output are derived from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and China Energy Statistics Yearbook. The SO_2 removal rate and unit GDP sewage charges come from the China Green Statistics Yearbook and the Green Yearbook of China, the total number of letters is from the green letters, and visits comes from the China Green Yearbook.

3.1.2. Sensor Data Value Incubation Mechanism. The sensor data itself are not the focus of our research, the key lies in the unexplored potential value behind the sensor data, and the hidden spatial value of the sensor data is boundless [29]. Sensor data, as a virtual production factor, also have a "tangible" value and an "intangible" value. Specifically, the entity of the sensor data refers to a measurable, fixed, and different magnitude from other entities and the hidden space of the sensor data. It refers to infinite possibilities that are boundless, changing, and effective. This paper introduces the concept of biological incubation and metaphorizes the realization of the industrial big data value as the incubation process of oviparous animals shown in Figure 2.

With the in-depth integration of the new generation of information technology and the real economy, enterprises continue to accumulate production, R&D, economic management, operation and maintenance, and other data in the manufacturing process, and the accumulated quantity is huge and various. Multisensor data originate from various data integrations in various links, including informatization data, Internet of things data, and cross-border data, and have many characteristics such as complexity, multisource, and heterogeneity. The collision and fusion of multisource heterogeneous data is valuable, and the construction of the multisensor data "resource pool" is the primary goal of realizing data. Multisource heterogeneous data utilize nutrients provided by the resource pool to release and magnify the value through the incubation mechanism, just like the hatching of oviparous animal embryos. The resource pool is called the cradle of value breeding. Sensor data cover product research and development, production, market, customers, logistics supply chain, after-sales service, finance, manpower, production equipment and instruments, sensors, products, environmental regulations, social economy, and other data, covering a long process, a variety of types, and a wide range. The quality-tested multisensor data are dazzling, and the multisensor data need to be classified, cataloged, and described in detail so that data users can better discover data and enterprise managers can efficiently manage data, and it is conducive to fully mining its value.

3.1.3. Combined Sensor Data Collection Technology. Single-point acquisition technology is the basis of multisensor data acquisition and has been widely used, but many limited counties are also exposed in the process of practical application. For example, the data are irrelevant, and the data collection cycle is long. In addition, data items collected by the single-point collection technology through each collection channel are discrete, and the collection and transmission of various types of data are independent, which ensures that the data will not interfere with one another, but also leads to the lack of interaction between the data. For the key relationship network, it is difficult to carry out accurate correlation analysis in the follow-up, and it is difficult to guarantee the utilization rate of the relationship between data. The application and implementation of complete and accurate data from the sensor data in all aspects of the industrial chain such as process design, production and processing, and workshop management; repair and maintenance plays an important role in improving product quality, optimizing processes, and enhancing user experience.

The combined technology is also suitable for data analysis applications of other digital control-based automation equipment (such as robots, laser-cutting machines, and production lines). The combined acquisition technology has broad application prospects in the open intelligent manufacturing ecosystem. Combination technology can collect various data items of industrial equipment in combination and establish a relationship network between data. The specific implementation process of the combination technology is as follows: First, the user uses the acquisition parameters to configure the interface acquisition parameters, needs to configure the parameters of the data to be collected, and defines the data acquisition period and the combination period of the

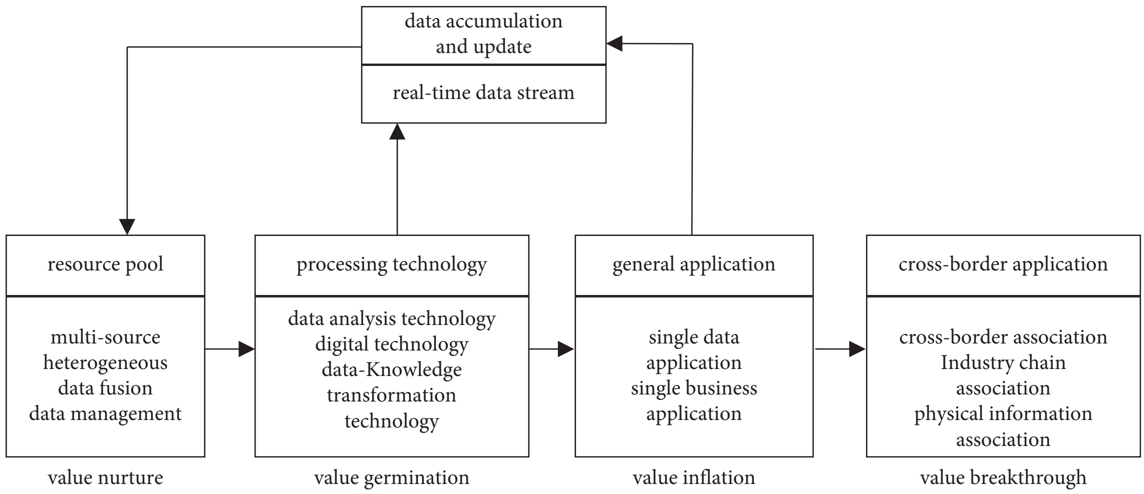

Figure 2: Sensor data value incubation mechanism.

collected data. Second, the data acquisition module continuously and periodically collects the equipment. After that, the local cached data are combined to form one or more sets of combined data; the fifth step is to cache the combined data in the database and perform it in the cloud persistent storage. The specific process is shown in Figure 3.

