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Measurement and Spatiotemporal Evolution of Science and Technology Innovation Efficiency Based on Sustainable Development: Evidence from China

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Abstract

This study evaluates regional science and technology (S&T) innovation efficiency across 30 Chinese provinces from 2011 to 2022, integrating a sustainable development perspective. Utilizing a non-oriented global frontier super-slack-based measure (SBM) model considering undesirable outputs, alongside kernel density estimation, cluster analysis, and the Moran's *I*, the research explores the spatiotemporal evolution of innovation dynamics. Results indicate that temporal efficiency progressed through three stages: initial universal low efficiency, a widening disparity gap, and a final phase of overall improvement and stabilization. Spatially, a "strong in the east, weak in the west" disequilibrium persists; however, high-efficiency clusters evolved from isolated "unipolar" points into integrated "multi-center block linkages" and linear belts. The distribution transitioned through four distinct phases: agglomeration, diffusion, reorganization, and equilibrium. Furthermore, spatial autocorrelation shifted from weak positive correlation and random distribution to a statistically significant positive correlation by 2022, signaling enhanced regional synergy. The findings suggest that while polarization is weakening and the national innovation baseline is rising, policy should focus on fostering these emerging innovation corridors to bridge the remaining east-west gap.

Keywords: urban planning; sustainability; super-SBM model; innovation efficiency; spatial-temporal; visual analytics

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1. Introduction

The 2025 Nobel Laureates in Economics, Joel Mokyr, Philippe Aghion, and Peter Howitt, systematically elucidated the mechanisms of innovation, knowledge accumulation, and institutional environments on "innovation-driven economic growth." Their work provides a solid theoretical foundation for countries to formulate policies that promote long-term growth. With the development of the digital economy, new products, business formats, and models are accelerating their iterations. Consequently, the roles of innovation chains, innovation capabilities, and innovation efficiency have become increasingly vital in regional competition. China has experienced rapid economic growth over the past 40 years of reform and opening up and is currently transitioning toward an intensive, innovation-driven development model. However, while overall innovation capabilities continue to improve, regional innovation efficiency in China still faces challenges regarding imbalances and environmental constraints. Therefore, scientifically and accurately measuring regional S&T innovation efficiency and revealing its inherent spatiotemporal evolution patterns and interactive correlations carry significant practical importance for optimizing the allocation of innovation resources and promoting regional collaborative innovation and sustainable development.

This paper applies the super-slack-based measure (Super-SBM) method, focusing on 30 provinces and municipalities in China (excluding Hong Kong, Macao, Taiwan, and Tibet), to explore regional S&T innovation efficiency and its spatiotemporal evolution characteristics. The study analyzes the temporal evolution, spatial evolution, and spatial correlation characteristics of regional

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S&T innovation efficiency in China to reveal its evolutionary path. Conducting efficiency measurement and spatial analysis in a large country with unbalanced development like China presents challenges such as data heterogeneity and significant environmental influences. The adaptation and innovation of relevant research methods in this study can provide a methodological reference for researching the innovation efficiency of other large, diversified economies or international unions, such as the European Union, the Association of Southeast Asian Nations, and India.

2. Literature Review

Improving S&T innovation efficiency is one of the primary tasks for regional development. Innovation efficiency represents the transformation efficiency of knowledge into new products, processes, and services, reflecting the innovation capability of a region [1]. Regional S&T innovation efficiency refers to the ability of a region, acting as an innovation agent, to convert S&T innovation inputs into S&T innovation outputs during the process of innovation activities. In a narrow sense, innovation efficiency refers to the ability of innovators to bring new products to the market [2]. In a broad sense, innovation efficiency encompasses both the technological innovation capability of new products and the capability to launch them into the market [3].

Measuring regional S&T innovation efficiency is a vital component of regional innovation system research, primarily encompassing the following three areas:

(1) Research on Measurement Methods. Scholars have extensively applied various models to measure and predict innovation efficiency, including the CCR model [4] and BCC model [5] within traditional Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) [6,7], and non-linear regression models for panel data [8].

(2) Research on Indicator Systems and Influencing Factors. Most scholars maintain that innovation efficiency should be measured by the input-output ratio [9]. The influencing factors and their underlying mechanisms constitute the core of regional S&T innovation efficiency research. Zhang and Zhang selected Chinese cities as research samples and explored how the expansion of credit scale by different credit entities exerts a significant positive impact on regional S&T innovation efficiency [10]. This efficiency is also influenced by industrial agglomeration, such as financial industry agglomeration and the collaborative agglomeration of digital industries and manufacturing. Yu et al. verified that the agglomeration of regional innovation factors can influence regional S&T innovation efficiency through transmission mechanisms such as openness levels, ecological environments, and information services [11]. Wang and Hu, using 30 Chinese provinces as samples, found that financial agglomeration positively affects regional S&T innovation efficiency through industrial structure upgrading; they also identified government support, informatization levels, and transportation infrastructure as critical factors [12]. Zhao and Wu utilized the Spatial Durbin Model to explore how the collaborative agglomeration of digital industries and manufacturing positively impacts innovation efficiency in a study area while generating positive spillover effects on neighboring regions [13]. Bai and Wan demonstrated that logistics industry agglomeration promotes regional innovation, exhibiting spatial spillover effects on S&T innovation efficiency under different spatial weight matrices [14]. From the perspective of regional digitalization and collaborative innovation theory, Ouyang et al. observed that digitalization significantly promotes regional S&T innovation efficiency to a certain extent, though regional heterogeneity exists [15]. The improvement of regional S&T innovation efficiency is closely linked to the digitalization process and the agglomeration of manufacturing with industries such as finance and logistics.

(3) Research on Spatiotemporal Evolution. Ma et al. measured the S&T innovation efficiency of China and seven specific research regions, analyzing the resulting spatiotemporal patterns [16]. Ye et al. conducted a comparative analysis of the spatiotemporal characteristics of technological innovation efficiency across universities, enterprises, and research and development (R&D) institutions [17].

(4) Research on Green Innovation Efficiency. Some scholars have explored the spatiotemporal evolution of innovation efficiency from the perspective of green innovation. For instance, Li et al.

used the EBM-GML method to measure China's green innovation levels from 2001 to 2019, evaluating its spatiotemporal distribution and convergence [18]. Liu et al. employed the super–SBM model to measure the green innovation efficiency of 11 cities in the Guangdong–Hong Kong–Macao Greater Bay Area and identified its influencing factors [19]. These studies indicate that research on innovation efficiency is shifting from a single economic output orientation toward a comprehensive evaluation of economic–environmental synergy.

In summary, most scholars currently employ the CCR and BCC models within traditional Data Envelopment Analysis (DEA) for calculations, utilizing spatial econometric methods for empirical analysis to reveal the temporal and spatial evolution characteristics of regional S&T innovation efficiency. However, traditional DEA models, due to their radial and oriented mathematical properties, fail to fully identify and measure "slack adjustment" during the efficiency evaluation process, which may lead to biased measurements [20]. While some researchers have adopted the super-SBM model—which distinguishes between efficient decision-making units—methodological differences persist in model configuration and indicator system construction. Specifically, one approach completely excludes undesirable outputs within the traditional innovation efficiency framework, while the other shifts the research focus entirely toward green innovation after incorporating environmental dimensions [21].

Regarding research content, regional S&T innovation efficiency is primarily placed within explanatory frameworks as a dependent variable to identify and test influencing factors and underlying mechanisms. In contrast, research that treats regional S&T innovation efficiency itself as the core observational object—systematically characterizing its spatiotemporal distribution, dynamic evolutionary trajectory, and spatial correlation characteristics—remains relatively limited. Furthermore, the spatiotemporal evolution has been examined across various scales, ranging from national-level assessments to specific urban agglomerations [22]. Among these, provincial-level studies [23] provide crucial in-sights into regional development; however, these studies often overlook the relationship between S&T innovation output and environmental constraints. Consequently, there is a critical need to construct an indicator system for measuring S&T innovation efficiency based on sustainable development to explore regional S&T innovation efficiency, its spatiotemporal evolution patterns, and its spatial correlation characteristics.

