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National Agricultural Science and Technology Parks in China: Distribution Characteristics, Innovation Efficiency, and Influencing Factors

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Abstract: This study aims to analyze the spatial distribution characteristics and innovation efficiency of national agricultural science and technology parks (NASTPs) and identify the main influencing factors on the parks' innovation and development. The goal is to optimize the allocation of science and technology innovation resources in these parks, promote national agricultural science and technology innovation, and enhance the quality of agricultural development. To achieve this, the paper employs spatial analysis methods and a three-stage DEA-Tobit model to conduct both macro and micro-level analyses. The research findings are as follows: (1) Distribution characteristics: NASTPs tend to exhibit a uniform distribution at the national scale, but at the provincial level, their distribution appears clustered and uneven. Specifically, three high-density areas and two sub-high-density areas have emerged on the eastern side of the Hu line, displaying a decreasing trend from east to west. (2) Innovation efficiency: By excluding the influence of environmental factors and random interference, the lack of scale efficiency (SE) emerges as the primary reason for the generally low innovation efficiency of NASTPs. (3) Environmental factors: Science and technology training exhibits a negative correlation with innovation efficiency in NASTPs. Leading enterprises, income level, innovation support, and demonstration and promotion show positive correlations with IE in NASTPs. To promote national agricultural science and technology innovation and enhance the quality of agricultural development, it is recommended, based on a central-level development perspective, to focus on the layout of the northeast and northwest regions. At the local level, expanding the scale of key enterprise inputs and increasing the demonstration and promotion of scientific and technological achievements are recommended. Additionally, at the NASTPs level, guiding the construction of a national agricultural high-tech industry demonstration zone is advised.

Keywords: national agricultural science and technology parks; distribution characteristics; innovation efficiency; influencing factors

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1. Introduction

Currently, China is actively pursuing a rural revitalization strategy aimed at achieving modernization of agriculture and rural areas. The central focus of this strategy is to shift agricultural production from a focus on quantity to one that prioritizes quality. In this context, national agricultural science and technology parks (NASTPs) serve as crucial platforms and catalysts for driving high-quality agricultural development through the integration of innovative scientific and technological elements. It is of great practical significance to study the distribution characteristics, innovation efficiency (IE), and influencing factors of park development. By doing so, policymakers can formulate effective recommendations to enhance quality and increase efficiency, ultimately realizing China's agricultural goals. In 2001, the Ministry of Science and Technology (MOST) spearheaded the establishment of NASTPs with the aim of industrializing scientific and technological achievements and fostering a globally competitive agricultural advanced technology industry cluster. Operating as a vital link between the market and patents, NASTPs utilize projects as vehicles and enterprises as pillars to facilitate the transformation of agricultural scientific and technological breakthroughs. By consolidating scientific and technological resources and elements, NASTPs drive the advancement of regional agricultural industries and promote rural economic development [1,2]. Over the course of more than two decades, NASTPs have emerged as vital enablers, playing a crucial role in ensuring national food security, expediting the transformation of agricultural scientific and technological breakthroughs, facilitating agricultural structural adjustments, and driving innovation in the institutional mechanisms of agricultural science and technology. Currently, China's agricultural sector is transitioning towards a phase of high-quality development. This transition poses both opportunities and challenges for the further advancement of NASTPs, which necessitates a reliance on scientific and technological progress to foster innovation-driven and endogenous development.

China's agricultural science and technology parks were established in the late 1980s and have undergone five distinct stages of development: "Nascent start (1980s–1993)→Rapid development (1994–2000)→Adjustment and development (2001–2009)→Comprehensive development (2010–2016)→Quality improvement and Upgrading (2017–present)" [3]. These stages have witnessed the evolution of the parks, from local governments independently exploring new models of agricultural and rural development, to the central government issuing regulations for park construction, to the central government taking the lead in promoting agricultural science and technology innovation within the parks, and finally to collaborative efforts between the central and local governments to enhance the construction level and innovation capacity of the parks [4]. Currently, the spatial structure of NASTPs primarily follows the "Core zone + Demonstration zone + Radiation zone" model. The core zone serves as the central area where economic entities within the NASTPs are concentrated, the demonstration zone provides raw materials and experimental demonstrations for the core zone, and the radiation zone promotes the large-scale dissemination of agricultural science and technology achievements related to the leading industries of the NASTPs. This development model plays a crucial role in China's agricultural science and technology innovation. However, despite the rapid progress of NASTPs, they also face challenges, such as an imperfect monitoring and evaluation system and limited support capacity for scientific and technological innovation. Therefore, an accurate assessment of the innovation level of NASTPs is essential for optimizing resource allocation within the zones, promoting agricultural science and technology innovation, fostering the vigorous development of agricultural high-tech industries, and facilitating the high-quality development of China's agriculture in the future.

The remarkable success of the Stanford Science and Technology Park has spurred the construction of science and technology parks in numerous countries and regions worldwide, aiming to bolster their innovation capacity [5]. Leveraging the parks' key attributes of agglomeration, openness, innovation, and demonstration, these endeavors drive high-level regional innovation, knowledge-intensive business incubation, and the development of high-tech industries, facilitating the transformation of scientific knowledge into technological practice [6]. In the realm of agricultural research, scholars have thoroughly analyzed the inherent operational mechanisms of industry–university–research interaction within agricultural science and technology parks, exploring various perspectives such as industrial clusters, multi-principal collaboration, and innovation ecosystems. This holds both practical and theoretical significance in promoting the development of innovation capacity within agricultural science and technology parks [7]. From an industrial clusters perspective, agribusiness agglomeration plays a crucial role in driving the advancement of science and technology innovation, serving not only as an innovation applicator, but also as an innovation creator [8–10]. Henriques [11] asserted that science and technology parks can serve as breeding grounds for innovation, fostering and nurturing novel science and technology enterprises. Additionally, they facilitate collaboration among industry, academia, and research, thereby promoting the transfer of university expertise to enterprises. This fosters the transformation of scientific and technological achievements and facilitates commercialization. From the perspective of multi-subject collaboration, regional cooperation and exchange play a pivotal role in enhancing social relationships between entities while concurrently bolstering the efficiency and effectiveness of cooperation. Furthermore, innovation-intensive zones can achieve regional synergistic innovation development by strengthening spatial linkages [12,13]. Through the examination of Kazakhstan and Russia as case examples, Mingaleva [14] employed descriptive statistics and analogy to assess the significance of innovative agribusiness projects in terms of agro-industry and overall economic development. Their findings highlight that the multi-agent model of financing innovative projects serves as an effective mechanism for promoting the development of agro-industrial complexes in both countries. The "government guidance, enterprise operation, farmer participation" management mechanism plays a vital role in ensuring the sustainable development of agricultural science and technology parks [15,16]. Taking China as a case study, Huo [17] conducted spatial autocorrelation analysis and employed the DEA model to investigate the value chain perspective. Their findings highlighted that agricultural science and technology parks serve as critical platforms for agricultural innovation and integrated transformation. Moreover, the government's involvement in innovation resource allocation, along with fostering linkages among enterprises and integrating agricultural elements, emerged as a significant model for driving science and technology-led agricultural development. Adopting an innovation ecosystem perspective, institutions such as firms, universities, research centers, and development organizations establish regional innovation networks and foster innovation ecosystems. These ecosystems facilitate talent development, cultivate innovation, enhance competitiveness, and promote the flow and diffusion of knowledge through learning [18,19]. Scholars emphasize the pivotal role of innovation in driving the development of agricultural science and technology parks. They extensively analyze the internal mechanisms of agricultural science and technology innovation within these parks from various perspectives. This analysis holds significant importance for the advancement of agricultural science and technology parks in China.

China's agricultural science and technology parks aim to aggregate innovative resources, promote scientific and technological innovation, facilitate the transformation of research outcomes, and elevate the agricultural industry. Presently, research predominantly centers on innovation capacity, spatial patterns, and operational mechanisms [20,21]. Scholars commonly employ data envelopment analysis, the AHP model, and cluster analysis to assess the parks' innovation capacity, attributing differences in innovation to park construction and development [22,23]. However, existing studies lack comprehensive analyses of spatial distribution and efficiency evaluation in parks. While some macro-level literature exists, it falls short in exploring distribution characteristics and internal differences based on spatial scales. At the micro level, research on innovation capacity and mechanisms is predominantly qualitative, and further exploration in quantitative research is needed. The traditional DEA model overlooks environmental factors and random disturbances when measuring park innovation efficiency [24,25]. This limitation hinders a profound understanding of spatial distribution patterns in NASTPs and impedes the comprehension of actual innovation efficiency levels and influencing factors. Conversely, the three-stage DEA model accounts for environmental exogenous variables and random shocks, offering efficiency values between 0 and 1. This suitability allows for the application of the truncated Tobit regression model, examining factors influencing park development.

The primary objective of this study is to analyze the spatial distribution characteristics and innovation efficiency of NASTPs. Additionally, this study seeks to identify the key environmental factors that influence the innovation and development of these parks. The findings will be used to propose appropriate development strategies aimed at enhancing the innovation capacity of NASTPs, promoting agricultural scientific and technological innovation at the national level, and improving the overall quality of agricultural development.

In this study, we focus on 287 parks in China at the macro level and employ spatial analysis to examine their distribution characteristics. At the micro level, we select a sample of 85 parks participating in the MOST assessment in 2021. We utilize a three-stage DEA-Tobit model to assess the parks' innovation efficiency and investigate the environmental factors influencing this efficiency. The Discussion and Conclusion section summarizes the spatial distribution characteristics of the parks and the factors influencing their innovation efficiency, while also acknowledging the limitations of existing research. Lastly, we propose recommendations for strategically planning park construction, enhancing park innovation efficiency, and guiding park development at the developmental level.