3.1.4. The Sensor Usage in the Work

① The efficiency of green innovation is closely related to the application of sensor technology. First of all, virtual sensor technology and network sensor technology can improve the monitoring range and transmission speed of sensors through fast Fourier transform and neural network intelligent recognition of sensor array signals. Second, through network sensors and multiagent cooperation technology, sensor networks can be deployed to objectively evaluate the green innovation efficiency of adjacent regions. Finally, sensor technology can enable the green development of high-carbon emission industries, focusing on enabling the production, manufacturing, operation, and control processes in the carbon emission field, reducing energy and resource consumption, and achieving the dual improvement of production efficiency and carbon efficiency.

② The measurement accuracy of green innovation efficiency is closely related to the sensor data. First, the measured data must be real-time data, and multi-sensor cooperative operation can collect real-time data. Second, the original data of the measurement must be multisource data, and multi-sensors can combine the combined acquisition technology through different channels and can collect and fuse data from different channels. Finally, the sensor data are beneficial to the storage and transmission of data, and the security performance of the data is very high.

3.2. Research Model

3.2.1. The TOPSIS Model of Entropy Weight.

The TOPSIS model of entropy weight is the fusion of the information entropy and TOPSIS model. Specifically, in the traditional TOPSIS model, the entropy method is used to determine the index weight. The entropy-weighted TOPSIS model is a method to approximate the ideal solution. The sample data are not strictly limited. It is mainly suitable for multi-index, multischeme decision analysis system evaluation. By constructing and calculating the Euclidean distance of the positive and negative ideal solutions, multiple decisions can be made.

The TOPSIS model of entropy weight is the fusion of the information entropy and TOPSIS model. Specifically, the entropy weight method is adopted to determine the index weight in the traditional TOPSIS model. The main purpose is to prevent subjective factors from being affected when the index weights are determined during the analysis, which enhances the objectivity of the evaluation results. The entropy-weighted TOPSIS model is a method to approximate the ideal solution. There is no strict restriction on the sample data. It is mainly applicable to multi-index and multischeme decision analysis system evaluation. By constructing and calculating the Euclidean distance of positive and negative ideal solutions, multiple decisions are made. The unit is rated for superiority and superiority (better than SFA or DEA). The main calculation steps are as follows [30]:

① Construct a decision matrix: There are m indicators participating in evaluation units, and there are n evaluation indicators for each evaluated unit. The structural decision matrix is as follows:

$$X = \left(x_{ij}\right)_{m\times n} (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n). \tag{1}$$

② Dimensionless decision matrix: The indicators are normalized, and the indicators are divided into positive indicators and negative indicators. The normalization formula for the positive and negative indicators is as follows:

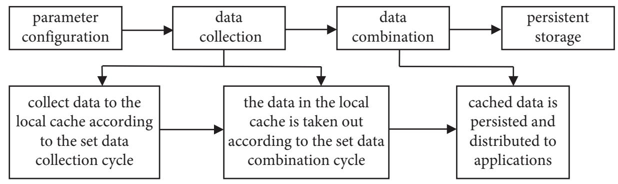

FIGURE 3: Flowchart of combined acquisition technology.

$$x_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \ (+)$$
$$x_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \ (-). \tag{2}$$

③ The information entropy of the indicator is calculated as follows:

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij});\ p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}. \tag{3}$$

④ The index entropy weight is calculated as follows:

$$w_j = -\frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)};\ w_j \in [0, 1], \sum_{j=1}^{n} w_j = 1. \tag{4}$$

⑤ The weight matrix is calculated as follows:

$$R = (r_{ij})_{m\times n}, r_{ij} = w_j \cdot x_{ij}. \tag{5}$$

⑥ The optimal solution and the worst solution are calculated as follows:

$$S_j^+ = \max(r_{1j}, r_{2j}, \cdots, r_{nj}), S_j^- = \min(r_{1j}, r_{2j}, \cdots, r_{nj}). \tag{6}$$

⑦ The distance between each unit is calculated, and the positive and negative ideal solutions using Euclidean distance are calculated as follows:

$$Sd_i^+ = \sqrt{\sum_{j=1}^{n} (S_j^+ - r_{ij})^2};\ Sd_i^- = \sqrt{\sum_{j=1}^{n} (S_j^- - r_{ij})^2}. \tag{7}$$

⑧ The relative progress of each unit is calculated as follows:

$$C_i = \frac{Sd_i^+}{Sd_i^+ + Sd_i^-}, C_i \in [0, 1]. \tag{8}$$

In formula (8), the greater the relative proximity C_i of each unit, the closer the evaluation target i is to the ideal solution. According to relative closeness, the higher the green innovation efficiency of the province, the higher the classification and ranking of each green innovation efficiency.

3.2.2. Exploratory Spatial Data Analysis. We use exploratory spatial data analysis (ESDA) to analyze the spatial and spatial relevance of green innovation efficiency. In the research process, the spatial weight matrix is generated to determine the weight of each spatial unit, and the spatial correlation analysis is performed according to the economic attributes of each unit. The spatial autocorrelation test determines whether the samples are spatially related, the correlation between them, and the spatial correlation of the description object. ESA has two types of analysis methods: global statistics and local statistics.

In this paper, the global spatial autocorrelation index Moran's I is used to measure the spatial correlation of the evaluation units in the province. The Moran index is an important indicator of the similarity of spatial neighboring unit elements. The Moran index is calculated as follows [31]:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{9}$$

$$G(d) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}. \tag{10}$$

In formula (9), $S^2 = 1/n\sum_{i=1}^{n}(x_i - \overline{x})^2, \overline{x} = 1/n\sum_{i=1}^{n} x_i S^2$ is the sample variance, n represents the number of spatial units, x_i represents the attribute value in the i area, W_{ij} represents the spatial unit neighbor weight, and $G(d)$ represents the global G coefficient. The Moran index is generally between −1 and 1. Greater than 0 indicates the positive autocorrelation, and the larger the data, the more obvious the spatial distribution agglomeration; smaller than 0 indicates the negative correlation; the smaller the data, the stronger the spatial negative correlation. The Moran index can be regarded as the correlation coefficient between the observed value and its spatial lag. The observation value and its spatial lag are drawn as a scatterplot, called Moran scatterplot, and Moran's I is the slope of the retracement regression line. In this formula, the global $G(d)$ coefficient usually normalizes $G(d)$ $Z(G) = (G - E(G))/\sqrt{\mathrm{Var}(G)}$. However, $E(d)$ and $\mathrm{Var}(G)$ represent the mathematical expectation and variance of $G(d)$, respectively. $Z(d)$ is positive for the presence of high-value clusters, and $Z(d)$ is responsible for indicating the existence of low-value clusters [32].