3. Materials and Methods

3.1. Selection of Indicators for Measuring Regional S&T Innovation Efficiency

To scientifically measure regional S&T innovation efficiency, the construction of the indicator system comprises two components: the selection of regional S&T innovation input indicators and regional S&T innovation output indicators. Currently, there is no universally accepted indicator system for measuring regional S&T innovation efficiency in existing scholarship. Therefore, this study refers to the indicator systems constructed by current researchers [24] while considering that indicators with local characteristics often lack unified national statistical standards. Using unconventional indicators can undermine the objectivity of the evaluation system and lead to unverifiable results. Consequently, an indicator system for measuring regional S&T innovation efficiency is constructed from three dimensions: regional S&T innovation inputs, regional S&T innovation desirable outputs, and regional S&T innovation undesirable outputs. This approach better highlights the actual performance of regional S&T innovation across common indicators. The specific measurement indicator system is shown in Table 1.

Table 1. The indicator system for measuring regional S&T innovation efficiency.

Variable	Primary Indicator	Secondary Indicator	Content	Unit
Regional S&T Innovation	Input Indicators	Labor Input	Full-time equivalent of R&D personnel	Person-years

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Efficiency		Capital Input	Internal expenditure on R&D funds	10,000 CNY
		Technology Output	Number of patent grants	Piece
		Knowledge Output	Number of S&T papers published	Paper
		Technology Diffusion	Turnover in the technology market	10,000 CNY
	Output Indicators	Market Performance	Sales revenue of new products of industrial enterprises above designated size	10,000 CNY
			Industrial wastewater discharge	10,000 Tons
		Undesirable Outputs	Industrial sulfur dioxide emissions	10,000 Tons
			Industrial smoke (powder) dust emissions	10,000 Tons

(1) Regional S&T Innovation Input Indicators. The knowledge production function categorizes inputs into human resources and financial resources [25,26]. Regarding human resource inputs, the full-time equivalent of research and development (R&D) personnel reflects the actual labor input of innovation more accurately than the total number of R&D personnel. Therefore, the FTE of R&D personnel in industrial enterprises above a designated size is selected as the labor input indicator. For innovation financial inputs, internal expenditure on R&D funds measures the financial support for innovation activities within a region and is thus selected as the capital input indicator. These two indicators integrate the human and capital dimensions required for regional S&T innovation, ensuring both rationality and feasibility.

(2) Regional S&T Innovation Output Indicators. S&T innovation output indicators generally include patents, papers, new products, and awards. Considering the difficulty of regional data acquisition and the consistency required for comparative analysis, this study selects the number of patent applications, the number of S&T papers, the turnover in the technology market, and the sales revenue of new products as the desirable output indicators. These indicators effectively reflect regional S&T innovation output. Specifically, the number of patent grants and S&T papers objectively represent a region's innovation capability and comprehensive S&T strength. New product sales revenue, representing the market performance aspect of S&T innovation efficiency, reflects the degree of coordinated development between S&T and the economy, as well as the transformation of innovation achievements into market value. Finally, the turnover in the technology market measures the liquidity and activity of technology as a commodity, reflecting knowledge spillovers, technology transfer, and collaborative innovation capabilities to a certain extent.

(3) Sustainable Development Indicators (Environmental Constraint Indicators). Industrial wastewater discharge, industrial sulfur dioxide emissions, and industrial smoke (powder) dust emissions are selected as undesirable output indicators. First, these three types of pollutants are direct by-products generated during industrial production and possess significant negative environmental externalities. Second, if efficiency evaluations focus solely on economic or innovation achievements, the environmental costs of growth may be obscured, leading to the misidentification of high-emission regions as high-efficiency regions. By incorporating these three pollutants into the model, it becomes possible to identify and reward regions that achieve pollution reduction while increasing innovation output, thereby measuring regional S&T innovation efficiency more precisely. These indicators represent the pressure on environmental media such as water and the atmosphere, forming a multi-dimensional undesirable output system. Furthermore, these indicators are monitored by authoritative agencies and provide continuous, comparable data, which facilitates empirical analysis

and ensures that the measurement of regional S&T innovation efficiency aligns with the requirements of sustainable development.

3.2. Model Construction

3.2.1. Super-SBM Model

The SBM model is an extension of Data Envelopment Analysis (DEA) designed to evaluate the efficiency of Decision-Making Units (DMUs) by incorporating slack variables, particularly in cases involving undesirable outputs. Traditional DEA models typically focus only on desirable positive outputs and require all inputs or outputs to be adjusted proportionally, thereby ignoring differences in individual slack variables. In contrast, the super-SBM model integrates undesirable outputs, providing a more comprehensive and realistic efficiency measurement. Furthermore, by incorporating additional constraints and slack factors, the super-SBM model can precisely calculate efficiency values even when they exceed 1, offering higher accuracy than traditional DEA models. This model also excels in distinguishing among efficient units and provides better differentiation in efficiency scores. By allowing independent adjustments of input and output items and optimizing the inefficient portions through slack variables, the model offers flexibility in analyzing the input-output efficiency of regional S&T innovation development. The linear programming model for the super-SBM [27] is expressed as follows:

$$z^* = min\frac{\frac{1}{u}\sum_{i=1}^{u}\frac{s1_i}{x_{i0}}}{\frac{1}{\mathrm{v}+k}\left(\sum_{r=1}^{v}\frac{s2_r}{y_{r0}}+\sum_{l=1}^{k}\frac{s3_l}{p_{l0}}\right)} \tag{1}$$

$$\text{s.t.}\begin{cases} s1 \geq \sum\limits_{j=1,\ \neq 0}^{J} \lambda_j x_j \\ s2 \leq \sum\limits_{j=1,\ \neq 0}^{J} \lambda_j y_j \\ s3 \geq \sum\limits_{j=1,\ \neq 0}^{J} \lambda_j p_j \\ s1 \geq x_0,\ \ s2 \leq y_0,\ \ s3 \geq p_0,\ \ b \geq 0,\ \ \lambda_j \geq 0 \end{cases} \tag{2}$$

In Equations (1) and (2), the parameters are defined as follows: u represents the number of regional S&T innovation input indicators (u = 2 in this study); v denotes the number of desirable output indicators (v = 4 in this study); and k signifies the number of undesirable output indicators (k = 3 in this study). The variable x_{i0} represents the input values, specifically labor and capital inputs; y_{r0} denotes the desirable output values, including technology output, knowledge output, technology diffusion, and market performance; and p_{l0} indicates the undesirable output values, namely the "three industrial wastes." The index j represents the number of research samples; s1, s2, and s3 are slack variables; and λ denotes the weight vector. Finally, z* represents the regional S&T innovation efficiency value; a larger z* value indicates higher regional S&T innovation efficiency.

3.2.2. Spatial Autocorrelation Analysis

Local and global spatial autocorrelations are the primary components of spatial autocorrelation analysis. These methods allow for the quantitative evaluation of the degree of spatial agglomeration, agglomeration characteristics, and the extent of differences within a region. The Moran's *I* and Local Indicators of Spatial Association (LISA) cluster maps are widely utilized by scholars to determine whether agglomeration occurs within a specific space and to assess the intensity of such phenomena. Therefore, this study employs ArcGIS 10.8.1 software to analyze the spatial correlation characteristics of innovation levels across regional units in China. Specifically, efficiency classification, the Getis-Ord

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Gi* index, and the Moran's *I* are used to measure the spatial correlation of regional S&T innovation efficiency. Based on the efficiency measurement results, regional S&T innovation efficiency is classified to measure the spatial heterogeneity characteristics of high- and low-efficiency clusters. Furthermore, relevant Moran's *I* values are calculated to measure and analyze the spatial correlation characteristics of regional S&T innovation efficiency throughout the study area. The formula for calculating the Moran's *I* is as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3}$$

In Equation (3), the parameters are defined as follows: I represents the Moran's *I*; n denotes the number of research regions (n = 30 in this study); w_{ij} signifies the spatial weight matrix; x_i and x_j represent the regional S&T innovation efficiency of region i and region j, respectively; and $\bar{x}$ denotes the average value of regional S&T innovation efficiency.