2. Research Framework

The research framework of this paper, presented in Figure 1, aims to analyze the spatial distribution characteristics and evaluate the IE of China's NASTPs. It also aims to identify the environmental factors that affect the IE of these parks. The specific research steps are divided into three parts. In the first part, the macro level explores the distribution characteristics of parks. The analysis includes the nearest neighbor index to examine the types of spatial distribution of NASTPs at the national scale, the geographical concentration index, the imbalance index, and the Lorenz curve to assess the degree of balanced distribution of NASTPs at the provincial scale, and the kernel density estimation to analyze the spatial agglomeration of NASTPs. The second part focuses on evaluating the innovation capacity of NASTPs from a micro level. This involves constructing a system of indicators for input, output, and environmental variables and utilizing a three-stage DEA model to analyze the overall IE evaluation, returns to scale (RTS) analysis, and IE improvement. The third part employs the Tobit model to study the influence of environmental variables on the IE of NASTPs. It investigates the main factors affecting IE, pure technical efficiency (PTE), and scale efficiency (SE). Finally, drawing upon the findings from both macro and micro analyses, this paper presents policy recommendations from three perspectives: the central government, local government, and park management. These recommendations aim to enhance the innovation efficiency of NASTPs and promote China's agricultural science and technology innovation capabilities for achieving high-quality agricultural development.

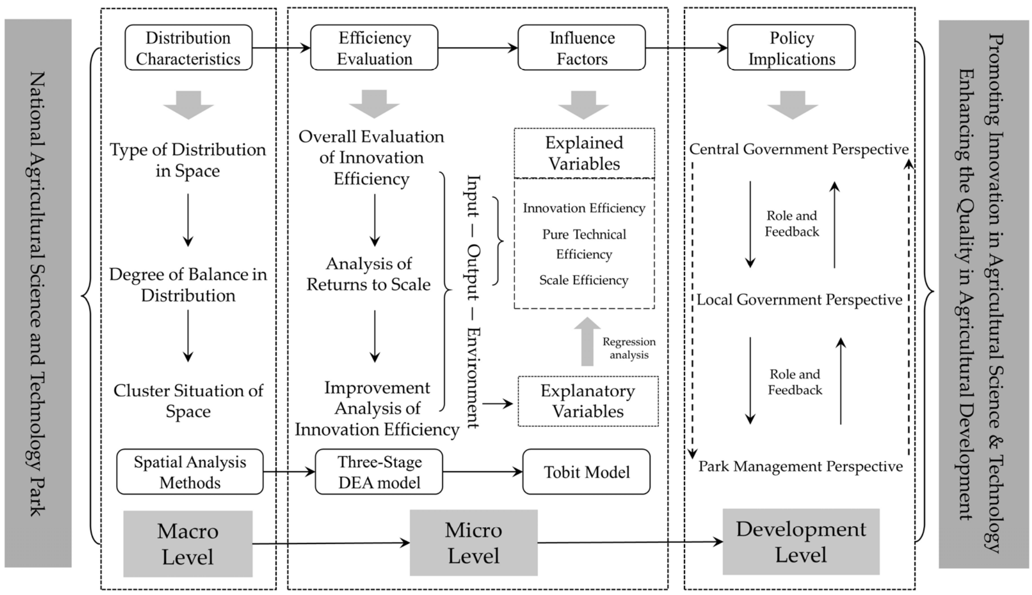

Figure 1. Research framework.

3. Materials and Methods

3.1. Data Source

To analyze the distribution characteristics, this study abstracted 287 NASTPs from across China as point elements, obtaining the list of parks from the website of the MOST. Geographical coordinate information for these parks was collected using the Baidu Maps Geocoding System to establish a spatial database. For the evaluation of IE and environmental factors, a sample of 85 NASTPs was selected. These parks are scheduled to be evaluated by the MOST in 2021, with a total of 87 parks participating (two parks had missing data). The data for the selected input, output, and environmental variables were obtained from official sources, including the website of the MOST, the National Science and Technology Assessment Centre, and the CSMAR database.

3.2. Data Methods

3.2.1. Spatial Analysis Methods

1. Nearest neighbor index

The nearest neighbor index is a useful tool for assessing the spatial arrangement of point-like elements and determining the type of their distribution [26]. This index provides a measure of the proximity between neighboring elements. The formula for calculating the nearest neighbor index is as follows:

$$R = \frac{r_1}{r_E} \tag{1}$$

$$r_E = \frac{1}{2}\sqrt{\frac{n}{A}} \tag{2}$$

where R is the nearest neighbor index, r_1 represents the observed nearest neighbor distance, r_E is the expected nearest neighbor distance, n is the total number of NASTPs, and A denotes the area of the study region. The nearest neighbor index provides insights into the spatial distribution pattern of NASTPs in China. When $R = 1$, it means that the distribution type of NASTPs in China is random; when $R > 1$, it suggests a uniform distribution; when $R < 1$, it signifies an agglomerative distribution.

2. Analysis of the degree of spatial equilibrium

The Geographic Concentration Index is a metric used to assess the concentration level of point-like elements within a specific region. It provides insights into the spatial distribution pattern of these elements [27]. The calculation formula for the geographic concentration index is as follows:

$$G = 100 \times \sqrt{\sum_{i=1}^{n}\left(\frac{P_i}{Q}\right)^2} \tag{3}$$

where G represents the geographical concentration index, P_i indicates the number of NASTPs in the i-th province, n represents the total number of provinces, municipalities, and autonomous regions, and Q represents the total number of NASTPs in China. G takes the values of [0, 100], with higher values indicating a more concentrated distribution of NASTPs and lower values indicating a more dispersed distribution.

The Imbalance Index is a useful tool for analyzing the distribution equilibrium of point-like elements within a region [28]. It is commonly calculated using the Lorenz curve method, which can be expressed by the following formula:

$$S = \frac{\sum_{i=1}^{n} Y_i - 50(n+1)}{100 \times n - 50(n+1)} \tag{4}$$

where S represents the Imbalance Index, n represents the number of provinces, municipalities, or autonomous regions, and Y_i represents the number of NASTPs in each province, municipalities, or autonomous region, sorted by the cumulative percentage of national agricultural science and technology parks in descending order. The value of S ranges between 0 and 1, with a higher value indicating a more uneven distribution of NASTPs. A value of $S = 0$ signifies an even distribution of NASTPs across each province, municipalities, or autonomous region. Conversely, if $S = 1$, it indicates that all NASTPs are concentrated in a specific province, municipalities, or autonomous region.

3. Kernel Density Analysis

Kernel density analysis is utilized to examine the density of spatial distribution of point-like elements within a region, enabling the assessment of the spatial cohesion among these elements [29]. The calculation formula for kernel density analysis is as follows:

$$f_h(x) = \frac{1}{nh}\sum_{i=1}^{n}\left(\frac{x - x_i}{h}\right) \tag{5}$$

where $f_h(x)$ represents the kernel density function, where $x - x_i$ denotes the distance between x to x_i, and h represents the width and is a positive value. The magnitude of $f_h(x)$ indicates the density of NASTPs, with larger values indicating a more concentrated distribution.

4. Spatial autocorrelation analysis

(1) Global Moran's Index

The first law of geography posits that anything on the Earth's surface is correlated, with stronger correlations observed among similar things [30]. This analysis of correlations between the distribution of elements based on spatial location is known as spatial autocorrelation analysis. The global Moran's I index is commonly employed to determine the presence of spatial autocorrelation among geographic elements [31]. The formula for Moran's I index is as follows:

$$I = \frac{n\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}[\omega_{ij}(x_j - \overline{x})(x_j - \overline{x})]}{(\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{n}\omega_{ij})\sum\limits_{i=1}^{n}(x_i - \overline{x})^2} \tag{6}$$

where n represents the total number of provinces (municipalities and autonomous regions) in China, m denotes the number of neighboring regions of region I, x_i and x_j stand for the number of parks in regions i and j, respectively, $\overline{x}$ represents the average value of the number of parks in each region, and ω_{ij} represents the value of spatial weights. The index value ranges from -1 to 1. A Moran's I value greater than 0 indicates positive spatial correlation among parks (i.e., high values clustered with high values, or low values clustered with low values); a Moran's I value less than 0 indicates negative spatial correlation among parks (i.e., high values clustered with low values, or low values clustered with high values); a Moran's I value equal to 0 suggests a random spatial distribution of parks. The magnitude of the value reveals the spatial aggregation and differentiation characteristics of areas with a high (or low) number of parks; a larger Moran's I value signifies more pronounced aggregation characteristics, whereas a smaller value indicates more pronounced differentiation characteristics.

(2) Local Moran's Index

The global Moran's I can only determine whether the research object exhibits aggregation in the study area as a whole. It cannot pinpoint the specific location or identify abnormal situations within the aggregated area. In contrast, the local Moran's I allows for the measurement of spatial correlation and differences between each area and its surrounding regions [32]. The calculation formula for the local Moran's I is as follows:

$$I_i = \frac{(x_i - \overline{x})\sum_{j=1}^{m} \omega_{ij}(x_j - \overline{x})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \tag{7}$$

where x_i and x_j represent the number of parks in regions i and j, respectively, ω_{ij} denotes the spatial vector matrix, and the value of I_i indicates the spatial relationship between area i and its surrounding units. If I_i is greater than 0, it signifies that both area i and the surrounding spatial units exhibit either high or low values. Conversely, if I_i is less than 0, it indicates that area i has a high (low) value while the surrounding spatial units exhibit low (high) values.

3.2.2. Three-Stage DEA Model

The three-stage DEA model analyzes the IE of NASTPs, allowing for the exclusion of environmental factors and random disturbance terms, and provides an accurate measure of the efficiency level for each decision-making unit (DMU) [33].

Stage 1: generalized DEA performance evaluation

Taking constant RTS into consideration, researchers such as Banker and Cooper discovered that by incorporating constraints into the CCR model, it becomes possible to exclude situations with constant RTS [34]. This led to the formulation of the DEA-BCC model, which can be expressed as follows:

$$\begin{gathered} \min\left[\theta - \varepsilon\left(\sum_{i=1}^{n} s_i^- + \sum_{r=1}^{s} s_r^+\right)\right] \\ s.t.\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{ij0}, i \in (1,2,\cdots,m) \\ \sum_{j=1}^{n} Y_{rj}\lambda_j + s_r^+ = \theta y_{rj0}, r \in (1,2,\cdots,s) \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \theta, \lambda_j, s_i^-, s_r^+ \geq 0, j = 1,2,\cdots,n \end{gathered} \tag{8}$$

where s_i^- and s_r^+ represent slack variables, m and s denote the number of input and output indicators, and x_{ij} and y_{rj0} represent the i-th input item and j-th output item of the j_0-th DMU. Additionally, a commonly used value is 10^{-6}, which represents a positive infinitesimal. θ is the PTE of the DMU$_j$. When θ = 1, s_i^- = 0, and s_r^+ = 0, it indicates that DMU$_j$ is strongly effective, signifying that the production factors of DMU$_j$ have reached their optimal combination and the output effect is at its best. This implies optimal technical efficiency. When θ = 1, s_i^- = 0, and s_r^+ = 0, it suggests that DMU$_j$ is weakly effective in DEA, and the relative comprehensive efficiency is weakly effective. For values between 0 and 1, DMU$_j$ is deemed ineffective in DEA, and the closer the value is to 1, the closer the efficiency is to being effective.