3.2.3. Spatial Econometrics Model. Maintaining the optimal allocation of government R&D investment and green supervision is not only a key factor for improving the efficiency of green innovation in China's provinces but also a key factor for achieving high-quality economic growth and the coordinated development of resources and the environment. The internal unity is Qingshan and Jinshan Yinshan. We make full use of previous research results to incorporate government R&D investment, green supervision, and regional green innovation capabilities into the same research framework and build a spatial measurement model of provincial green innovation efficiency based on the traditional Cobb–Douglas production function.

Moderately intensive government R&D investment has a positive impact on green innovation, which can reduce innovation costs and risks and drive local R&D investment with leverage. Appropriate types of green regulations can stimulate green innovation and produce compensation, thereby reducing energy consumption and improving the level of technology. Safeguarding the optimal allocation of government R&D investment and the green regulation is not only a key factor in improving the efficiency of green innovation in China's provinces but also in achieving the high-quality growth of the economy and the coordinated development of resources and environment. Lucid waters and lush mountains are invaluable assets. We fully draw on previous research results, incorporate government R&D input, green regulation, and regional green innovation capabilities into the same research framework, and build a spatial measurement model of provincial green innovation efficiency based on the traditional Cobb–Douglas production function. The specific model [33] is as follows:

$$\mathrm{EIE}_{i,t} = A \bullet \mathrm{GRD}_{i,t}^{\alpha} \bullet \mathrm{ENR}_{i,t}^{\beta}. \tag{11}$$

In order to eliminate the heteroscedasticity and the influence of different dimensions, the logarithm of each side of (11) is processed, and an econometric model is constructed as follows:

$$\ln\mathrm{EIE}_{i,t} = \alpha + \beta_1 \ln\mathrm{GRD}_{i,t} + \beta_2 \ln\mathrm{ENR}_{i,t} + \varepsilon_{i,t}. \tag{12}$$

In the formula, the variable EIE represents the green innovation efficiency, the variable GRD represents the government R&D input cost, the variable ENR represents the green regulation, A represents a constant term, α and β_1 or β_2, respectively, represent the government R&D input and green regulation elasticity coefficient, and $\varepsilon_{i,t}$ represents the random error [34].

Spatial econometrics was originally derived from the statistical analysis of spatial data. The integration of spatial statistics and econometrics not only changes the classical assumptions of traditional econometrics but also promotes spatial econometrics as an independent discipline and is widely used in many fields of natural sciences and social sciences. Spatial econometrics research focuses on the issue of spatial self-first. There are four main reasons for the source of spatial autocorrelation, which is also an important area for the application of spatial metrology analysis. The first is externality. For example, in economic fields such as endogenous economic growth theory and new economic geography theory, the analysis is concentrated on the influence of changes in the characteristics of related units of a given unit. The second one is the spillover effect. For example, the behavior of the interpreted variable is also affected by the change of the explanatory variable of the adjacent observation unit. The third reason is to ignore important variables. For example, there is a lack of important spatial structure latent variables, which will have an impact on different spatial observation units, and the spatial measurement model needs to be analyzed. The last one is spatial heterogeneity and mixing effects.

The spatial econometrics was first proposed by some scholars. It is widely used in various disciplines and has been recognized by the academic community. In the nearly 40 years of the development of spatial econometrics, a variety of spatial econometric models have emerged. Among them, the spatial error model (SEM) and the spatial lag model (SLM) are the two most used spatial measurement models in the empirical analysis. The former could be applied to the spatial correlation of error terms, and the latter is applicable that there is a spatial lag that is interpreted as a variable. They proposed a spatial Durbin model (SDM) with both SEM and SLM properties, which greatly enriched SEM and SLM. This article builds three spatial econometric models of SDM, SLM, and SEM based on the basic econometric model [35]. The specific model is as follows.

Model 1. The spatial Durbin model is expressed as

$$\begin{aligned}\ln\mathrm{GIE}_{i,t} = {} & \rho W\ln\mathrm{GIE}_{i,t} + \beta_0 + \beta_1 \ln\mathrm{GRD}_{i,t} + \beta_2 \ln\mathrm{SOO}_{i,t} \\ & + \beta_3 \ln\mathrm{USD}_{i,t} + \beta_4 \ln\mathrm{EP}_{i,t} + \beta_5 W\ln\mathrm{GRD}_{i,t} \\ & + \beta_6 W\ln\mathrm{SOO}_{i,t} + \beta_7 W\ln\mathrm{USD}_{i,t} + \beta_8 W\ln\mathrm{EP}_{i,t} + \varepsilon_{i,t}.\end{aligned} \tag{13}$$

Model 2. The spatial lag model is expressed as

$$\begin{aligned}\ln\mathrm{GIE}_{i,t} = {} & \rho W\ln\mathrm{GIE}_{i,t} + \beta_0 + \beta_1 \ln\mathrm{GRD}_{i,t} + \beta_2 \ln\mathrm{SOO}_{i,t} \\ & + \beta_3 \ln\mathrm{USD}_{i,t} + \beta_4 \ln\mathrm{EP}_{i,t} + \varepsilon_{i,t}.\end{aligned} \tag{14}$$