3.3. Data Sources and Regional Classification

This study selects 30 provinces, autonomous regions, and municipalities in China as research samples. Due to data availability, Tibet, Hong Kong, Macao, and Taiwan are excluded. To facilitate a comparative analysis, the economic regions are divided into four major areas: Eastern, Central, Western, and Northeastern China. Specifically, the Northeastern region includes Liaoning, Jilin, and Heilongjiang. The Eastern region comprises Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western region encompasses Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. To reflect the differences in regional innovation efficiency among these 30 regions, this study utilizes the super-SBM model to calculate the efficiency values for each region, followed by a systematic ranking and comparison.

Statistical data were obtained from the China Statistical Yearbook on Science and Technology, the China Statistical Yearbook on Environment, and the China City Statistical Yearbook for the period 2011–2024. Missing data were primarily addressed using data from provincial statistical yearbooks, with any remaining gaps filled via the interpolation method. The administrative boundary vector data were sourced from the National Platform for Common Geospatial Information Services, under the examination number GS (2024) 0650, and were processed using the WGS 1984 World Mercator projection coordinate system. Considering that regional innovation activities typically exhibit a time lag—where S&T innovation inputs require a certain duration to be transformed into innovation outputs—this study lags the output data by one year [28]. The four specific time points of 2013, 2016, 2019, and 2022 were selected because they represent fixed intervals that facilitate the analysis of long-term trends and cyclical changes [29]. This selection also allows for a more intuitive comparison of periodic transitions in spatial structures, such as cold-spot and hot-spot distributions or gradient patterns.

4. Measurement Results of Regional Innovation Efficiency

To ensure the comprehensiveness and comparability of the measurement results, a super-SBM model considering undesirable outputs was selected to calculate the regional S&T innovation efficiency of 30 regions in China from 2011 to 2022. The results are presented in Table 2. The trends of average efficiency and the regional efficiencies are shown in Figures 1 and 2.

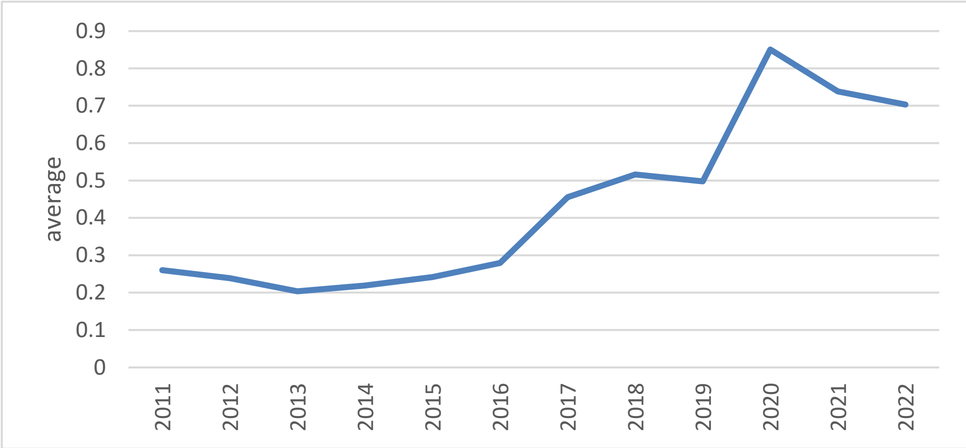

Figure 1. Trend of Regional S&T Innovation Efficiency in China.

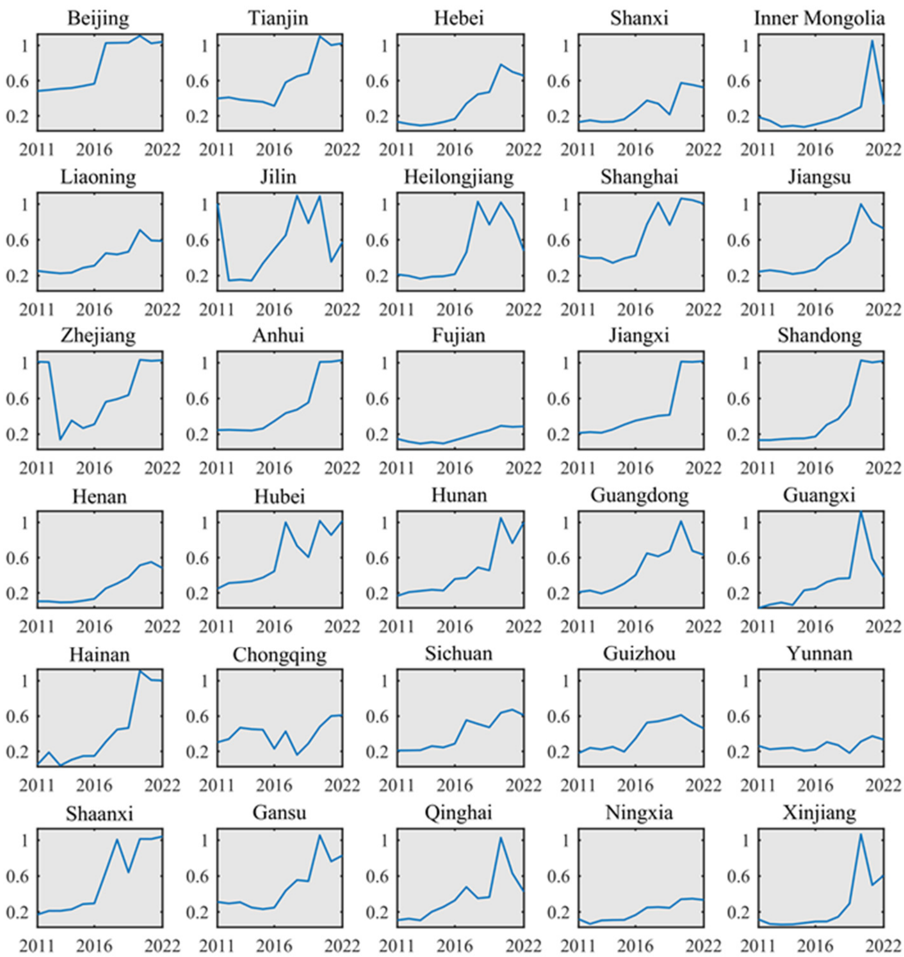

Figure 2. Trend of Regional S&T Innovation Efficiency in Various Regions.

Table 2. The indicator system for measuring regional S&T innovation efficiency.

Region	Efficiency				Region	Efficiency			
	2013	2016	2019	2022		2013	2016	2019	2022
Beijing	0.509	0.565	1.032	1.041	Henan	0.092	0.133	0.375	0.481
Tianjin	0.385	0.313	0.684	1.024	Hubei	0.321	0.446	0.606	1.020
Hebei	0.091	0.165	0.470	0.656	Hunan	0.222	0.358	0.456	1.002
Shanxi	0.131	0.258	0.215	0.524	Guangdong	0.194	0.401	0.677	0.633

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Inner Mongolia	0.077	0.103	0.236	0.331	Guangxi	0.091	0.248	0.368	0.380
Liaoning	0.225	0.311	0.467	0.588	Hainan	0.041	0.149	0.466	1.001
Jilin	0.155	0.497	0.787	0.576	Chongqing	0.469	0.231	0.291	0.610
Heilongjiang	0.166	0.216	0.771	0.477	Sichuan	0.214	0.288	0.472	0.610
Shanghai	0.397	0.424	0.767	1.005	Guizhou	0.223	0.345	0.571	0.460
Jiangsu	0.244	0.270	0.574	0.727	Yunnan	0.235	0.222	0.183	0.334
Zhejiang	0.139	0.311	0.637	1.027	Shaanxi	0.212	0.295	0.640	1.041
Anhui	0.244	0.346	0.554	1.029	Gansu	0.308	0.248	0.543	0.829
Fujian	0.094	0.132	0.243	0.287	Qinghai	0.106	0.328	0.364	0.426
Jiangxi	0.216	0.351	0.416	1.017	Ningxia	0.105	0.166	0.245	0.334
Shandong	0.144	0.173	0.522	1.020	Xinjiang	0.059	0.092	0.293	0.607

Based on the analysis of the S&T innovation efficiency values for each province from 2011 to 2022, as shown in Table 2, Figures 1 and 2, the overall regional S&T innovation efficiency in China exhibited a significant upward trend during the observation period. According to the annual mean values, the efficiency scores gradually improved from a relatively low level, with many provinces generally surpassing 1.0 after 2020. This trend reflects the substantial progress China has made in promoting regional S&T innovation, with a notable average annual growth rate in overall efficiency.