Stage 2: SFA regression model

The dependent variables in this study are the slack variables, while the independent variables are the environmental variables. The model was constructed through regression using Stochastic Frontier Analysis (SFA) as follows:

$$S_{ni} = f^n(z_i; \beta^n) + v_{ni} + u_{ni}, n = 1,\cdots,N, i = 1,\cdots,I \tag{9}$$

The deterministic feasible relaxation frontier, denoted as $f^n(z_i; \beta^n)$, is characterized by the coefficient β^n that needs to be estimated. The error mixture term v_{ni} + u_{ni} is assumed to follow a normal distribution v_{ni}~$N^+(0, \sigma^2{}_{\mathrm{vn}})$, representing statistical noise, while $u_{ni} \geq 0$

reflects managerial inefficiency. Additionally, it is assumed that u_{ni}~$N^{+}(u^{n}, \sigma^{2}{}_{\mathrm{un}})$, and that v_{ni}, u_{ni}, and z_i are independent of each other.

The formula is adjusted by manipulating the input variables to ensure that all DMUs operate under the same external conditions. The adjusted formula is given below:

$$x_{ni}^{A} = x_{ni} + [\max\{z, \beta^{n}\} - z_i\beta^{n}] + [\max\{\nu_{ni}\} - \nu_{ni}], n = 1, \cdots, N, i = 1, \cdots, I \tag{10}$$

where $x^{A}{}_{ni}$ and x_{ni} represent the input quantity after adjustment and before adjustment, respectively. The first bracket on the right side of Equation (10) is used to adjust the environment variables, while the second bracket ensures that all DMUs are placed at the same luck level.

Stage 3: The adjusted input data (denoted as $x^{A}{}_{ni}$) replace the original input data x_{ni}, while the output data y_{ni} remain unchanged. Subsequently, the BCC model is applied using these adjusted inputs to obtain the actual efficiency values that account for the effects of environmental factors and statistical noise.

3.2.3. Tobit Model

Considering that the IE value of the NASTPs falls within the range of 0 to 1, the appropriate regression model to use when the dependent variable is truncated or censored is the Tobit regression model [35]. This model utilizes maximum likelihood estimation and is capable of analyzing both continuous numerical variables and dummy variables. In the Tobit model, truncation occurs at the lower bound when L = 0, and at the upper bound when U = 1. The formulation of the Tobit model employed in this paper is presented below:

$$Y_a = \begin{cases} 1, & \beta^{T}Z_a + e_a \geq U \\ \beta^{T}Z_a + e_a, & L < \beta^{T}Z_a + e_a < U \\ 0, & \beta^{T}Z_a + e_a < L \end{cases} \tag{11}$$

where Y_a represents the IE value of the a-th park obtained through the three-stage DEA method, Z_a denotes the observable environmental variable, T represents the coefficient to be estimated, and e_a represents the residual term, which is an independent variable satisfying e_a~$N(0, \sigma^{2})$.

4. Results

4.1. Spatial Distribution Characteristics of NASTPs

4.1.1. Types of Spatial Distribution

On a national scale, most of the NASTPs in China are concentrated in the eastern region, east of the Hu line, while the western side exhibits less distribution and greater dispersion. Figure 2 illustrates that the NASTPs exhibit an even spatial distribution pattern. The analysis of the nearest neighbor index indicates an average observed distance of 96,895.52 km, with an expected observed distance of 90,886.75 km, resulting in a nearest neighbor index (R) of 1.07 (>1). Geographically, 73% of the country's NASTPs are located in four regions: East China, Central China, Northwest China, and Southwest China. Among these regions, East China has the highest number of NASTPs, benefiting from significant advantages in terms of agricultural resource endowment and geographical location. Notably, the provinces of Shandong, Jiangsu, Anhui, and Zhejiang alone account for 21.95% of the country's NASTPs. Central China, Northwest China, and Southwest China follow closely, each accounting for 16.03% of the country's NASTPs. On the other hand, North China, Northeast China, and South China have a relatively lower number of parks, accounting for 12.89%, 7.32%, and 6.27% respectively.

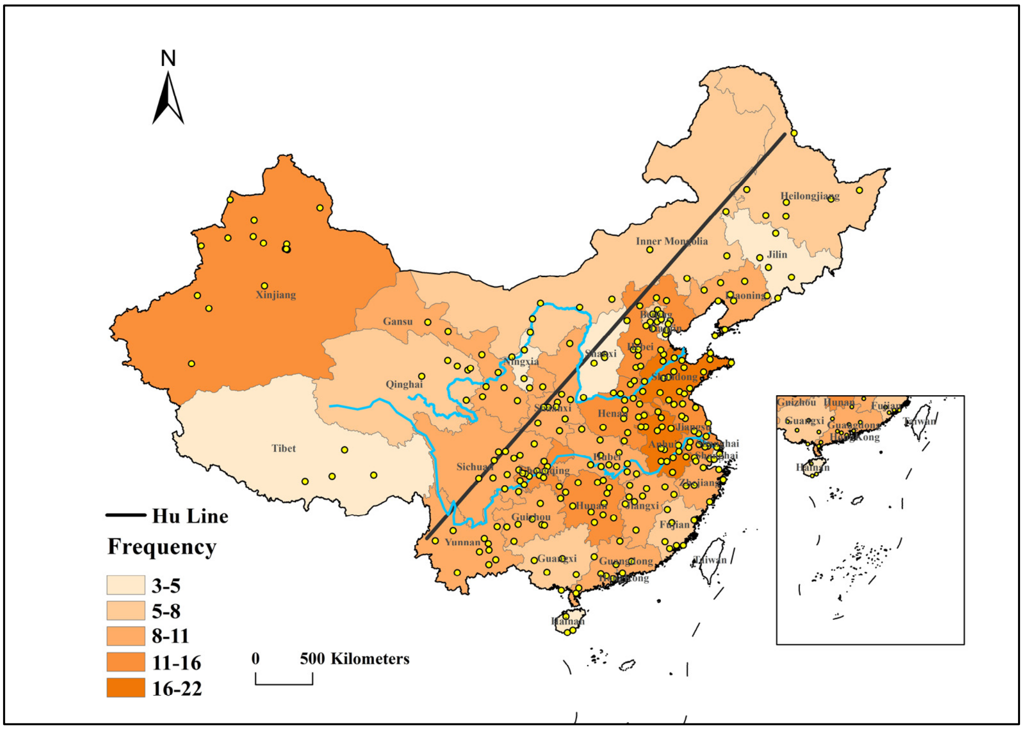

Figure 2. Spatial distribution of national agricultural science and technology parks (NASTPs).

4.1.2. Balanced Spatial Distribution

At the provincial scale, the distribution of NASTPs exhibits a relatively higher concentration but with less pronounced unevenness. The geographic concentration index, calculated using Formula (3), assumes an even distribution of 287 NASTPs among 31 provinces (including municipalities and autonomous regions). The theoretical number of NASTPs in each province is 9.26, resulting in a geographical concentration index of $G_0 = 17.96$. In reality, the geographical concentration index of NASTPs is $G = 20.01$, indicating a higher concentration than the theoretical distribution ($G > G_0$). Assessing the imbalance index of NASTPs using Formula (4), we find that $S = 0.28$ (<1), indicating a relatively lighter imbalance in the distribution. The Lorenz curve (Figure 3) displays an upward convex trend, but with a less pronounced curvature, further supporting the notion of a lightly imbalanced distribution of NASTPs.

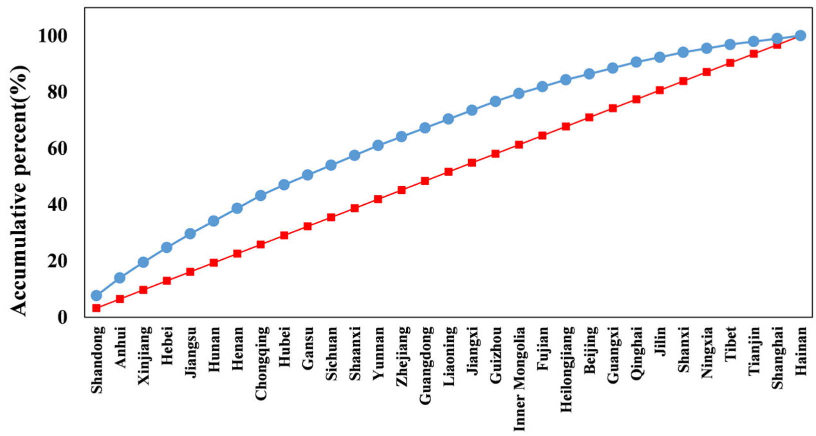

Figure 3. Lorenz curve of the spatial distribution of national agricultural science and technology parks (NASTPs).

4.1.3. Spatial Distribution Density

The kernel density analysis (Figure 4) reveals the formation of three primary high-density zones and two secondary high-density zones in the nationwide distribution of NASTPs. The first high-density zone encompasses the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Chengdu-Chongqing region. Within the Beijing-Tianjin-Hebei region, the core is Beijing, and it extends southward to include Tianjin, Baoding, and Langfang. The Yangtze River Delta is centered around Nanjing and extends northward to include Xuzhou, Chuzhou, Wuhu, and Xuancheng. The Chengdu-Chongqing region, with Chongqing as its core, radiates to the surrounding areas, encompassing Chongqing municipality, as well as Nanchong, Suining, Guang'an, and Yibin in Sichuan province. The two secondary high-density areas are the Hunan-Hubei-Jiangxi region and the Jiangsu-Shandong-Henan-Anhui intersection. The density of the Hunan-Hubei-Jiangxi region gradually decreases in a circular pattern at the junction of the three provinces, forming a spreading area in central China. The Jiangsu-Shandong-Henan-Anhui intersection zone is located between the Beijing-Tianjin-Hebei region and the Yangtze River Delta. It is influenced by these two high-density zones and forms a "Circular agglomeration zone of the lower Yangtze River plain and the Yellow Huaihai plain" [36]. Overall, NASTPs are primarily concentrated in regions characterized by abundant agricultural resources, dense populations, and economic development.