Model 3. The spatial error model is expressed as

$$\begin{aligned}\ln\mathrm{GIE}_{i,t} = {} & \beta_0 + \beta_1 \ln\mathrm{GRD}_{i,t} + \beta_2 \ln\mathrm{SOO}_{i,t} \\ & + \beta_3 \ln\mathrm{USD}_{i,t} + \beta_4 \ln\mathrm{EP}_{i,t} + (1 - \rho W)\varepsilon_{i,t}.\end{aligned} \tag{15}$$

The choice of different models is mainly based on judgment rules [36]. The SLM model and the SEM model are screened using the LM-error and LM-lag, robust LM-error test, and robust LM-lag test. If both models are applicable, the corresponding Wald test and the LR test are carried out to determine whether the SDM model can be simplified into an SLM model or an SEM model. Finally, the Hausman test is used to determine whether the fixed or random effect is used to determine the most superior spatial econometric model.

3.3. Theoretical Introduction

3.3.1. Spillover Effect Theory

① The development of one aspect of a thing drives the development of other aspects of the thing.

② There is an impact of the increase in aggregate demand and national income in a certain region on other countries.

③ Spillover effects: There are technology spillover effects. Multinational corporations are the main inventors of the world's advanced technologies and the main source of supply for the world's advanced technologies. Multinational corporations realize their technology transfer through the internalization of foreign direct investment. This kind of technology transfer behavior brings external economy to the host country, that is, technology spillover. A technology spillover is a specific situation of positive externality. It is neither the benefit obtained within the economic activity itself nor the benefit obtained by the user of the product of the activity. In other words, this kind of interest is external to the economic activity itself and produces an external economy to society.

3.3.2. Analysis of the Spatial Spillover Effect Mechanism. The so-called spillover effect refers to when an organization conducts an activity. It will not only produce the expected effect of the activity but also affect people or society outside the organization. Spillover effects are divided into economic benefit effects and technology spillover effects:

① Arrow first explained the role of spillover effects in economic growth with externalities. He believes that new investment has a spillover effect. Companies that invest in not only can increase productivity by accumulating production experience, but other companies can also increase productivity by learning from those companies that invest.

② Paul Romer proposed a knowledge spillover model. Knowledge is different from ordinary commodities in that knowledge has spillover effects. This enables the knowledge produced by any manufacturer to increase the productivity of the whole society. "Endogenous technological progress" is the driving force of economic growth. In Romer's model, the total production function describes the stock of capital, labor, and the stock and output of creative technology and the relationship between.

③ Palente studied the relationship between technology diffusion, learning-by-doing, and economic growth. He designed a learning-by-doing model for a specific manufacturer to select technology and absorb time. He believes that before and after absorbing various technologies, the proprietary technical knowledge accumulated by manufacturers through learning-by-doing is ready for further introduction of technologies.

4. Empirical Analysis

4.1. Green Innovation Efficiency Analysis. This paper uses the TOPSIS model of entropy to measure the green innovation efficiency of 30 provinces (cities) in mainland China and classifies the eastern, central, northeastern, and western regions, respectively, see Table 2 for more details.

Analysis of the form is as follows:

① In terms of time, China's provincial-level green innovation efficiency is changing year by year, and the overall trend is improving year by year. Over time, the efficiency of green innovation in each province has been improved to varying degrees, and the degree of difference is also diverse. This is mainly because, on the one hand, green technology is promoted and applied on a larger scale as each province's GDP and infrastructure continue to improve, and its economic base continues to be consolidated. On the other hand, the government's investment in energy consumption and green pollution has increased significantly. In addition, from the point of view of time, in the vicinity of 2008, most provinces have experienced a small decline in green innovation efficiency, which is mainly affected by the financial crisis.

② From the provincial dimension, the overall efficiency of green innovation in China's provinces is low, and the overall development is uneven and uncoordinated, showing a low trend in the east, high, and middle. The gap between green innovation efficiency between provinces is very prominent, and the individual provinces are almost zero. At the theoretical level of the two mountains, Jiangsu (0.7374), Guangdong (0.7335), Shanghai (0.6213), Zhejiang (0.5866), Beijing (0.5504), Shandong (0.5340), and other six provinces (A grade) have already marched toward the goal of lucid waters and lush mountains. They all performed well in the coordination of economic growth and resource and green load. 17 provinces (B-grade, C-class, and D-class) such as Tianjin (0.4831), Fujian (0.3156), and Henan (0.3025) failed to achieve economic growth and coordinated development of resources and environment and failed to achieve green water. The remaining seven provinces (E-level) have a large space for green innovation efficiency.

③ From the regional dimension, it descends from east to west, east (0.4882), national (0.2720), central (0.2245), northeast (0.2098), and western (0.1182) regions. The trend of the four major regions is shown in Figure 4. Through testing the green efficiency growth rate of the four major economic regions, it is found that the growth in the central region is

Table 2: China's provincial green innovation efficiency.