From a regional comparison perspective, provinces and municipalities with outstanding efficiency performance primarily include Beijing, Shanghai, Zhejiang, and Anhui. In most years, particularly during the later stages of the study, the efficiency values of these regions remained consistently above 1.0. Specifically, Beijing has maintained an efficiency value higher than 1.0 since 2017, reaching 1.109 in 2020 and consistently ranking among the top in the country for several years. This underscores the leading role of Beijing as a national S&T innovation center. Similarly, Shanghai, Zhejiang, and Anhui steadily entered the high-efficiency zone after 2020, demonstrating strong innovation sustainability.

Further analysis reveals that the S&T innovation efficiency of the eastern coastal regions and certain central provinces is generally higher than that of the western regions. This indicates a gradient difference from east to west, which correlates with economic development levels, the concentration of scientific research resources, and the intensity of policy support. Simultaneously, the mean efficiency of municipalities directly under the central government and developed coastal provinces is significantly higher than that of inland provinces. This further substantiates the spatial agglomeration effect of innovation resources and achievement transformation capabilities.

Overall, China's regional S&T innovation efficiency has shown an integrated improvement across the temporal dimension. Regarding the spatial pattern, it exhibits a distribution characteristic of gradual decline from east to west. High-efficiency regions are predominantly concentrated in the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and certain innovation-active provinces in central China. This distribution reflects the synergistic results of China's S&T innovation system construction and regional development strategies.

5. Spatiotemporal Analysis of Regional S&T Innovation Efficiency

5.1. Kernel Density Analysis

Based on the measurement of China's regional S&T innovation efficiency and the analysis of basic evolutionary trends and regional differences, this study further employs the kernel density estimation method using Matlab to explore the evolutionary trends of regional S&T innovation efficiency.

In general, kernel density estimation plots utilize smooth curves to describe the morphological characteristics of data distribution. Specifically, the height of the peaks reflects the intensity of data concentration, the position of the peaks indicates the central tendency of the data, and the number of peaks reveals multipolar characteristics within the distribution. Based on these principles, this study conducts a dynamic spatiotemporal analysis of the evolutionary characteristics of China's regional

S&T innovation efficiency from 2011 to 2022 by integrating three dimensions—peak height, peak position, and peak quantity—in conjunction with changes along the timeline. The specific temporal evolution of the kernel density is illustrated in Figure 3.

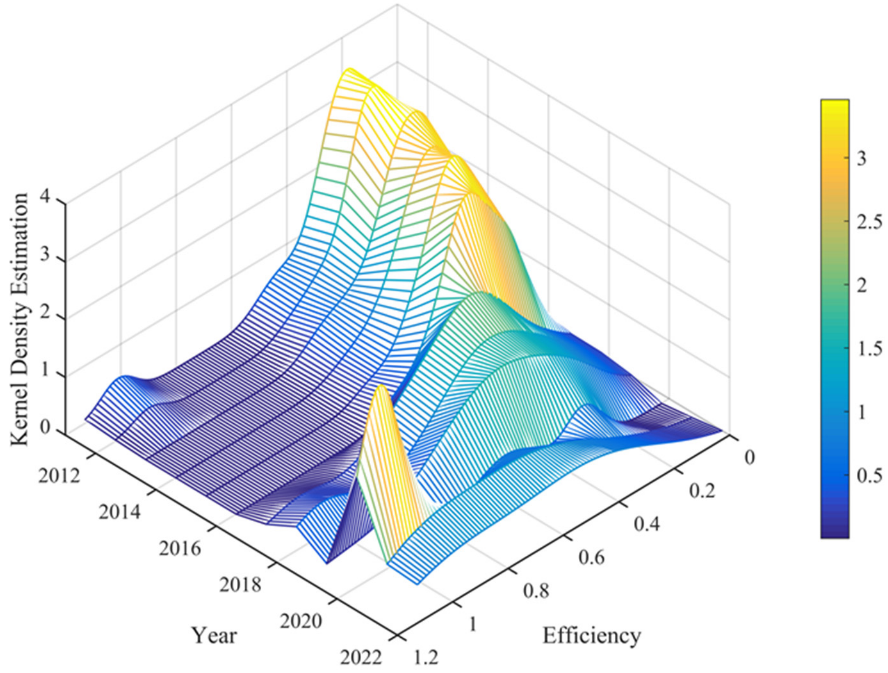

Figure 3. Three-dimensional kernel density estimation.

5.1.1. Time Series Analysis

According to Figure 4, it can be observed that the overall distribution morphology of regional S&T innovation efficiency in China shifted from a highly right-skewed state toward convergent equilibrium during the period from 2011 to 2022.

In the early stage of the study period (2011–2016), the distribution of efficiency values exhibited a significant right-skewed (positively skewed) characteristic (skewness > 1.1). During this time, the peak density was extremely high (> 3.0), with the peak position concentrated in the low-efficiency interval of 0.1–0.3. This indicates that the vast majority of provinces had low S&T innovation efficiency, with only a few provinces (such as Zhejiang) achieving higher efficiency, thereby forming a “long tail.”

Starting in 2017, the distribution morphology underwent a fundamental transformation. The peak height decreased significantly (< 2.0), and the peak position shifted continuously to the right (moving from 0.39 toward higher values). By 2021–2022, the distribution transitioned into an approximately symmetric or even left-skewed pattern (with skewness turning negative), while the kurtosis indicated a platykurtic distribution (flat peak). This shift signifies that the concentration interval of efficiency values has moved away from the low-level range, and the overall distribution has become more balanced and concentrated at higher levels.

The trajectory of the peak position illustrates that the “center of gravity” of the efficiency distribution continuously migrated toward the high-efficiency interval. During 2011–2016, the peak fluctuated slightly within the low-value range of 0.16–0.29. From 2017 to 2019, the peak shifted rightward at an accelerated pace, rising from 0.39 to 0.50 and entering the medium-efficiency interval.

In 2020, the peak experienced a “leapfrog” jump, reaching 1.045 and entering the high-efficiency interval (> 1.0) for the first time. This aligns with the raw data indicating that numerous provinces surpassed an efficiency value of 1.0 in 2020, suggesting that many regions (such as Anhui, Hubei, and

Hunan) reached the efficiency frontier around this period. During 2021–2022, although the peak position retreated from its high point to the 0.57–0.72 range, it remained significantly higher than the levels observed prior to 2019. This indicates that the concentration interval of S&T innovation efficiency has stabilized at a higher level.