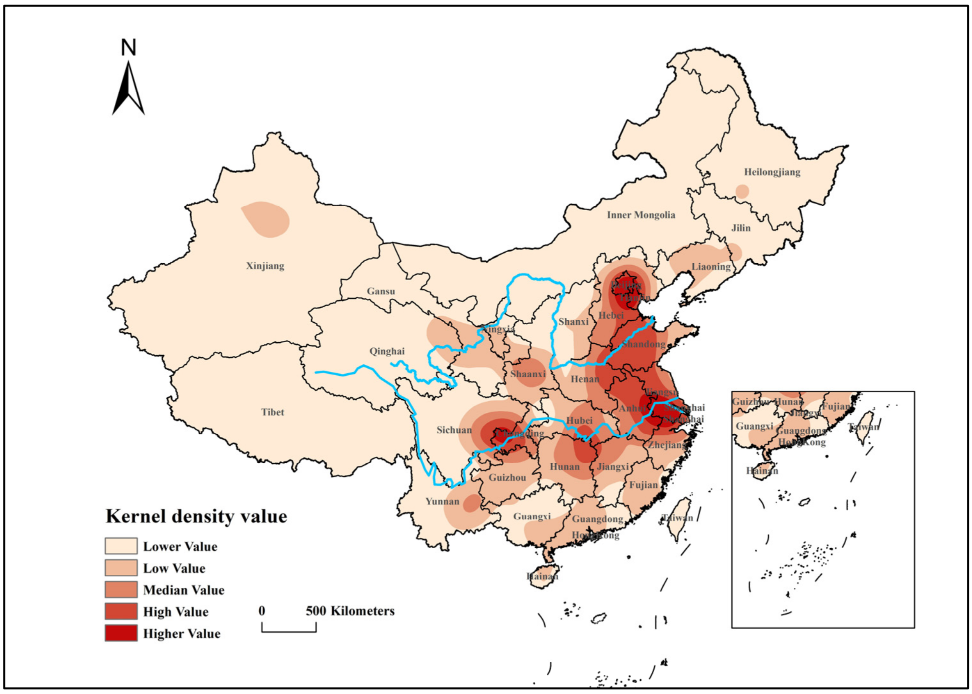

Figure 4. Kernel density analysis of the spatial distribution of national agricultural science and technology parks (NASTPs).

4.1.4. Spatial Autocorrelation Analysis

Using Chinese provinces as the fundamental spatial units, the global Moran's I was computed using Geoda software for the overall spatial distribution of NASTPs. The calculated index was found to be 0.151, with a Z-value of 1.548 and a p-value of 0.067. These results passed the significance test at the 10% level, signifying a significant global spatial autocorrelation characteristic in the distribution of NASTPs. However, since global autocorrelation analysis alone cannot effectively reveal the local state, further analysis is necessary. Figure 5 illustrates the use of LISA cluster analysis to explore the local spatial autocorrelation level. The findings indicate that four provinces, namely Shandong, Henan, Hubei, and Anhui, exhibit high spatial agglomeration characteristics, while Guangdong

Province demonstrates both high and low agglomeration. Additionally, 18 provinces (municipalities and autonomous regions), including Shanghai and Beijing, do not exhibit significant agglomeration, aligning with the results of the global spatial autocorrelation analysis.

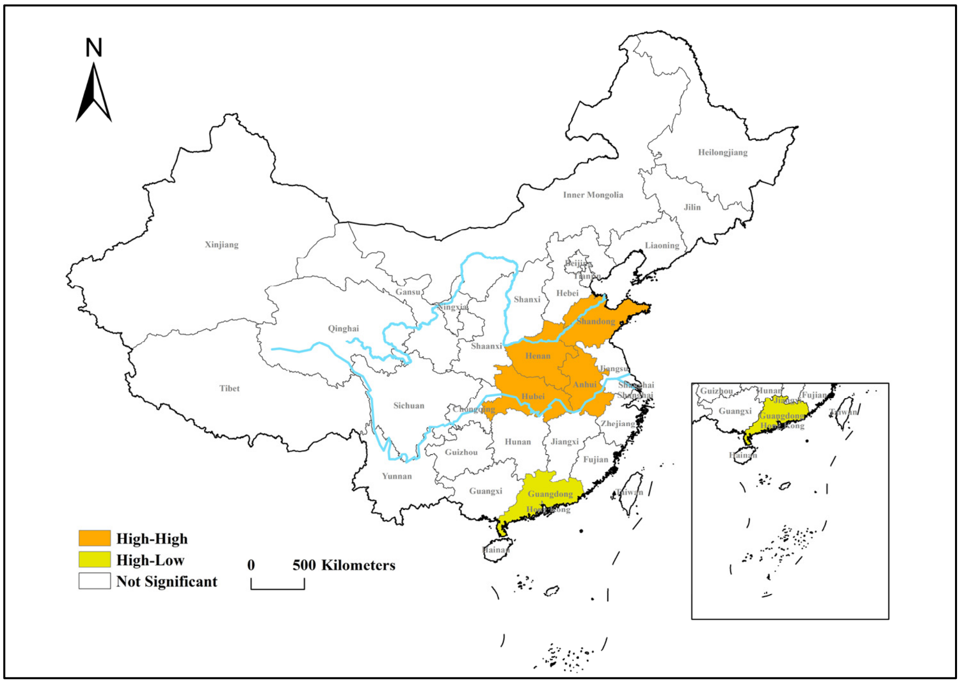

Figure 5. Local indices of spatial association (LISA) aggregation diagrams.

4.2. Analysis of Innovation Efficiency in NASTPs

4.2.1. Selection of Variables

Input–output variables. Regarding input variables, the innovation inputs in parks primarily consist of land, capital, and public service resources that facilitate the operation and production of NASTPs. This study incorporates insights from existing literature [37–39] and identifies park area, R&D input, and service platform as key indicators of input variables. In terms of output variables, in this paper, the assessment of the innovation output of parks focuses on two key variables: economic performance and R&D outcomes. We adopt the criteria used by scholars in the United States and Japan to measure this innovation output [40,41]. Considering data availability, the annual gross output value and the number of authorized patents are chosen as indicators to represent the economic performance and R&D achievements of the parks, respectively.

Environmental variables. This study draws on Simar and Wilson's research [42], which suggests that environmental variables should adhere to the "separation hypothesis". The following environmental variables have been selected. (1) Leading enterprises: These enterprises serve as primary drivers of industrial innovation and play a crucial role in the evolution of industrial structure within NASTPs [43–45]. They also serve as important channels for the transformation of technological achievements in NASTPs. The selection of the number of leading enterprises above the municipal level in the park can effectively indicate the park's development level. (2) Income level: The development of NASTPs requires substantial human and financial resources, and variations in the availability of production factors across different NASTPs can affect IE. The per-capita disposable income of farmers in the park was selected to indicate the income level, which not only characterizes the effectiveness of the park's economic development, but also reflects the impact of the park's technological achievements in integrating and involving farmers. (3) Innovation support is crucial for NASTPs, with high-tech enterprises serving as the core driving force behind innovation, thereby enhancing their innovation capacity. The number of high-tech enterprises selected is indicative of the park's innovation quality and development [46–48]. (4) Science and technology training: Compared with other countries, China's system of scientific and technological specialists stands out as a unique institutional innovation. Its purpose is to guide diverse scientific and technological innovators and entrepreneurial talents to engage in scientific and technological entrepreneurship and services within rural areas. This system aims to address the talent and science and technology gaps in the countryside. Practice has proved that the implementation of science and technology training programs in the park facilitates the effective integration of patents and modern agriculture through technical training [49]. This integration is beneficial for enhancing the park's agricultural science and technology innovation capacity. (5) Geographical distance: Previous studies have highlighted the impact of geographical location on the development of economic entities [50]. Consequently, the geographical distance between NASTPs and the prefecture-level city to which they belong may influence the innovation capacity of enterprises within NASTPs [51]. (6) Research projects: Drawing on research conducted by German scholars, it has been revealed that government funding for major R&D projects can effectively mobilize the participation of high-level research teams and scientific research platforms. Furthermore, it motivates business entities such as high-tech enterprises, leading enterprises, and small and medium-sized enterprises (SMEs) within the park to actively engage in project research, development, and cooperation. Consequently, this funding is conducive to promoting the innovation output of enterprises in the park. Therefore, the number of R&D projects was selected as an environmental variable that influences the innovation efficiency of the park [52,53]. (7) Demonstration and promotion: The introduction and dissemination of new technologies, products, and facilities within the park play a crucial role in enhancing the efficiency of technology diffusion and strengthening technological innovation capacity [54,55]. This contributes to the high-quality development of NASTPs. The specific variables are described in Table 1.

Table 1. Definition of variables.

Type	Name	Symbol	Description
Input variables	Park area	km^2	Land area of the NASTPs
	R&D input	CNY 10 thousand	Total R&D investment by enterprises and government in the NASTPs
	Service platform	number	The sum of the number of academician workstations, investment and financing platforms, agricultural products monitoring, and inspection platforms and agricultural products e-commerce platforms in the NASTPs
Output variables	Economic performance	CNY 10 thousand	Annual gross output of the NASTPs
	R&D achievements	number	Number of authorized patents
Environmental variables	Leading enterprises	number	Number of leading enterprises above municipal level in the NASTPs
	Income level	CNY	Per-capita disposable income of farmers in the NASTPs
	Innovation support	number	Number of high-tech enterprises in the NASTPs
	Science and technology training	number	Number of science and technology correspondent
	Geographical distance	km	Distance from the prefecture-level city
	Research projects	number	Number of major R&D tasks at provincial and ministerial level or above
	Demonstration extension	number	Number of new technologies, products. and facilities introduced and promoted in the NASTPs

4.2.2. Stage 1: DEA Model Empirical Results

The findings from the initial stage indicate that SE plays a predominant role in the IE of NASTPs, highlighting the need for improvement in technology resource allocation and technological R&D innovation within these parks. Table 2 presents the measurement of the IE for 85 NASTPs using DEAP2.1 software, without considering environmental factors and random disturbances. The mean IE value for the parks was found to be 0.566, with a mean PTE value of 0.649 and a mean SE value of 0.873. Notably, the SE value surpasses the PTE value.