	Province	Mean	Level	2005	2007	2009	2011	2013	2015	2017	2019	2021	Growth rate (%)
East region	Beijing	0.5504	A	0.5650	0.5460	0.5950	0.5585	0.6957	0.5369	0.5156	0.5213	0.4680	17.52
	Tianjin	0.4831	B	0.4333	0.5176	0.5571	0.5267	0.5729	0.4287	0.4292	0.4467	0.4072	
	Hebei	0.2459	C	0.2556	0.2458	0.2499	0.2583	0.2192	0.2401	0.2394	0.2538	0.2429	
	Shanghai	0.6213	A	0.7603	0.7324	0.6731	0.6792	0.6531	0.5712	0.5277	0.5113	0.4838	
	Jiangsu	0.7374	A	0.6028	0.6200	0.6298	0.6008	0.7024	0.8001	0.8645	0.9280	0.9044	
	Zhejiang	0.5866	A	0.3904	0.3527	0.4749	0.5640	0.6536	0.6526	0.6719	0.7313	0.7529	
	Fujian	0.3156	B	0.2509	0.2768	0.3308	0.3114	0.3277	0.2922	0.3286	0.3054	0.2893	
	Shandong	0.5340	A	0.4651	0.4779	0.5013	0.5022	0.5363	0.5854	0.5793	0.5825	0.5461	
	Guangdong	0.7335	A	0.5473	0.5316	0.6452	0.6430	0.7340	0.8579	0.8858	0.8697	0.9068	
	Hainan	0.0746	E	0.0126	0.1165	0.1601	0.1647	0.0499	0.0649	0.0659	0.0531	0.0322	
Central region	Shanxi (1)	0.1129	D	0.0968	0.0956	0.1009	0.1445	0.1245	0.1238	0.1127	0.1090	0.0957	52.10
	Anhui	0.2430	C	0.1681	0.1720	0.1840	0.1771	0.2057	0.2615	0.3243	0.3495	0.3756	
	Jiangxi	0.1541	D	0.1257	0.1123	0.1284	0.1636	0.1658	0.1563	0.1740	0.1683	0.2186	
	Henan	0.3025	B	0.2556	0.2518	0.2529	0.2887	0.2708	0.3218	0.3198	0.3747	0.3628	
	Hubei	0.2882	B	0.2891	0.2804	0.2580	0.2555	0.2769	0.2893	0.2909	0.3263	0.3224	
	Hunan	0.2464	C	0.1980	0.1887	0.2002	0.1922	0.1998	0.2509	0.3077	0.3333	0.3486	
Northeast region	Liaoning	0.2743	B	0.2715	0.2990	0.2903	0.3024	0.2753	0.2719	0.2537	0.2651	0.2090	−11.20
	Jilin	0.2042	C	0.1700	0.1439	0.1109	0.2319	0.2433	0.2427	0.2310	0.1827	0.2185	
	Heilongjiang	0.1510	D	0.1602	0.1687	0.1703	0.1724	0.1436	0.1543	0.1306	0.1243	0.1069	
Western region	Neimenggu	0.1056	D	0.0561	0.0538	0.0947	0.0975	0.0997	0.1286	0.1364	0.1450	0.1341	−8.78
	Guangxi	0.1555	D	0.1663	0.1268	0.1531	0.1329	0.1430	0.1717	0.1721	0.1578	0.1622	
	Chongqing	0.2721	B	0.2289	0.2639	0.2746	0.2291	0.3375	0.3104	0.2332	0.2816	0.3120	
	Sichuan	0.2597	C	0.3140	0.2958	0.2709	0.2797	0.2703	0.2367	0.2202	0.2357	0.2222	
	Guizhou	0.0545	E	0.0558	0.0564	0.0541	0.0620	0.0428	0.0536	0.0517	0.0548	0.0584	
	Yunnan	0.0924	E	0.0951	0.0935	0.0940	0.0927	0.0775	0.0804	0.0908	0.0988	0.1074	
	Shanxi (2)	0.2010	C	0.2854	0.2403	0.1995	0.2091	0.1778	0.1959	0.1662	0.1770	0.1601	
	Gansu	0.0683	E	0.0873	0.0625	0.0572	0.0719	0.0606	0.0698	0.0806	0.0739	0.0406	
	Qinghai	0.0061	E	0.0134	0.0071	0.0042	0.0201	0.0018	0.0000	0.0003	0.0002	0.0030	
	Ningxia	0.0214	E	0.0272	0.0114	0.0182	0.0177	0.0095	0.0237	0.0337	0.0259	0.0185	
	Xinjiang	0.0640	E	0.0723	0.0701	0.0742	0.0697	0.0560	0.0610	0.0546	0.0609	0.0602	

*Category division criteria, A: 0.5–1; B: 0.26–0.5; C: 0.2–0.26; D: 0.1-0.2; E: 0-0.1. Growth $\text{Rate}_{2005\text{-}2021} = (\text{RGIC}_{2021} - \text{RGIC}_{2005})/\text{RGIC}_{2005}$.

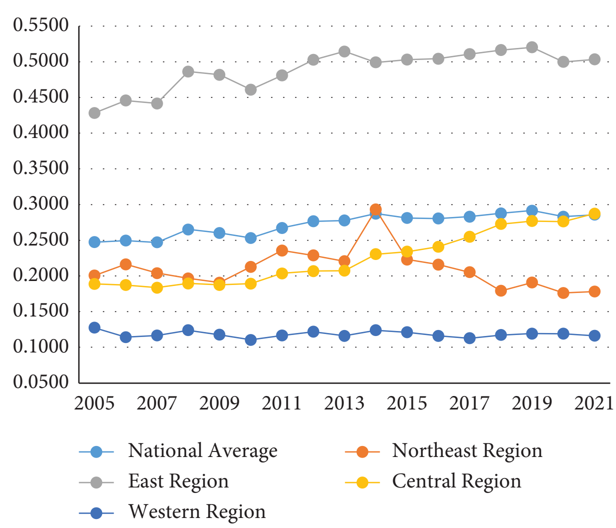

Figure 4: Trends of green innovation efficiency in the four major economic regions.

particularly prominent, with a growth rate of 52.10% and an increase of 17.52% in the east, both greater than the national average growth rate of 15.50%. Both the northeast and the west have experienced negative growth rates of −11.20% and −8.78%, respectively. Both the northeast and west have seen negative growth. This is because the lack of national guidance and support for R&D directions and key points is

Table 3: China's provincial green innovation efficiency global Moran index.