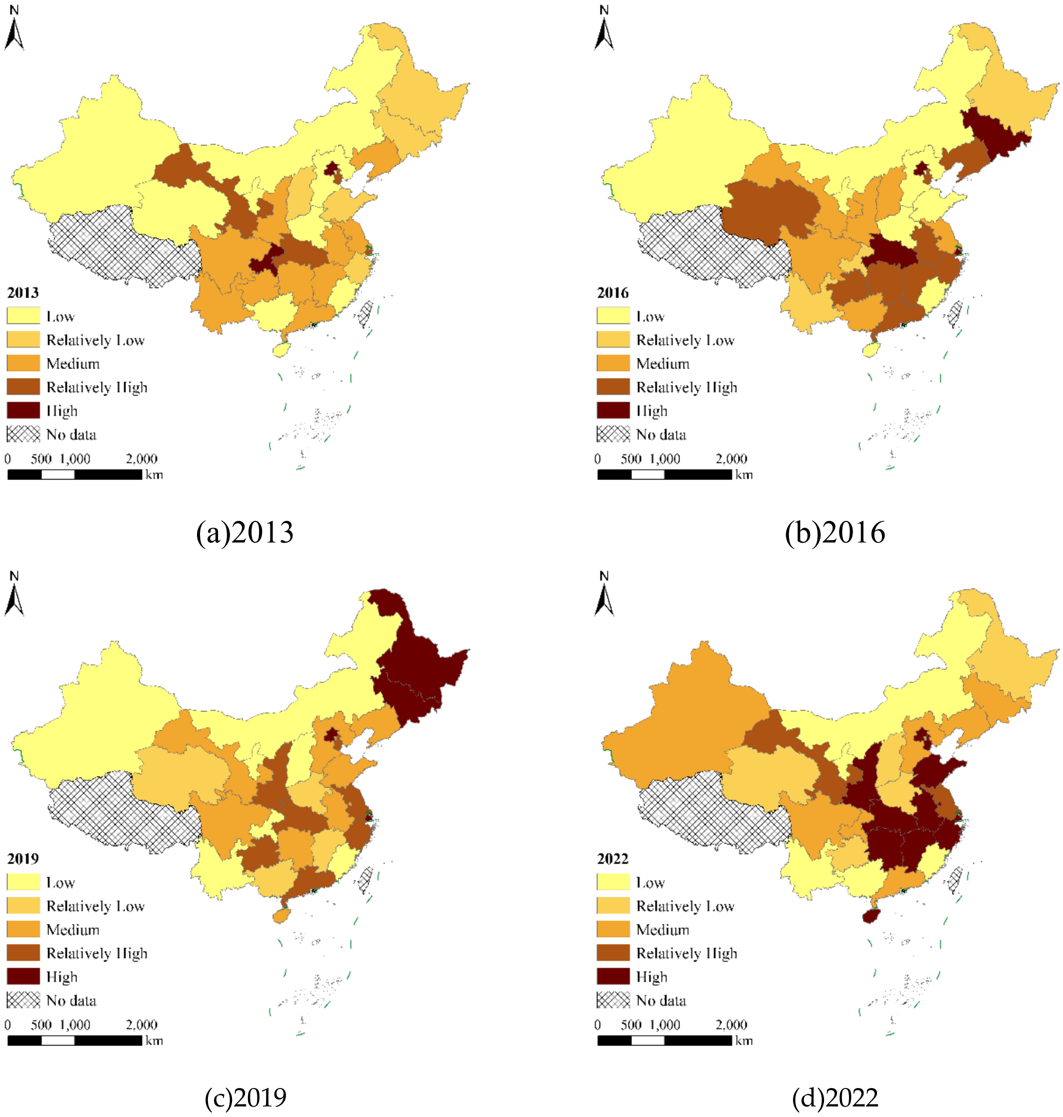

Figure 4. Distribution of regional S&T innovation efficiency in China.

5.1.2. Spatial Evolution Analysis

(1) Overall efficiency mean shows a steady decline. The average value of kernel density estimates fluctuated within a narrow range around 0.76 between 2011 and 2020 (with a change rate within ±0.8%), exhibiting extremely high stability. However, in 2021 and 2022, the average value experienced a significant decrease (falling by 3.44% and 2.61%, respectively), while the median (0.84 in 2022) surpassed the mean (0.72). Combined with the left-skewed distribution characteristic, this phenomenon of "decreasing mean and higher median" indicates that the growth momentum of efficiency improvement may be slowing down. The overall efficiency distribution has entered a stage of high-level convergence or a plateau period, where the number of high-efficiency regions is increasing while the growth rate of the overall mean efficiency is decelerating.

(2) The dispersion of efficiency values first expanded and then significantly contracted. This process can be divided into three distinct stages. In the early stage (2011–2016), the standard deviation remained at a high level of 1.04–1.09, and the coefficient of variation (CV) consistently exceeded 1.35, reflecting vast efficiency disparities and a highly fragmented distribution among provinces. During

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the middle stage (2017–2020), both the standard deviation and CV began to decline; notably, in 2018–2019, the CV dropped to 0.66–0.78, indicating a narrowing of both absolute and relative gaps between provinces. In the late stage (2021–2022), the degree of dispersion decreased sharply. By 2022, the standard deviation fell to 0.30 and the CV to 0.42—the lowest values in the entire observation period. This demonstrates that after years of development, regional S&T innovation efficiency has exhibited a clear convergence trend, with regional disparities significantly diminishing.

(3) The overall distribution morphology of efficiency values can be summarized as follows: it transitioned from an initial state of "high right-skewness, low-value clustering, and wide disparities," through a middle "catch-up and diffusion" phase characterized by rightward peak shifts and narrowing gaps, and finally toward a relatively balanced state of "upward shift of gravity, concentrated distribution, and convergent disparities." The year 2020 serves as a critical leapfrog node, while the 2021–2022 data suggest that efficiency improvement may be transitioning from a phase of universal high-speed growth to a new stage of balanced development. This process intuitively reflects the dynamic evolution of China's regional innovation from being led by individual growth poles to achieving collaborative development.

In summary, the distribution of China's regional S&T innovation efficiency has undergone a transformation from concentration to dispersion and, ultimately, toward gradual stabilization. The period of 2012–2015 saw the formation of individual efficiency centers (e.g., Zhejiang). 2016–2019 catalyzed a polycentric pattern, although large fluctuations in the primary peak reflected an unstable regional innovation landscape. Finally, the shift from a four-peak structure to a smooth plateau during 2020–2022 indicates that regional S&T innovation efficiency values have become more spatially balanced.

5.2. Analysis of Cluster Distribution Characteristics

To more intuitively observe the characteristics of the spatial correlation of China's regional S&T innovation efficiency and reveal the evolutionary trends of spatial correlation patterns between different regions, this study employed ArcGIS 10.8.1 software. Using the Natural Breaks (Jenks) classification method, the spatial evolution characteristics of S&T innovation efficiency levels for the years 2013, 2016, 2019, and 2022 were categorized. The color gradient, ranging from light to dark, represents the efficiency levels of different regions in a given year: low efficiency, relatively low efficiency, medium efficiency, relatively high efficiency, and high efficiency. The specific results are illustrated in Figure 5.

(1) Significant regional disparities in S&T innovation efficiency persist, alongside a substantial increase in high and relatively high-efficiency regions. The number of high-efficiency provinces grew from two in 2013 (Beijing and Chongqing) to ten in 2022, covering vital regions such as Beijing–Tianjin–Hebei, the Yangtze River Delta, and the middle reaches of the Yangtze River. Concurrently, the number of "low-efficiency troughs" has decreased, indicating a rising baseline for national innovation efficiency. The distribution structure transitioned from a typical "pyramid" in 2013 (13 low/relatively low-efficiency provinces vs. 2 high-efficiency provinces) to a "spindle" shape in 2022. This shift, where the numbers of high-tier and low-tier provinces are converging, suggests a more balanced overall efficiency distribution.

(2) Notable diffusion and polycentricity of high-efficiency innovation zones. High-efficiency regions evolved from a mono/dual-core state in 2013 (Beijing and Chongqing) to a multi-core coexistence in 2016 (Beijing, Jilin, Shanghai, and Hubei), ultimately forming a wide-ranging, polycentric network by 2022 (encompassing 10 provinces including Beijing, Tianjin, Shanghai, Zhejiang, and Anhui). Furthermore, the low-efficiency areas have steadily contracted; the count of low-efficiency provinces fell from six in 2013 (including Hebei, Inner Mongolia, Fujian, Henan, Guangxi, and Hainan) to just two in 2022 (Inner Mongolia and Ningxia). By 2022, a continuous belt of high efficiency emerged, characterized by the Beijing–Tianjin innovation highland and the Yangtze River Delta innovation corridor (Shanghai, Zhejiang, Jiangsu, and Anhui), marking an evolution from point-like dispersion to belt-like agglomeration.