Table 2. Innovation efficiency (IE) of the 85 national agricultural science and technology parks (NASTPs) in stages 1 and 3.

NASTPs	IE		PTE		SE		RTS	
	Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage 3
Beijing Fangshan	0.767	0.343	0.801	0.635	0.957	0.54	IRS	IRS
Beijing Miyun	0.381	0.259	0.413	0.62	0.922	0.418	IRS	IRS
Hebei Dachang	1	0.766	1	0.957	1	0.8	-	IRS
Hebei Gu’an	0.431	0.186	0.439	0.381	0.984	0.488	IRS	IRS
Hebei Zhuozhou	0.886	1	1	1	0.886	1	DRS	-
Hebei Luanping	0.512	0.618	0.575	0.623	0.89	0.991	DRS	DRS
Hebei Fengning	0.206	0.301	0.207	0.373	0.993	0.808	DRS	IRS
Hebei Xinji	0.379	0.445	0.38	0.539	0.997	0.827	IRS	IRS
Hebei Weixian	0.253	0.264	0.267	0.502	0.95	0.526	IRS	IRS
Inner Mongolia Bayan Nur	0.538	0.471	0.538	0.586	1	0.804	-	IRS
Inner Mongolia Tongliao	0.069	0.179	0.075	0.3	0.922	0.596	IRS	IRS
Inner Mongolia Erdos	0.2	0.28	0.213	0.428	0.936	0.653	IRS	IRS
Liaoning Jinzhou	1	0.587	1	0.858	1	0.684	-	IRS
Jilin Bai Shan	0.617	0.672	0.848	0.748	0.728	0.898	DRS	DRS
Heilongjiang Jiamusi	1	1	1	1	1	1	-	-
Shanghai Chongming	0.611	0.5	0.643	0.733	0.95	0.681	IRS	IRS
Jiangsu Zhenjiang	0.646	0.748	0.684	0.82	0.945	0.913	DRS	IRS
Jiangsu Yangzhou	0.164	0.228	0.194	0.391	0.848	0.583	IRS	IRS
Anhui Bozhou	1	1	1	1	1	1	-	-
Anhui Xuancheng	0.265	0.372	0.331	0.419	0.801	0.89	DRS	IRS
Anhui Lu’an	0.282	0.249	0.421	0.603	0.671	0.414	IRS	IRS
Anhui Huainan	0.452	0.328	0.493	0.585	0.916	0.561	IRS	IRS
Fujian Longyan	0.303	0.43	0.303	0.486	0.998	0.885	DRS	IRS
Fujian Shaowu	0.336	0.216	0.381	0.556	0.883	0.388	IRS	IRS
Fujian Sanming	0.786	0.516	0.808	0.763	0.973	0.677	IRS	IRS
Jiangxi Yichun	0.235	0.202	0.265	0.436	0.887	0.464	IRS	IRS
Shandong Weihai	0.637	0.706	0.637	0.781	1	0.904	-	IRS
Shandong Heze	0.442	0.323	0.443	0.449	0.998	0.718	IRS	IRS
Shandong Jinan	1	0.555	1	0.881	1	0.631	-	IRS
Shandong Zaozhuang	0.483	0.369	0.625	0.616	0.774	0.6	IRS	IRS
Shandong Weifang	1	1	1	1	1	1	-	-
Shandong Liaocheng	0.472	0.5	0.485	0.646	0.974	0.774	IRS	IRS
Shandong Qixia	0.588	0.377	0.627	0.728	0.938	0.518	IRS	IRS
Shandong Zoucheng	1	0.777	1	0.909	1	0.855	-	IRS
Shandong Bincheng	0.353	0.423	0.353	0.485	1	0.873	-	IRS
Shandong Junan	0.49	0.412	0.542	0.639	0.903	0.644	IRS	IRS
Henan Shangqiu	0.388	0.48	0.486	0.513	0.798	0.936	DRS	DRS
Henan Luohe	0.33	0.289	0.426	0.589	0.774	0.49	IRS	IRS
Henan Jiaozuo	0.492	0.749	0.825	0.876	0.596	0.855	DRS	DRS
Henan Anyang	0.843	0.961	1	0.967	0.843	0.994	DRS	DRS
Henan Zhumadian	1	0.743	1	0.761	1	0.977	-	DRS
Henan Zhoukou	0.669	0.838	1	0.947	0.669	0.885	DRS	DRS
Hubei Yichang	1	1	1	1	1	1	-	-
Hubei Huangshi	1	1	1	1	1	1	-	-
Hunan Ningxiang	1	1	1	1	1	1	-	-
Hunan Chenzhou	0.881	0.947	0.901	1	0.977	0.947	DRS	IRS
Hunan Shaoyang	0.811	0.641	0.838	0.854	0.968	0.751	DRS	IRS
Guangdong Shaoguan	1	1	1	1	1	1	-	-
Guangxi Hezhou	0.486	0.187	0.601	0.667	0.808	0.281	IRS	IRS

Table 2. *Cont.*

NASTPs	IE		PTE		SE		RTS	
	Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage 3
Hainan Lingshui	1	0.886	1	1	1	0.886	-	IRS
Chongqing Changshou	0.517	0.333	0.762	0.618	0.678	0.539	IRS	IRS
Chongqing Jiangjin	1	0.452	1	0.824	1	0.549	-	IRS
Chongqing Yongchuan	1	0.995	1	1	1	0.995	-	IRS
Chongqing Fuling	1	0.767	1	0.816	1	0.94	-	IRS
Sichuan Bazhong	0.181	0.388	0.236	0.389	0.766	0.999	DRS	-
Sichuan Mianyang	0.573	0.829	1	1	0.573	0.829	DRS	DRS
Sichuan Suining	0.167	0.25	0.169	0.359	0.986	0.696	IRS	IRS
Guizhou Tongren	0.074	0.121	0.078	0.243	0.946	0.501	IRS	IRS
Guizhou Liupanshui	0.566	0.397	0.567	0.519	0.998	0.764	IRS	IRS
Guizhou Chishui	0.331	0.545	0.336	0.667	0.985	0.817	DRS	IRS
Yunnan Xuanwei	0.802	0.457	0.833	0.695	0.963	0.658	IRS	IRS
Yunnan Dali	0.54	0.558	0.647	0.61	0.835	0.914	DRS	IRS
Yunnan Baoshan	0.215	0.567	0.806	0.812	0.266	0.698	DRS	DRS
Yunnan Mile	0.064	0.106	0.124	0.548	0.513	0.193	IRS	IRS
Tibet Naqu	0.232	0.028	1	1	0.232	0.028	IRS	IRS
Shaanxi Tongchuan	0.212	0.076	0.853	0.533	0.248	0.143	IRS	IRS
Gansu Baiyin	0.435	1	0.678	1	0.643	1	DRS	-
Gansu Gannan	0.093	0.152	0.144	0.402	0.646	0.379	IRS	IRS
Gansu Linxia	0.386	0.552	0.451	0.576	0.856	0.958	DRS	IRS
Qinghai Haixi	0.245	0.434	0.249	0.589	0.983	0.736	DRS	IRS
Qinghai Hainan	1	0.576	1	0.707	1	0.815	-	IRS
Qinghai Haibei	0.185	0.053	1	0.619	0.185	0.085	IRS	IRS
Ningxia Zhongwei	1	0.797	1	1	1	0.797	-	IRS
Xinjiang Shawan	0.712	0.438	0.769	0.797	0.926	0.55	IRS	IRS
Xinjiang Wensu	0.535	0.348	0.589	0.67	0.909	0.519	IRS	IRS
Xinjiang Hu Yanghe	0.936	0.877	0.959	0.914	0.975	0.959	DRS	IRS
Beijing Yanqing	0.596	0.352	0.651	0.9	0.915	0.391	IRS	IRS
Inner Mongolia Hellinger	0.341	0.426	0.342	0.476	0.995	0.895	DRS	IRS
Jilin Yanbian	0.368	0.294	0.383	0.534	0.961	0.551	IRS	IRS
Henan Puyang	0.235	0.238	0.291	0.506	0.807	0.47	IRS	IRS
Guizhou Bijie	0.774	0.492	0.783	0.816	0.989	0.603	DRS	IRS
Yunnan Chuxiong	0.242	0.291	0.266	0.446	0.909	0.652	IRS	IRS
Ningxia Yinchuan	1	0.124	1	0.809	1	0.154	-	IRS
Xinjiang Hami	0.18	0.071	0.28	0.804	0.642	0.088	IRS	IRS
Shenzhen Bao'an	0.722	0.823	0.872	0.871	0.828	0.946	DRS	IRS
Mean value	0.566	0.512	0.649	0.703	0.873	0.704		

4.2.3. Stage 2: Empirical Results of SFA Model

The findings from the second stage of analysis indicate that the selection of environmental indicators has been refined, and it has been identified that the redundancy in park inputs primarily stems from management inefficiency. Consequently, it is necessary to eliminate certain environmental variables. To address this, the SFA model was employed in this study, employing the first-stage input redundancy as the explanatory variable and the seven environmental variables as covariates in a regression analysis. Table 3 demonstrates that the LR values of all three SFA models successfully passed the 1% significance test. Furthermore, the majority of environmental variables exhibited significance at the 1% or 5% level. Based on these results, the following conclusions can be drawn.

Table 3. Stage 2 stochastic frontier analysis (SFA) estimation results.