Years	Moran's I	Z value
2005	0.303***	2.775
2006	0.361***	3.238
2007	0.377***	3.368
2008	0.405***	3.564
2009	0.414***	3.633
2010	0.364***	3.221
2011	0.419***	3.668
2012	0.387***	3.408
2013	0.349***	3.104
2014	0.263***	2.420
2015	0.293***	2.699
2016	0.321***	2.932
2017	0.326***	2.993
2018	0.328***	2.999
2019	0.323***	2.961
2020	0.300***	2.783
2021	0.312***	2.885

Note. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$. The same is given as in the following table.

Table 4: LM test and Hausman test.

Tests	Eastern region (SLM)		Central region (SLM)		Northeast and western regions (SEM)	
	Statistics	P value	Statistics	P value	Statistics	P value
LM lag	7.787	0.005	12.84	0.001	2.443	0.018
Robust LM lag	—	—	7.138	0.008	—	—
LM error	1.226	0.268	6.165	0.013	7.851	0.005
Robust LM error	—	—	0.460	0.498	—	—
Hausman	32.975	0.001	45.993	0.001	22.099	0.050

Note. "—" means no inspection is required.

even more serious although the northeast has strong R&D personnel and high-level infrastructure, and most of the northeast manufacturing companies are old companies. It is still difficult to form new growth poles by using traditional technologies. Due to economic strength, historical reasons, resource endowments, and other reasons, the western region's green innovation research and development lags. The weak technological transformation capacity of the western region is a bottleneck, restricting the development of green innovation.

4.2. Spatial Autocorrelation Test. We use the exploratory spatial data analysis method to calculate the global Moran index of China's provincial green innovation efficiency through Stata 15.0 software, and the Monte Carlo simulation method is used to test the significance of Moran's I. The results are shown in Table 3.

The analysis of the form is as follows.

Moran's I fluctuated between 0.263 and 0.419, and both were significant at the 1% level, rising first and then rising and rising (N-type), indicating that there is a significant positive spatial correlation in regional green innovation. In order to further show a spatial correlation, Moran scatterplots were drawn for 2005, 2010, 2014, 2018, and 2021. There are obviously four quadrants in the Moran scatterplots: the first quadrant is high-value clustering (H-H), the second quadrant is a low value surrounded by a high value (L-H), the third quadrant is low-value clustering (L-L), and the fourth quadrant is surrounded by a low value (H-L). Most of the provinces fall in the first and third quadrants. The result rejects the hypothesis that green innovation efficiency is spatially randomized, which further confirms the agglomeration of China's provincial green innovation efficiency in the geospatial space.

4.3. Spatial Spillover Effect. After reshaping the indicators of the green evaluation system, green innovation efficiency (EIE) was selected as the explanatory variable and government R&D investment and green regulations were used as the explanatory variable to test the spatial spillover effect of green innovation efficiency in the eastern, central, northeastern, and western regions of China. It also analyzes the spatial and temporal differentiation characteristics of green innovation efficiency in the four major economic regions.

The Moran index can test whether the sample data have spatial autocorrelation but cannot determine the specific form of the spatial model. Therefore, it is necessary to select the appropriate model through the spatial measurement model screening rule. According to Elhorst et al and Anselin et al. judgment rules, the LM test and the Hausman test were

Table 5: Estimation results of spatial measurement models for fixed effects.

Variables	Eastern region (SLM)				Central region (SLM)				Northeast and western regions (SEM)			
	(11)	(12)	(13)	(14)	(21)	(22)	(23)	(24)	(31)	(32)	(33)	(34)
Constant	−5.509***				−4.941***				−5.573***			
lnGRD	0.282***	−0.363***	0.375***	−0.410	0.553***	0.012***	0.057***	0.204	1.003***	0.468***	0.971***	0.594***
lnSOO	−0.051	0.236***	−0.093	0.165***	−0.288***	−0.063***	−0.208***	−0.144*	0.145*	−0.314***	0.186***	−0.360***
lnUSD	−0.098	−0.099	−0.061	−0.091	−0.155***	0.047	−0.058	0.169***	0.032	0.014	−0.002	0.004
lnEP	0.395***	0.086***	0.437***	0.075***	0.053***	0.041***	0.125***	0.027	0.293***	−0.030***	0.360***	0.143***
$W*\ln GRD$	0.477***	−0.269***	0.541***	−0.375***	−0.164	0.082***	−0.120	−0.656*	−0.641***	0.619***	−0.525*	−0.031
$W*\ln SOO$	−0.043	0.083***	−0.240	−0.469***	0.598***	0.085***	0.679***	−0.096	−0.143	−0.107***	0.112	−0.299
$W*\ln USD$	0.263***	0.170	0.220***	0.130	0.166***	−0.060	−0.057	0.457***	−0.040	−0.027	−0.008	0.208***
$W*\ln EP$	−0.305***	−0.084***	−0.061	−0.074	−0.063***	−0.061***	0.125***	−0.047	−0.044	−0.027***	0.167	0.165***
σ^2	0.199	0.111	0.176	0.090	0.020	0.013	0.019	0.009	0.857	0.228	0.813	0.230
R^2	0.709	0.847	0.768	0.868	0.876	0.924	0.899	0.950	0.516	0.879	0.574	0.886
$\mathrm{Log}-L$	−103.87	−49.21	−88.58	−36.88	−110.08	−139.25	−121.91	−116.03	−319.67	−154.62	−304.88	−146.98

*Combine the northeast region with the western region due to the number of samples.