(3) S&T innovation efficiency exhibits a marked East–West gradient. In 2013, the distribution showed significant gradient differences and initial clustering: Beijing and eastern coastal provinces like Shanghai and Jiangsu displayed higher efficiency, while western and certain central provinces remained in the low-efficiency range. By 2016, the polarization effect of core hubs intensified, with Beijing and Shanghai consolidating their status as national innovation poles, while Hubei and Jilin emerged as new growth poles. In 2019, diffusion and restructuring effects became prominent; while the radiation from core areas lifted the efficiency of surrounding provinces like Tianjin and Anhui, regions like Heilongjiang and Chongqing experienced fluctuations or declines, reflecting intensified regional competition. By 2022, the landscape reached a networked equilibrium. The Yangtze River Delta (Shanghai, Jiangsu, Zhejiang, and Anhui) integrated into a continuous high-efficiency highland, and central provinces (Hubei, Hunan, and Jiangxi) rose collaboratively. However, internal differentiation in the Northeast and slower progress in southwestern provinces (e.g., Yunnan and Guangxi) indicate that challenges in regional coordinated development remain.

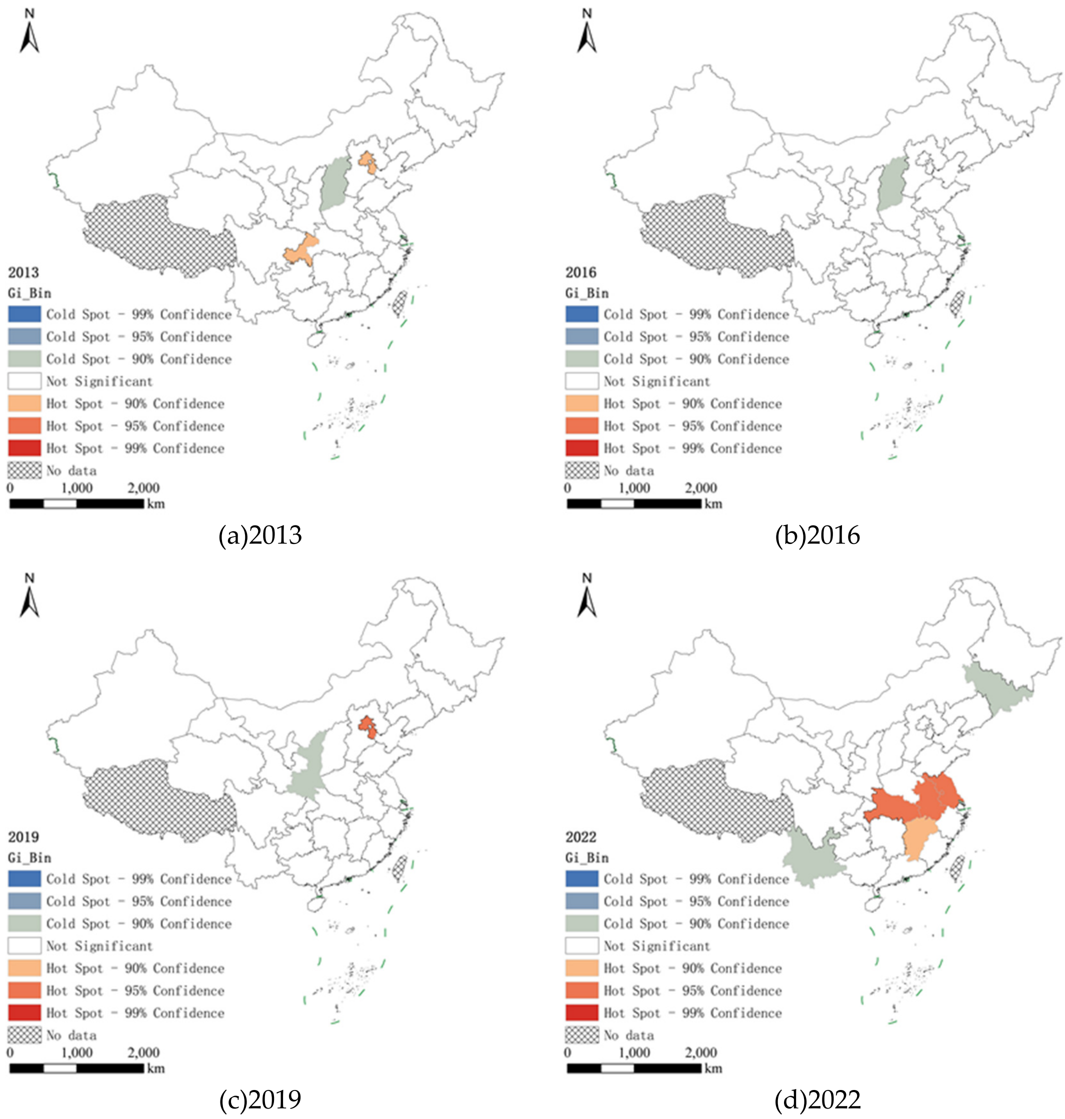

Figure 5. Hot spot distribution map of regional S&T innovation efficiency in China.

Overall, China's regional S&T innovation efficiency clusters have exhibited significant efficiency improvements and spatial transformations over the past decade. The leading positions of first-tier cities such as Beijing and Shanghai have been continuously consolidated, while the outstanding performance of provinces like Zhejiang, Anhui, Hubei, and Hunan has become a key driving force for the overall national efficiency improvement. The evolution of regional S&T innovation efficiency is characterized by the "coexistence of spatial polarization and collaborative diffusion": core areas continue to strengthen, and emerging growth poles continue to rise, forming multiple high-efficiency blocks such as Beijing–Tianjin–Hebei, the Yangtze River Delta, and the middle reaches of the Yangtze River. Conversely, some low-efficiency regions remain stagnant, highlighting the difficulty of breaking through developmental bottlenecks. The sustained leadership of Beijing and Shanghai underscores the powerful resource aggregation and source functions of national-level S&T innovation centers; meanwhile, the rapid rise of places like Anhui and Jiangxi demonstrates the feasibility of achieving innovation catch-up through industrial transfer and integration into core metropolitan circles. High-efficiency clusters are clearly aggregating toward advantageous regions like Beijing–Tianjin–Hebei and the Yangtze River Delta.

Ultimately, the cluster distribution of China's regional S&T innovation efficiency has progressed through four evolutionary stages: "Gradient Emergence—Core Polarization—Diffusion and Restructuring—Networked Equilibrium." The regional evolution data of cluster distribution reveals the phenomena of multi-center breakthroughs and block-based linkage. Observations indicate that after core regions (e.g., Beijing and Shanghai) surpassed and stabilized at an efficiency value of 1.0 around 2017–2020, their surrounding and economically linked provinces showed a concentrated upward trend in efficiency levels in subsequent years (e.g., 2021–2022). This reflects the time lag of innovation spillovers and the significant spatial spillover effects of China's regional S&T innovation efficiency. High-efficiency areas have expanded from a scattered point-like distribution in 2013 to a cross-provincial continuous belt-like distribution by 2022; meanwhile, low-efficiency areas have shrunk from a fragmented patch-like distribution in 2013 to scattered residual points in 2022. This represents the networking of China's high-efficiency regional S&T innovation clusters.

5.3. Hot spot Analysis

To better examine the relative relationships of S&T innovation efficiency among different sub-regions within China, the Getis-Ord Gi* local spatial autocorrelation index was employed. This index was spatialized using ArcGIS software to conduct a hotspot and coldspot analysis, as illustrated in Figure 5.