Environment Variables	Park Area Redundancy	R&D Input Redundancy	Service Platform Redundancy
Constants	−28.788 ***	−18,480.622 ***	−4.340 ***
	(2.403)	(61.758)	(1.135)
x_1	41.578 ***	5027.254 ***	1.511
	(3.388)	(15.508)	(1.021)
x_2	13.488 ***	13,841.022 ***	2.940 ***
	(3.617)	(223.597)	(0.770)
x_3	−625.229 ***	−42,477.730 ***	−15.796 ***
	(31.791)	(14.191)	(0.996)
x_4	40.893 ***	19,753.214 ***	5.542 ***
	(4.970)	(88.108)	(2.123)
x_5	39.067 ***	2537.944 ***	2.420 ***
	(3.011)	(2.541)	(0.905)
x_6	10.330	8470.789 ***	−3.871 ***
	(4.841)	(98.243)	(0.999)
x_7	0.996 ***	16,932.444 ***	5.059 ***
	(6.544)	(290.831)	(1.192)
σ^2	363,383.360 ***	818,995,890 ***	138.084 ***
	(1.003)	(1.000)	(1.002)
γ	1.000 ***	1.000 ***	1.000 ***
	(1.37964×10^{-7})	(5.3593×10^{-7})	(5.6266×10^{-6})
Log	−585.315	−931.840	−268.737
LR	83.966 ***	43.136 ***	46.927 ***

Note: *** denote significant at the 1% statistical levels, with standard deviations in parentheses.

Leading enterprises (x_1). The number of leading enterprises has a significantly positive impact on the redundancy of park area and R&D inputs, whereas it does not have a significant impact on the redundancy of service platforms. This suggests that an increase in the number of leading enterprises leads to higher redundancy in the park's land area and R&D capital investment. This tendency towards resource concentration hinders the full utilization of certain input factors, leading to resource wastage.

Income level (x_2). The effect of income level on park area, R&D inputs, and service platform redundancy was significantly positive. This finding suggests that higher per-capita disposable income of patents leads to increased redundancy of input factors in the NASTPs. Moreover, it indicates the presence of a threshold effect on IE [56–58]. Once the threshold is reached, higher per-capita disposable income of patents can further promote the IE of the NASTPs.

Innovation support (x_3). Innovation support has a significantly negative effect on the redundancy of park area, R&D investment, and service platform. This suggests that an increase in the number of high-tech enterprises can reduce the redundancy of input factors in the NASTPs and effectively utilize resources such as land, R&D funds, and public service platforms, leading to cost savings in input factors.

Science and technology training (x_4). Science and technology training has a significantly positive effect on the redundancy of park area, R&D investment, and service platform. This demonstrates that an increase in the number of science and technology correspondent leads to an increase in the redundancy of input elements in the park. As the primary beneficiaries of science and technology correspondent are farmers, the park must allocate significant resources for their support. However, the utilization efficiency of farmers' key resources is relatively low, resulting in the inevitable wastage of certain input elements.

Geographical distance (x_5). Geographical distance has a significantly positive effect on the redundancy of park area, R&D inputs, and service platform. This suggests that a greater distance from the prefecture-level city reduces the possibility of inter-organizational cooperation and innovation [59], thereby increasing the redundancy of input factors in the NASTPs and leading to management inefficiency.

R&D projects (x_6). R&D projects had a significantly positive effect on the redundancy of R&D inputs, while the effect on the redundancy of service platforms was significantly negative. This indicates that despite the gathering of science and technology innovation resources in the NASTPs and the improvement of operational efficiency in service platforms such as academician workstations and testing centers, the increase in the number of major R&D tasks has led to certain R&D inputs being underutilized, resulting in increased input redundancy.

Demonstration and promotion (x_7). Demonstration and promotion have a significantly positive effect on the redundancy of park area, R&D inputs, and service platforms. This suggests that the demonstration and promotion of new technologies, products, and facilities lead to an increase in the redundancy of input factors in the NASTPs. This increase is attributed to the differences in resource endowment and administrative jurisdiction among parks [60], which serve as important constraints on the demonstration and promotion of agricultural technologies, resulting in the wastage of certain input factors.

The analysis above indicates that environmental variables play a crucial role in shaping the direction and intensity of the impact of IE generated by various NASTPs across different environments. Consequently, it is necessary to eliminate the influence of random factors associated with environmental variables and readjust the original input–output variables.

4.2.4. Stage 3: Empirical Results of Adjusted DEA Model

The results of Stage 3 were analyzed across three areas: overall IE, RTS, and improvements in IE. The IE of the 85 NASTPs was reassessed by comparing the results of Stage 1 and Stage 3 using adjusted input variables and the original output variables (Table 2).

Analysis of overall IE. The overall management level of the park is relatively low, resulting in a moderate level of IE. This lower IE can be attributed to a combination of PTE and SE, both of which are influenced by significant environmental factors. Overall, in comparison to Stage 1, the average IE of the 85 NASTPs decreased from 0.566 to 0.512 in Stage 3. The average PTE increased from 0.649 to 0.703, while the average SE decreased from 0.873 to 0.704. (1) Specifically, after adjusting inputs, the IE of 37 industrial parks, including Hebei Zhuozhou and Jilin Baishan, increased, accounting for 43.53%. However, the IE of 42 other industrial parks, such as Beijing Fangshan and Shanghai Chongming, decreased. The remaining industrial parks showed no change in efficiency. (2) Following the adjustment of inputs, the PTE of 48 industrial parks increased. The largest increase of 341.94% was observed in Yunnan Mile. On the other hand, 24 industrial parks experienced a slight decrease, with the smallest decline of only 0.11% recorded in Shenzhen Baoan. Additionally, 13 industrial parks remained unchanged, accounting for 15.29% of the total. (3) After adjusting inputs, the SE of 15 industrial parks increased. The largest increase of 162.41% was observed in Yunnan Baoshan. However, 63 industrial parks experienced a decrease, with the largest decline of 87.93% recorded in Tibet Nagqu. This was followed by Xinjiang Hami and Ningxia Yinchuan, which saw decreases of 86.29% and 84.6%, respectively. Additionally, seven parks remained unchanged, accounting for 8.24% of the total.

Analysis of RTS. After adjusting inputs, among the 85 NASTPs, 66 NASTPs have shown an increase in RTS, accounting for 77.65%. Additionally, 10 NASTPs have remained unchanged in RTS, while 9 NASTPs have experienced a decrease in RTS. These findings align with the reality of the study's subjects, which mainly consist of the seventh batch of NASTPs established in December 2015, as well as some renovated NASTPs. Given their relatively short time of establishment, the management and resource allocation of these NASTPs have not yet reached optimal levels, which hinders the improvement of their IE. For instance, the Xuancheng NASTP in Anhui Province has focused on agricultural science and technology innovation since its establishment. However, the park faces challenges such as low efficiency, lack of experience in industrial system construction, inadequate incubation of leading enterprises in agricultural product processing, and limited introduction of high-level science and innovation teams. To enhance the IE of the park, it is recommended to moderately expand the scale of R&D.

IE improvement analysis. To assess the innovation status of different NASTPs, this study adopts the approach of Meng Tao [61] and Xu Shubin [62]. It establishes the PTE value of 0.9 as the critical point and the SE value of 0.75 as the critical point. Based on these criteria, the NASTPs are classified into five types, as presented in Table 4 and Figure 6: (1) "Innovation Pioneer" NASTPs exhibit frontier-level PTE and SE values, serving as benchmarks for other NASTPs to strive for improvement. (2) "Innovation Good" NASTPs have high levels of both PTE and SE, but still fall short of optimal efficiency. To enhance their performance, these NASTPs should focus on rational allocation of scientific and technological resources and improving management practices. (3) "SE Improvement" NASTPs have low IE primarily due to inadequate SE. The key improvement area for these NASTPs lies in enhancing their SE. (4) "PTE Improvement" NASTPs experience low IE primarily due to sub-optimal PTE. These NASTPs should prioritize strengthening park mechanism innovation and system construction. (5) "Innovation Lag" NASTPs have low PTE and SE values. To improve their performance, these parks should optimize innovation resources, enhance the design of their management systems, and appropriately expand their scale of R&D.

Table 4. Distribution of the 85 national agricultural science and technology parks (NASTPs).

Types	Grading Criteria	National Agricultural Science and Technology Park
Innovation Pioneer	PTE = 1 SE = 1	Hebei Zhuozhou, Heilongjiang Jiamusi, Anhui Bozhou, Shandong Weifang, Hubei Yichang, Hubei Huangshi, Hunan Ningxiang, Guangdong Shaoguan, Gansu Baiyin
Innovation Good	$0.9 \leq$ PTE < 1 $0.75 \leq$ SE < 1	Hebei Dachang, Shandong Zoucheng, Henan Anyang, Henan Zhoukou, Hunan Chenzhou, Hainan Lingshui, Chongqing Yongchuan, Sichuan Mianyang, Ningxia Zhongwei, Xinjiang Huyanghe
SE Improvement	$0.9 \leq$ PTE < 1 $0 \leq$ SE < 0.75	Beijing Yanqing, Tibet Naqu
PTE Improvement	$0 \leq$ PTE < 0.9 $0.75 \leq$ SE < 1	Hebei Luanping, Hebei Fengning, Hebei Xinji, Inner Mongolia Bayannur, Jilin Baishan, Jiangsu Zhenjiang, Anhui Xuancheng, Fujian Longyan, Shandong Weihai, Shandong Liaocheng, Shandong Bincheng, Henan Shangqiu, Henan Jiaozuo, Henan Zhumadian, Hunan Shaoyang, Chongqing Fuling, Sichuan Bazhong, Guizhou Liupanshui, Guizhou Chishui, Yunnan Dali, Gansu Linxia, Qinghai Hainan, Inner Mongolia Hellinger, Shenzhen Baoan
Innovation Lag	$0 \leq$ PTE < 0.9 $0 \leq$ SE < 0.75	Beijing Fangshan, Beijing Miyun, Hebei Gu'an, Hebei Weixian, Inner Mongolia Tongliao, Inner Mongolia Erdos, Liaoning Jinzhou, Shanghai Chongming, Jiangsu Yangzhou, Anhui Lu'an, Anhui Huainan, Fujian Shaowu, Fujian Sanming, Jiangxi Yichun, Shandong Heze, Shandong Jinan, Shandong Zaozhuang, Shandong Qixia, Shandong Junan, Henan Luohe, Guangxi Hezhou, Chongqing Changshou, Chongqing Jiangjin, Sichuan Suining, Guizhou Tongren, Yunnan Xuanwei, Yunnan Baoshan, Yunnan Mile, Shaanxi Tongchuan, Gansu Gannan, Qinghai Haixi, Qinghai Haibei, Xinjiang Shawan, Xinjiang Wensu, Jilin Yanbian, Henan Puyang, Guizhou Bijie, Yunnan Chuxiong, Ningxia Yinchuan, Xinjiang Hami