Table 6: Direct and indirect effect coefficients.

Variables	Eastern region (SLM)			Central region (SLM)			Northeast and western regions (SEM)		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
lnGRD	−0.554***	−0.088***	0.456***	0.580***	0.267***	0.313***	0.305***	0.925***	0.619***
lnSOO	0.121***	−0.019	0.102	−0.342***	0.597***	0.254***	−0.334***	0.234***	−0.567***
lnUSD	0.029	−0.005	0.024	−0.172***	0.185***	0.013	0.053	0.189	−0.137
lnEP	0.378***	−0.060	0.317***	0.059**	0.169**	−0.008	−0.024	0.036	−0.059

carried out on the indicators of green innovation efficiency in different regions (Table 4). According to the Hausman test, the spatial spillover effect of green innovation efficiency needs to adopt the fixed-effect model. Which fixed effect model is used? It can be seen from the LM test that the SLM, SLM, and SEM models are more advantageous as the spatial measurement model in the eastern, central, northeast, and western regions. Mixed regression effects, spatially fixed effects, time-fixed effects, and double-fixed effects tests were performed on the selected models, see Table 5. It is judged by combining the goodness of fit ($R2$) and the log-likelihood value. It can be seen in Table 5 that relatively high $R2$ and log-L are the double fixed-effect model, the mixed fixed-effect model, and the double fixed-effect model and that the goodness of fit and natural log-likelihood function values of these three models are 0.868 and −36.882, 0.876 and −110.078, and 0.886, and −146.98, respectively, indicating that the overall interpretation ability of model (14), model (23), and model (32) is stronger. To further illustrate the interaction mechanism between the explanatory variables and the explained variables, the direct and indirect effect coefficients were calculated using the three selected models, as shown in Table 6.

The analysis of the form could be conducted according to the following perspectives:

① The perspective of government R&D investment has an enormous impact on the efficiency of green innovation and has significant spatial spillover effects. Nonetheless, the spatial spillover effects between varied regions are quite different, and influence strength varies. For example, for the eastern region, government R&D investment inhibits green innovation (−0.410), while central and northeastern and western government R&D inputs will promote green innovation efficiency, with correlation coefficients of 0.553 and 0.594, respectively. The spatial spillover effect of government R&D investment shows the same pattern. For the eastern region to improve the R&D investment of the provincial government, it will inhibit the green innovation efficiency of neighboring provinces and cities and promote the R&D investment of the provincial and municipal governments in the central, northeast, and western regions. The efficiency of green innovation in neighboring provinces and cities has surged. On the other hand, the influence of R&D investment from the eastern region to the central region to the western region on the efficiency of green innovation has gradually increased, and the spatial spillover effect has gradually increased. The main reason that could explain for the fact is that the economic base and innovation resources in the eastern region are relatively sufficient and that enhancing government R&D investment will not significantly promote the efficiency of green innovation. On the contrary, it may cause a waste of resources and corporate speculation.

② The perspective of green supervision: It can be seen from the results of the spatial measurement model test that different types of green supervision have different mechanisms for green innovation efficiency. The command-based green regulation and the public-participating green regulation have a significant impact on green innovation efficiency, both at a level of 1%. However, the impact of different regional green regulations on the efficiency of green innovation is diametrically opposed. For example, the directive green regulations (0.165) in the eastern region promoted green innovation, while the central, northeastern, and western regions did inhibit green innovation, with correlation coefficients of −0.228 and −0.360, respectively. From the perspective of spatial spillover effects, R&D investment and mandatory green regulations in the eastern region have negative spillover effects. The command-type green regulation and the incentive-type green regulation in the central region have positive spillover effects and incentive green regulations in the northeast and western regions, and public participation in green regulations has a positive spillover effect. From the eastern region to the central region to the northeast and western regions, the spatial spillover effect intensity gradually weakened.

③ The perspective of direct and indirect effects: The direct effect value and significance reflect the relationship between each explanatory variable and the regional innovation efficiency, and the indirect effect reflects whether the variable has a spatial spillover effect. Through the direct effect, it is found that the R&D input and the command-type green regulation coefficient of the eastern region are negative, indicating that it has a negative direct effect on the efficiency of green innovation. The R&D input coefficients of the central, northeastern, and western regions are positive, indicating that they have a positive direct effect on the efficiency of green innovation, and the command-type green regulation coefficient is negative, demonstrating a negative direct effect on the efficiency of green innovation. Through the indirect effect, it is found that the R&D input coefficient of the eastern region is negative, indicating that it has a negative spatial spillover effect on green innovation. The R&D input and green regulation coefficients of the central, northeastern, and western regions are positive, indicating that they have a positive spatial spillover effect on green innovation.

5. Conclusion and Measures

5.1. Conclusion. In order to analyze the spatial and temporal differentiation characteristics of China's provincial green innovation efficiency, this paper uses the entropy weight TOPSIS model and the spatial econometric model to measure the green innovation efficiency of 30 provinces in China and tests the R&D investment, green regulation, and green innovation of China's four major economic zones. The benefit spatial spillover effect is as follows:

① The efficiency of green innovation in China's provinces is changing volatility year by year, and the overall trend is increasing year by year. Over time, the efficiency of green innovation in each province has improved to varying degrees, and the degree of difference is also diverse. In addition, from the point of view of time, in the vicinity of 2008, most provinces have experienced a small decline in green innovation efficiency, which is mainly affected by the financial crisis. On the other hand, China's provincial green innovation efficiency is generally low, and overall development is uneven and uncoordinated, showing a low trend in the east, high, middle, and west. The gap between green innovation efficiency among provinces is very prominent, and the individual provinces are almost zero. Finally, China's provincial green innovation efficiency descends from east to west, east (0.4882), national (0.2720), central (0.2245), northeast (0.2098), and western (0.1182) regions. Through testing the green efficiency growth rate of the four major economic regions, it is found that the growth in the central region is particularly prominent, with a growth rate of 52.10% and an increase of 17.52% in the east, both greater than the national average growth rate of 15.50%. Both the northeast and the west have experienced negative growth rates of −11.20% and −8.78%, respectively.