In 2013, hot spots were concentrated in Beijing, Tianjin, and Chongqing, aligning with their categorized status as "high" or "relatively high" efficiency regions. Notably, while Chongqing emerged as a spatially isolated western hotspot, its efficiency values fluctuated drastically in subsequent years (shifting from high to relatively low, then low, and finally medium). This suggests that in the early stages, Chongqing functioned as a statistically significant "isolated peak" rather than a stable "growth pole" with sustained radiation capabilities. Conversely, cold spots appeared in Shanxi, consistent with its "relatively low efficiency" status and marking it as a local innovation trough.

During 2016 and 2019, hotspots remained stable within the Beijing–Tianjin–Hebei core (Beijing and Tianjin), confirming the area's continuity and stability as a national-level innovation engine. Cold spots migrated from Shanxi (2016) to Shaanxi (2019). Interestingly, although Shaanxi was categorized as having "relatively high efficiency" in 2019, it was identified as a coldspot. This indicates that while its own efficiency was high, it was surrounded by lower-efficiency neighbors (e.g., Gansu, Ningxia, and Henan), failing to form a local high-efficiency cluster. This phenomenon substantiates earlier findings regarding "internal regional imbalance" and "geographic limitations of S&T innovation efficiency spillovers."

By 2022, large-scale hotspots with high confidence levels emerged in the middle and lower reaches of the Yangtze River (Hubei, Anhui, Jiangsu, and Jiangxi), forming a continuous belt (Hubei, Anhui, and Jiangsu reached 95% confidence). This directly visualizes the formation of the "Yangtze River Delta–Middle Reaches of the Yangtze River Innovation Corridor." Meanwhile, cold spots appeared in Jilin and Yunnan, provinces characterized by "medium" and "low" efficiency, respectively. This suggests that not only are these provinces underperforming individually, but their broader local regions have also stagnated, becoming efficiency cold spots in the national innovation network.

In summary, prior to 2019, hotspots were largely confined to the initial cores (Beijing and Tianjin), indicating limited early-stage radiation. It was not until 2022 that extensive, high-significance hotspot regions appeared in the Yangtze River Delta and the middle reaches of the Yangtze River. This reinforces the kernel density analysis observation: significant diffusion effects occur only after core regions surpass an efficiency threshold of 1.0. It implies that core areas must accumulate sufficient innovation energy—reaching the efficiency frontier—before they can generate strong spatial spillovers through industrial chains, talent flow, and technical cooperation.

The contrast between Shaanxi (high efficiency but a cold spot) and the middle reaches of the Yangtze River (collaborative hotspots) highlights that spatial spillover requires more than just high individual performance; it necessitates geographical proximity, industrial correlation, infrastructure connectivity, and policy synergy. The regional connectivity and integrated economic ties in the Yangtze River Delta and its middle reaches provided the necessary conditions for this "resonant" efficiency overflow.

5.4. Moran's I Analysis

To further confirm the spatial correlation characteristics of China's regional S&T innovation efficiency, a spatial autocorrelation analysis was conducted in conjunction with the cluster characteristics discussed above. Moran's *I* scatter plots were generated, as shown in Figure 6. Simultaneously, the global Moran's *I* values, p-values, z-scores, and standard deviations (sd) for the selected years were recorded; the specific numerical results are presented in Table 3.

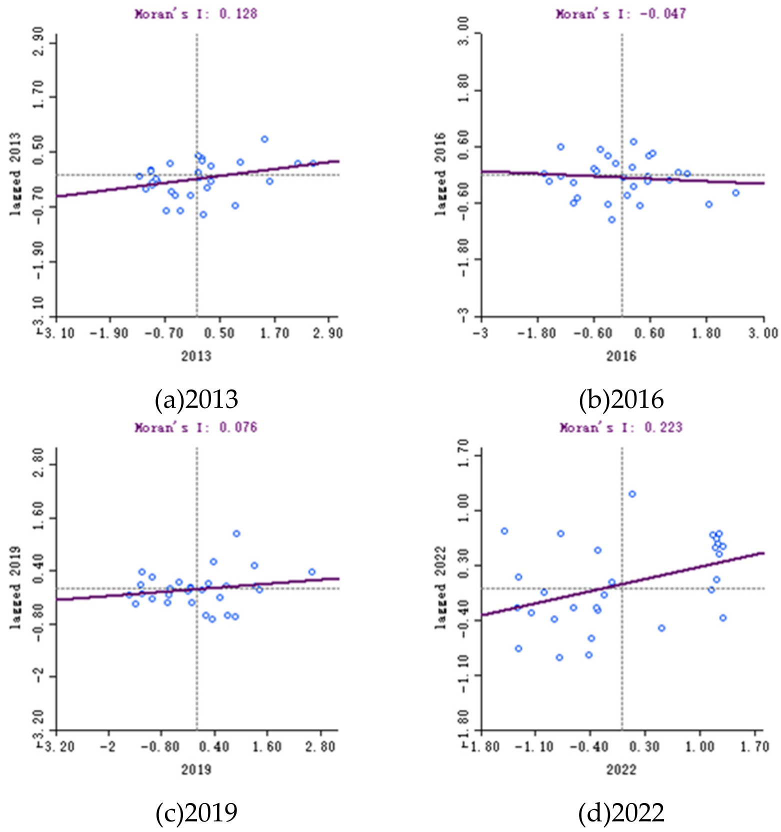

Figure 6. Moran scatterplot.

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Table 3. Moran's *I* related values.

Year	Moran's *I*	p	z	sd
2013	0.128	0.085	1.412	0.119
2016	-0.047	0.476	-0.109	0.120
2019	0.076	0.156	1.000	0.116
2022	0.223	0.020	2.150	0.124

In 2013, regional S&T innovation efficiency exhibited a weak positive spatial autocorrelation, indicating a slight tendency for high-efficiency provinces to cluster together and low-efficiency ones to do the same. However, the p-value (0.085) exceeded the standard significance level (0.05), suggesting that this positive correlation was not statistically significant. This aligns with previous findings: in 2013, high-efficiency "points" (e.g., Beijing, Chongqing) coexisted with low-efficiency "surfaces" (e.g., the vast central and western regions). Although embryonic hotspots were visible in the Beijing–Tianjin and Yangtze River Delta regions, high- and low-value areas were spatially interleaved, failing to form continuous, statistically significant clusters. Spatial spillover effects were weak, leaving the overall landscape relatively discrete.

By 2016, the Moran's *I* turned negative and approached zero, with the p-value far exceeding 0.05, indicating a lack of significant spatial autocorrelation. The efficiency values across provinces essentially followed a random spatial distribution. This reflects a transitional phase characterized by "intensified polarization without widespread diffusion." While core poles like Beijing and Shanghai strengthened and provinces like Jilin and Hubei surged, these high-efficiency "points" remained surrounded by lower-efficiency neighbors, failing to drive regional synergy. These high-efficiency provinces distributed like "islands," breaking the global clustering patterns of high-high or low-low values and resulting in statistical randomness.

In 2019, the Moran's *I* turned positive again, though the value remained small and the p-value, while lower, remained non-significant. Radiation effects from core areas (e.g., Beijing, Zhejiang) began to emerge, lifting the efficiency of neighboring provinces like Hebei and Anhui from low to medium levels. However, this diffusion was limited and uneven. With some provinces (e.g., Heilongjiang, Chongqing) experiencing fluctuations and others (e.g., Shaanxi) remaining "isolated" despite high individual efficiency, the global spatial autocorrelation remained weak and unstable.

By 2022, the Moran's *I* rose above 0.2, and the p-value (0.020) fell below the 0.05 threshold, confirming a statistically significant positive spatial autocorrelation. This signifies that high-efficiency provinces were significantly clustered with other high-efficiency provinces, quantifying the formation of the "block-based linkage and networked" pattern discussed earlier. In regions like the Yangtze River Delta and the middle reaches of the Yangtze River, multiple provinces simultaneously entered high-efficiency tiers, forming geographically continuous and statistically significant clusters. This result corroborates the Getis-Ord Gi* analysis, proving that spatial spillovers of innovation elements became significant and widespread after 2020, demonstrating clear agglomeration characteristics.