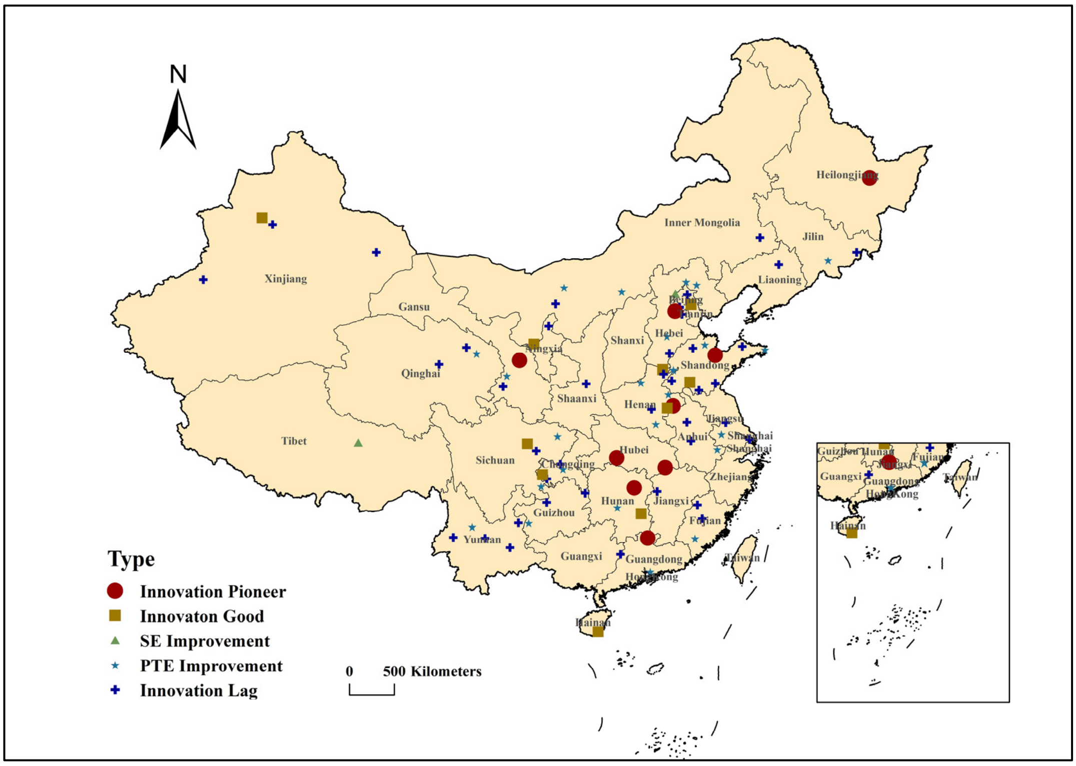

Figure 6. Spatial distribution of various types of national agricultural science and technology parks (NASTPs).

4.3. Analysis of Factors Influencing IE in NASTPs

In this study, we investigate the influence of environmental variables on the innovation efficiency of parks using the cross-section Tobit model for regression analysis and marginal effect analysis on the adjusted efficiency. Before conducting regression, this paper performs simple descriptive statistics for each variable, and presents the statistical results in Table 5. Moreover, it is found that there are no outliers among the variables. Subsequently, a series of tests, including the multicollinearity test, normality test, autocorrelation test, and heteroskedasticity test, are sequentially carried out for the selected variables. The results demonstrate that the VIF values for all variables are below 5, with an average VIF value of 1.55, indicating the absence of multicollinearity. The Jarque Bera test results support the original hypothesis, confirming that the sample probability follows a normal distribution. The value of the Durbin–Watson (DW) statistic, close to 2, suggests independence between the model residual and independent variables, indicating a well-constructed model. Additionally, homoscedasticity and heteroscedasticity are tested using the rank correlation coefficient method, and the results show no significant correlations between the absolute value of residual error and the respective variables, thereby indicating the absence of homoscedasticity and heteroscedasticity. Consequently, the model has successfully passed all the tests, and the regression results are presented in Table 6 and Figure 7.

Leading enterprises exert a significant positive influence on the IE of the NASTPs, as confirmed by passing the 1% significance test. This positive impact is primarily attributed to the SE. As depicted in Figure 7, the marginal effect of an increasing number of leading enterprises stimulates the park's innovation capacity, fostering the progressive enhancement of the associated agricultural industrial system and the application of agricultural technology in the NASTPs. This, in turn, generates a scale effect, facilitating the improvement of industrial quality and the optimization of the industrial structure within the park.

Table 5. Variables descriptive statistics.

Variables	N	Min	Max	Mean	Standard Deviation
IE	85	0.028	1	0.512	0.285
PTE	85	0.243	1	0.703	0.213
SE	85	0.028	1	0.704	0.253
x_1	85	0	1	0.190	0.188
x_2	85	0	1	0.222	0.173
x_3	85	0	1	0.034	0.110
x_4	85	0	1	0.124	0.182
x_5	85	0	1	0.222	0.215
x_6	85	0	1	0.094	0.153
x_7	85	0	1	0.105	0.171

Note: IE is the innovation efficiency; PTE is the pure technical efficiency; SE is the scale efficiency; x_1 is the leading enterprises; x_2 is the income level; x_3 is the innovation support; x_4 is the science and technology training; x_5 is the geographical distance; x_6 is the R&D projects; x_7 is demonstration and promotion.

Table 6. Tobit model regression analysis results.

Variables	IE	PTE	SE
x_1	0.627 ***	0.245	0.587 ***
	(0.198)	(0.172)	(0.180)
x_2	0.448 **	0.419 **	0.234
	(0.183)	(0.165)	(0.165)
x_3	2.139 *	0.538	2.653 **
	(1.147)	(0.538)	(1.028)
x_4	−0.479 **	−0.139	−0.472 **
	(0.213)	(0.191)	(0.190)
x_5	0.171	0.002	0.195
	(0.138)	(0.124)	(0.124)
x_6	0.050	0.106	−0.038
	(0.255)	(0.236)	(0.228)
x_7	0.421 **	0.320 *	0.278 *
	(0.179)	(0.169)	(0.161)
Constants	0.226 ***	0.544 ***	0.482 ***
	(0.071)	(0.063)	(0.064)
Log likelihood	−13.650	−10.936	−3.281
Prob > chi2	0.000	0.025	0.000

Note: ***, **, and * denote significant at the 1%, 5%, and 10% statistical levels, respectively, with standard deviations in parentheses.

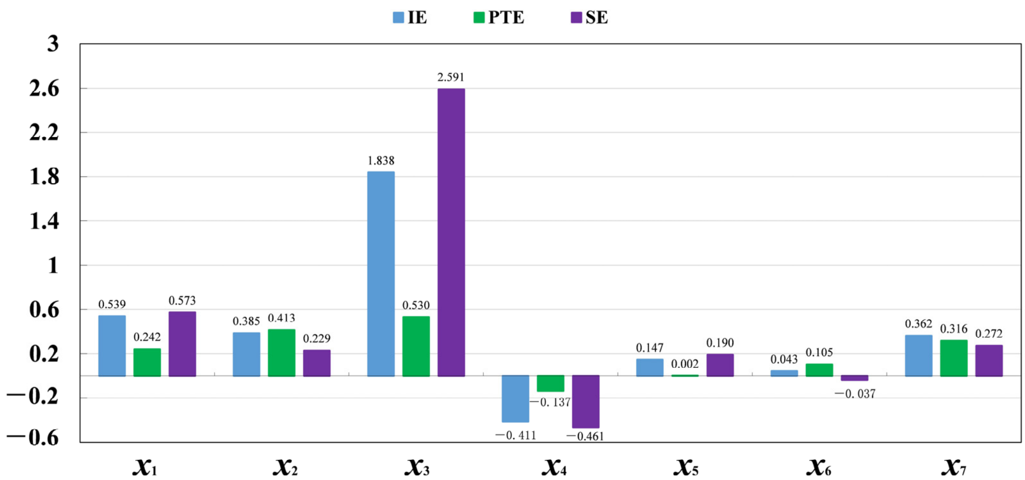

Figure 7. Marginal effects of the variables. Note: x_1 is the leading enterprises; x_2 is the income level; x_3 is the innovation support; x_4 is the science and technology training; x_5 is the geographical distance; x_6 is the R&D projects; x_7 is demonstration and promotion.

Income level positively impacts the IE of the park, as evidenced by passing the 5% significance test, with PTE being the primary driver of this positive effect. The rise in farmers' income levels indicates the park's commendable development in terms of system and management levels, enabling the rational allocation of scientific and technological resources and fostering enhanced efficiency in agricultural science and technology innovation within the park.

Innovation support positively influences both IE and SE in the NASTPs, passing significance tests at the 10% and 5% levels, respectively. Figure 7 highlights the substantial contribution of high-tech enterprises to the IE of the NASTPs, underscoring their significant advantage in technological innovation. This advantage facilitates resource conservation within the NASTPs, eases capital pressure, and enables the utilization of surplus resources to support the scale production of park enterprises.

Science and technology training negatively affects the IE and SE of the park, with statistically significant results at the 5% level. This can be attributed to the need for optimization in the team structure of science and technology personnel within the park. Moreover, the limited presence of science and technology personnel at the provincial and municipal levels makes it challenging to mitigate entrepreneurial risks during the process of guiding farmers in innovation and entrepreneurship, resulting in resource wastage.

Neither geographical distance nor research projects exhibited statistical significance. This can be attributed to two factors. Firstly, the park's geographical location is well-suited, thereby mitigating the influence of geographical distance on the park's IE. Secondly, the park has a limited number of major R&D projects, which restricts significant advancements in its innovation capabilities.

Demonstration and diffusion exert a positive influence on the IE, PTE, and SE in the NASTPs, with statistical significance levels of 5%, 10%, and 10%, respectively. This implies that greater demonstration and extension efforts in the NASTPs enhance the adoption of novel technologies, products, and facilities by farmers, and strengthen the technology diffusion effect. As a result, the management level of the NASTPs improves, leading to higher land output rates, better resource utilization, and the attainment of optimal labor production scales.