② According to the results of the spatial autocorrelation test, the Moran index fluctuates between 0.263 and 0.419, and both are significant at the 1% level, which grows continuously, which fully shows that there is an obvious positive spatial correlation for China's provincial green innovation efficiency. In order to further show a spatial correlation, Moran scatterplots were drawn for 2005, 2010, 2014, 2018, and 2021. We found that the Moran scatterplots of China's provincial green innovation efficiency clearly have four quadrants: the first quadrant is a high-value cluster (H-H), the second quadrant is a low value surrounded by a high value (L-H), the third quadrant is a low-value cluster (L-L), and the fourth quadrant is a high value surrounded by a low value (H-L). It can be seen from the Moran scatterplots that most of the provinces fall in the first and third quadrants. This result rejects the hypothesis that green innovation efficiency is spatially randomly distributed, further confirming the existence of China's provincial green innovation efficiency in the geospatial space and agregation phenomenon.

③ In different regions, the spatial spillover effects and impact mechanisms of government R&D investment, green regulations, and green innovation are quite different. From the eastern region to central region to northeast and western regions, the impact of government R&D investment on green innovation has gradually increased and the impact of green regulations on green innovation has gradually weakened, so the spatial spillover effect has gradually increased.

5.2. Future Research

① The research in this paper does not involve the analysis of influencing factors. Future research can analyze the influence mechanism of green innovation efficiency through models from different perspectives of influencing factors.

② The sensor data collection model proposed in this paper is relatively simple, but in reality, it is often more complex. Future research can collect multi-source data and integrate it more maturely through the Internet of things technology.

③ This paper takes China's regional green innovation efficiency as the research object and draws the phenomenon of spatial aggregation of green innovation efficiency. Future research can choose different research objects to demonstrate the conclusions of this research.

5.3. Measures. Based on the above conclusions, the following measures can be drawn:

① At present, the manufacturing enterprises of sensors are mainly concentrated in the Yangtze River Delta and gradually form a regional spatial layout dominated by central cities such as Beijing, Shanghai, Nanjing, Shenzhen, Shenyang, and Xi'an. Among them, nearly half of the major sensor enterprises are located in the Yangtze River Delta region, and the others are in turn in the Pearl River Delta, Beijing-Tianjin region, central region, and northeast region. The government should speed up the standardization, performance normalization, function integration, and structure standardization of sensor products, accelerate the formulation of relevant standards and specifications, and improve the product quality control capability with standardization. The government should strengthen technological innovation in sensor material preparation and special equipment, create a "diamond" for sensor R&D and manufacturing, and provide tamp tool support for improving the quality of sensor products. The government should accelerate the research and development of new sensor materials, new technologies, new processes, and new tools, strengthen systematic management, and improve the product quality control ability with refined management. The government should strengthen the development of special sensors under complex environmental conditions, enhance stability, reliability, and durability, and improve the sensor guarantee level under harsh conditions and high-intensity operation conditions.

② The green innovation efficiency in the northeast and western regions is relatively low, but most of them belong to China's key development areas and have a strong resource and green-carrying capacity. To improve the efficiency of green innovation in the northeast and the west, the government should support it from the policy level of R&D capital investment and green innovation subsidies, reduce the burden of green innovation, and stimulate the vitality of enterprise innovation. On the other hand, it is necessary to establish a green and low-carbon development concept and achieve pollution reduction and emission promotion. The development of the central region is in full swing, and the economic foundation is strong. The government should give guidance from the policy level. The western region is a region of innovation and backwardness. We should bear in mind that making rapid progress while avoiding the old road of "the first pollution after treatment" in developed areas. The eastern coastal areas are economically developed and have high efficiency in green innovation. Their pressure to undertake green innovation costs is relatively small, but their resource and green-carrying capacity have begun to weaken. The government should strengthen the economic structure and resource consumption, etc., by building an open and innovative ecological environment. The government should create a good atmosphere for innovation and encourage enterprises to carry out more green innovation activities.

③ A coordinated and open economic system should be established to break the administrative barriers among provinces. Green innovation efficiency has a positive spatial spillover effect, and the existence of administrative barriers among provinces hinders the spatial spillover of green innovation. A coordinated and open economic system not only promotes the spatial balance of population, economy, resources, and environment but also promotes the flow and sharing of innovation factors among provinces and contributes to the "strong alliance" of green innovation among provinces. The continuous spatial spillover effect produces positive radiation, which drives the provinces with low green innovation efficiency to improve together.

④ A multigreen regulation policy should be implemented, combining appropriate provincial and regional innovations and formulating appropriate regulatory combinations. Command-based green regulations can stimulate green product innovation more than market-incentive green regulations. For green process innovation, the incentive effect of the market-incentive green regulation is relatively better, because the incentive green regulation has greater flexibility and stability, which enables enterprises to have a certain degree of freedom of choice and provides enterprises with green process innovation and strong external economy incentives. In addition, the public should be encouraged to participate in the formulation of green regulations and become implementers and supervisors of regulations and policies. Green laws and regulations of public participation are an effective incentive for green innovation.

Data Availability

The experimental data are mainly downloaded from the EPS data platform. The website of this data platform is https://www.epsnet.com.cn/index.html#/Index. The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

The authors carried out the proof of the main results and approved the final manuscript.

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