6. Conclusions and Discussion

6.1. Conclusions

(1) By applying a non-oriented Super-SBM model considering undesirable outputs to measure the regional S&T innovation efficiency in China, and analyzing the characteristics of its spatiotemporal evolution, this study draws the following conclusions:

(2) Based on the kernel density analysis, China's regional S&T innovation efficiency has achieved an overall leap and structural reconfiguration during the observation period. The distribution of regional S&T innovation efficiency has undergone a significant transformation from an initial state of "high right-skewness, low-value clustering, and wide disparities" toward a state of "upward shift

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of gravity, concentrated distribution, and convergent disparities." The dynamic evolution exhibits a clear four-stage characteristic: "Clustering–Polarization–Diffusion–Equilibrium."

Early Stage (2011–2016): The distribution was characterized by significant right-skewness, with a high peak density concentrated in the low-efficiency interval, reflecting large inter-provincial disparities.

Middle Stage (2017–2020): The distribution morphology underwent a fundamental change. The peak shifted continuously to the right, leaping into the high-efficiency interval in 2020, while the degree of dispersion gradually narrowed.

Recent Stage (2021–2022): The distribution became approximately symmetric or even left-skewed, entering a state of high-level convergence and relative equilibrium. Although the mean decreased slightly, the median remained at a high level, indicating that the momentum for efficiency improvement has stabilized and regional gaps have significantly closed.

This evolutionary path reflects a transition in China's regional S&T innovation from unipolar leadership driven by policy to a stage of multi-point collaborative development accelerated by market activation and factor mobility, ultimately forming a new pattern of high-quality balanced development.

(3) Based on the cluster characteristic analysis, the overall distribution structure of China's regional S&T innovation efficiency has evolved from an initial "pyramid" shape to a recent "spindle" shape. The number of high-efficiency provinces has increased significantly to 10, covering several vital regions such as Beijing–Tianjin–Hebei and the Yangtze River Delta. Meanwhile, the range of low-efficiency "troughs" has contracted substantially, indicating a rising baseline for national innovation efficiency and a more balanced overall distribution.

From the perspective of spatial evolution, high-efficiency clusters have undergone a diffusion and upgrading process, moving from a "mono/dual-core" state to "multi-core coexistence," and finally forming a "networked continuous belt." Notably, the Beijing–Tianjin–Hebei and Yangtze River Delta regions have matured into continuous innovation highlands. This evolution exhibits a four-stage characteristic of "Gradient Emergence—Core Polarization—Diffusion and Restructuring—Networked Equilibrium." This validates the existence of a "core-periphery" structure in innovation activities while simultaneously demonstrating a new trend of multi-center breakthroughs and block-based linkages. Once the efficiency of core regions surpassed critical thresholds, their radiation and spillover effects drove the concentrated improvement of associated regions in subsequent years.

(4) Based on the hotspot and coldspot analysis, the spatial correlation pattern of China's regional S&T innovation efficiency underwent significant structural changes between 2013 and 2022. In the early stages (2013 and 2019), significant hotspots were highly concentrated in the initial core of Beijing and Tianjin, while coldspots appeared sporadically in provinces such as Shanxi and Shaanxi. This indicates that the spatial spillover of innovation activities was limited during this period, and the radiation effect had not yet fully materialized. It was not until 2022 that large-scale, high-confidence hotspots emerged in the middle and lower reaches of the Yangtze River (including Hubei, Anhui, Jiangsu, and Jiangxi), forming a continuous region. This marks a new phase where high-efficiency clusters have evolved from isolated points into multi-point, integrated areas.

(5) The Moran's I exhibited a fluctuating upward trend, with spatial autocorrelation characterized by the sequence of "weak positive correlation – random distribution – weak positive correlation – significant positive correlation." This trajectory reflects the dynamic transition of China's regional S&T innovation from polarization toward a balanced equilibrium. The statistically significant Moran's I in 2022 provides robust global spatial evidence for the formation of "high-efficiency innovation corridors" and "block-based linkages." It demonstrates that China's regional innovation activities have evolved from a discrete, "point-like" distribution in the early stages into a "networked" structure characterized by strong spatial dependence and synergy.

6.2. Policy Implications

(1) Implement a "Trinity" Development Model of "Regional Strategic Focus, Spatial Planning Reshaping, and Institutional Integrated Innovation." To avoid falling into a low-level "gradient trap," regions should actively engage in "asymmetric competition" by strengthening strategic focus and providing category-specific guidance. Localities should be encouraged to leverage their unique resource endowments to layout future industries. Furthermore, by establishing cross-regional innovation communities, an overall breakthrough can be achieved through dynamic synergy.

(2) Consolidate and upgrade "High-Efficiency Core Areas" to strengthen global competitiveness and radiation source functions. It is essential to build a polycentric innovation network by referencing the "Yangtze River Delta" model to construct regional S&T innovation corridors. These corridors should be strategically laid out along rail transit lines, major arterial roads, and the distribution of scientific and educational resources. By establishing channels for the flow of regional innovation factors, the cost of factor mobility can be reduced, effectively transforming geographic proximity into structural advantages within the innovation network.

(3) Promote the "Periphery–Center" collaboration model in marginal areas. In this model, core regions are responsible for introducing front-end links of the innovation chain (such as R&D and design), while collaborative peripheral regions provide spatial carriers and undertake the transformation and production stages. This approach achieves functional complementarity, effectively integrating peripheral areas into the innovation networks of high-efficiency regions and alleviating the developmental bottlenecks of the "innovation troughs.

(4) Accelerate Relocation, Transformation, and Industrial Upgrading for Resource-Based and Traditional Industrial Regions. Regions facing transition bottlenecks and path dependency should actively phase out outdated capacity and undertake the transfer of emerging industries. For ecologically sensitive or resource-depleted areas, a strategy of integrating ecological restoration with the introduction of green technology sectors—such as new energy and new materials—should be adopted. This approach effectively transforms ecological constraints into new drivers of sustainable development.

(5) Establish a four-level spatial governance system comprising "High-Efficiency Cores, Innovation Corridors, Periphery–Center Synergy, and Underperforming Area Transformation." This system leverages the growth engines of regional S&T innovation to foster a polycentric network. By integrating core leadership with peripheral coordination and driving the revitalization of low-efficiency regions, the system ensures a comprehensive and tiered approach to spatial management.

In summary, to achieve breakthroughs in regional S&T innovation, China should construct a development model characterized by "Regional Strategic Focus, Spatial Planning Reshaping, and Institutional Integrated Innovation." Such a model is essential to avoid the "gradient trap," where regions at different development levels become stagnant in fixed positions, leading to further widening of disparities. Through asymmetric competition, the strategic deployment of future industries, and the formation of cross-regional innovation communities, a collaborative and dynamic regional S&T innovation system can be successfully established.

6.3. Limitations and Future Outlook

While this study provides a comprehensive analysis, certain limitations remain to be addressed in future research:

Refinement of the Indicator System. The indicators selected for measuring regional S&T innovation efficiency could be further refined. Future studies should aim to incorporate more granular variables—such as qualitative measures of innovation output or specific indicators for digital transformation—to build a more sophisticated and robust evaluation framework.

Expansion of Geographic Scope. Due to data accessibility constraints, this study does not include Tibet, Hong Kong, Macao, and Taiwan. Consequently, the specific roles and evolutionary trajectories of these regions within China's broader S&T innovation landscape remain unobserved. As data acquisition methods improve, integrating these regions will be a priority to provide a truly national perspective.

Exploration of Influencing Factors. This study confirmed the existence of significant spatial spillover effects in regional S&T innovation efficiency. Building on these measurement results, future research can employ spatial econometric models (such as the Spatial Durbin Model) to explore the underlying driving factors. Identifying these drivers will provide a more scientific basis for optimizing innovation policies, allocating resources effectively, and narrowing regional disparities to foster high-level collaborative innovation.

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Conflicts of Interest: The authors declare no conflicts of interest.

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