5. Discussion

To enhance the innovation capacity of China's national agricultural science and technology parks, foster national agricultural science and technology innovation, and improve agricultural development, this paper adopts a comprehensive approach based on three levels: macro, micro, and development. Utilizing spatial analysis methods and econometric empirical models, the study explores the spatial distribution characteristics, innovation efficiency, and influencing factors of these parks. The primary goal is to gain insights into the overall innovation and development of national agricultural science and technology parks. Furthermore, the research aims to optimize the allocation of scientific and technological innovation resources within the parks and propose relevant measures and suggestions for the future. This includes rational site planning for the parks, refining their operations and management, and clearly defining their development direction. The paper focuses on three main points.

5.1. Integration with Previous Studies

Currently, academics primarily focus on studying the development effects of the park, which include industrial agglomeration, the demonstration and promotion of agricultural science and technology, regional economy, and ecological and environmental impacts. Most scholars utilize comprehensive evaluation methods to assess the development effectiveness of agricultural science and technology parks. The findings indicate that several factors hinder the development of agricultural high-tech industries and the transformation of scientific and technological innovations in these parks. These constraints include a lack of human and financial resources, imperfect operation and management mechanisms, and small-scale operations, all of which impede the sustainable development of agricultural science and technology parks [5,63].

The research on assessing the Innovation capacity of agricultural science and technology parks predominantly relies on qualitative theoretical analyses. Regarding quantitative research, it mostly involves constructing an index system for quantitative assessment, lacking in-depth empirical and mechanism analyses. There is a significant dearth of literature focusing on quantitative investigations into the distributional characteristics, efficiency evaluation, and influencing factors of agricultural science and technology parks. Consequently, this paper aims to contribute to the field in three significant ways. Firstly, it utilizes geographic information to examine the distributional characteristics of 287 parks in China, employing spatial analysis methods to gain a macro-level understanding of the parks' spatial layout across the country. Secondly, it selects data from 85 parks participating in the 2021 assessment by the MOST to study their actual innovation efficiency at a micro level, while accounting for environmental factors. By classifying parks according to their efficiency levels, the study proposes improvement directions. Lastly, the research analyzes the impact of environmental factors on the innovation efficiency of parks and identifies key influencing factors to clarify the future direction for improvement.

5.2. Comparative Study with Internationally Relevant Agricultural Parks

Both China's national agricultural science and technology parks and international agricultural parks share a common objective of advancing agricultural science and technology research and innovation, enhancing agricultural production efficiency, and promoting sustainable agricultural development [1,64]. Regarding technological innovation, demonstration, and promotion, both domestic and foreign parks emphasize agricultural science and technology innovation, industrial synergy, and commercial promotion. They encourage farmers to adopt new technologies and varieties by introducing advanced agricultural technologies and implementing demonstrations. Additionally, concerning resource gathering and cooperation, both domestic and foreign parks serve as platforms for collecting innovation resources from agricultural research institutions, universities, enterprises, and expert teams, fostering the sharing and collaboration of agricultural science and technology resources.

However, China's national agricultural science and technology parks exhibit unique development characteristics compared to other countries and regions. Regarding scale and layout, Chinese parks tend to be larger, encompassing a wide range of agricultural industries, and aligned with the geographical distribution of China's population. In contrast, international agricultural science and technology parks may be smaller, with a focus on specific agricultural fields or technology clusters, as observed in Japan and the Netherlands [65,66]. Policy support and management mechanisms also vary across countries and regions. China's parks receive robust government backing, as they are expected to serve as centers for radiating and driving high-quality agricultural development in surrounding areas. For better-developed regions, the government optimizes the regional industrial structure and enhances industry quality through the diffusion and spatial spillover effects of the parks. In contrast, for less-developed regions, the government improves park management and enhances the scale effect of the regional agricultural industry through the aggregation of elements in the parks and their demonstration and promotion functions. In the international arena, policy support for agricultural parks may differ depending on each country's legal and administrative systems and economic environment. As for management mechanisms, China's national agricultural science and technology parks are typically government-led and -supported, with the government playing a pivotal role in park planning, policy formulation, and resource allocation. Conversely, parks in other countries and regions may adopt a more market-oriented approach, relying on private enterprises and market mechanisms for development. Additionally, China's parks operate with a multi-tiered management system, involving a hierarchical structure between the central government, local governments, and park management committees to ensure policy coordination and implementation, whereas international park management systems tend to be relatively simpler and more flexible.

5.3. Research Limitations and Future Prospects

This study has two main limitations. Firstly, the data used for the NASTPs are based on sectional data, which lack analysis of the temporal dimension. Additionally, different types of NASTPs exhibit significant variations in operational scale and development mode, necessitating the examination of changes in construction effectiveness and IE over time. Secondly, the index system for measuring the IE of NASTPs requires improvement, as it does not encompass factors such as information construction, brand cultivation, and industrial integration. Future research should integrate these factors and comprehensively explore the spatial evolution and influence mechanisms of IE in NASTPs over time. This will provide valuable insights for optimizing the allocation of science and technology innovation resources in NASTPs.

6. Conclusions and Policy Implications

6.1. Conclusions

This study employs a combination of the nearest neighbor index, geographic concentration index, imbalance index, kernel density analysis, and spatial autocorrelation analysis to investigate the spatial distribution characteristics of 287 NASTPs throughout China. The research focuses on 85 NASTPs evaluated by the MOST in 2021. Furthermore, the three-stage DEA model and Tobit model are utilized to analyze the factors influencing IE and environmental impact in NASTPs. The findings are summarized as follows.

At the national scale, the distribution of NASTPs tends to be relatively even, while at the provincial level, it appears clustered and uneven. Overall, the regions of East China, Central China, Northwest China, and Southwest China have the highest concentration of NASTPs, with relatively minor variations among them. At the provincial level, the distribution of parks is more concentrated, with an imbalance index of only 0.28, suggesting a tendency toward even distribution across all provinces (municipalities and autonomous regions). However, the distribution of parks exhibits significant variation, displaying a spatial pattern of denseness in the east and sparseness in the west.

The NASTPs exhibit three high-density zones and two sub-high-density zones on the east side of the Hu line. The high-density areas include the Beijing-Tianjin-Hebei region, radiating southward with Beijing as the center; the Yangtze River Delta region, radiating northward with Nanjing as the center; and the Chengdu-Chongqing region, radiating around Chongqing as the center. The secondary high-density areas consist of the Hunan-Hubei-Jiangxi region and the Jiangsu-Shandong-Henan-Anhui convergence zone, which form a ring-shaped agglomeration known as the "Lower Yangtze River Plain—Yellow Huaihai Plain". These zones follow a decreasing circle pattern. In general, the park's spatial density distribution decreases from east to west, with all high-density areas situated on the east side of the Hu line. This distribution aligns with China's geographic population distribution and reflects the region's abundant agricultural resources, dense population, and developed economy.

There are notable variations in the IE among different types of NASTPs, with SE being a predominant factor in most cases. After adjusting the input–output variables, the PTE of most parks improves, but the IE and SE decline, resulting in an overall lower efficiency level. Particularly, low SE appears as the main reason for the parks' sub-optimal IE. By employing the three-stage DEA method for correction, the average IE of the parks decreases by 0.054, while the average PTE increases to 0.703, and the average SE decreases to 0.704. These findings suggest that most parks have not yet achieved the optimal resource allocation, management level, and scale effect. Based on the specific efficiency values of each park, they can be categorized into "Innovation pioneer", "Innovation good", "SE improvement", "PTE improvement", and "Innovation lag" groups, which will guide the direction of future improvements for each type of park.

Strengthening enterprise cultivation support and increasing demonstration and promotion efforts in NASTPs can effectively enhance the park's science and technology IE. The IE of the park is positively correlated with leading enterprises, income level, innovation support, demonstration, and promotion. On the other hand, it is inversely proportional to science and technology training. This suggests that providing adequate material and financial support can alleviate management inefficiencies in the park, thereby promoting the improvement of PTE and SE, which is an effective approach at this stage. The study reveals that high-tech enterprises and leading enterprises play pivotal roles in driving the IE of the park, with high-tech enterprises displaying the strongest innovation capacity and making significant contributions to the park's overall IE. Leading enterprises, in turn, have a positive and active impact on enhancing the park's SE. Furthermore, effective demonstration and promotion activities in the park lead to greater adoption of new technologies by farmers, resulting in increased labor productivity and higher incomes, consequently bolstering the park's IE.

6.2. Policy Implications

Based on the aforementioned findings, three policy insights can be derived. In the future, the central government should consider the spatial distribution balance and prioritize the establishment of NASTPs in the northeast and northwest regions. The Northeast region, being China's primary grain-producing region, can leverage the agricultural science and technology innovation within the park to enhance the efficiency of agricultural resource utilization, thereby fostering the integrated development of grain production in both quantity and quality. The Northwest region possesses a vast territory, abundant sunlight, and diverse biological resources, making it well-suited for the development of specialized agriculture. Establishing NASTPs in this region can effectively cater to the high technological requirements of specialized agriculture.

Local governments should prioritize the cultivation of high-tech enterprises and industry leaders, while also enhancing the demonstration and promotion of agricultural science and technology achievements. Firstly, NASTPs should moderately increase investment in innovation for high-tech enterprises and industry leaders. Furthermore, they can foster the integration of capital, technology, markets, and other factors by introducing incubation platforms such as hackerspace. This will enhance the competitiveness of the park's leading industries and their capacity for technological innovation. Secondly, there should be an increase in the appointment of provincial and municipal science and technology correspondents, optimization of the structure of the correspondent team, and active promotion of the establishment of a science and technology information service platform. These efforts will facilitate both online and offline science and technology training activities to broaden the reach of agricultural science and technology demonstration and promotion.

At the management perspective of NASTPs, they are crucial to adopt the national agricultural high-tech industry demonstration zones as the development direction and goal. This strategic approach aims to address the challenges hindering regional agricultural development. The national agricultural high-tech industry demonstration zones are led by scientific and technological innovation, driven by reform and innovation, guided by national strategies, focused on improving quality and increasing efficiency, and in accordance with the model of "one leading industry in one park". They foster the development of distinctive industrial clusters with strong competitiveness, effectively showcasing the leadership and demonstration of leading industries with regional advantages. This represents the main development direction for NASTPs.

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