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Prioritize Innovation Capability and Spatial Variation of National High-Tech Zones in China Based on the Catastrophe Progression Method

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Abstract

This research aims to prioritize innovation capability and spatial variation of national high-tech zones in China based on the catastrophe progression method. The first step is to establish a feasible index system for assessing the innovation capability of high-tech zones; after that, it is to Evaluate the innovation capability of 169 national high-tech zones in China using the Entropy Weight Method (EWM) and the Catastrophe Progression Method (CPM), then use the weighted average method to convert the innovation capability evaluation results of 169 high-tech zones into values for each province's high-tech zones in China. The last step utilizes visualization tools for spatial variation analysis.

The research results found that a comprehensive innovation capability evaluation system has been constructed, consisting of levels 1, 2, and 3, which have 4, 8, and 28 indicators, respectively. The evaluation results reveal that prioritizing provinces regarding innovation capability and spatial variation of high-tech zones for the top three are 1) Beijing, 2) Shanghai, and 3) Guangdong. At the same time, the bottom three are 167) Hainan, 168) Qinghai, and 169) Ningxia. From the priority and using the visualization, results indicate that High-tech zones in eastern China found that (Beijing, Shanghai, and Guangdong) have significantly higher innovation capabilities than those in central and western regions due to richer resources, advanced infrastructure, and more substantial policy support. Central regions (Wuhan, Hefei) also show high capabilities from recent investments and government support, while western areas generally lag, needing improved infrastructure, increased investment, and more substantial policy support.

Keywords: prioritize innovation capability and spatial variation; high-tech zones in China; Entropy Weight Method (EWM); Catastrophe Progression Method (CPM)

Introduction

In recent years, China's national high-tech zones (after this, referred to as "high-tech zones") have played a crucial role in the country's innovation-driven development strategy. These zones are vital regional and national development engines that promote technological innovation and economic growth. Assessing the innovation capability of high-tech zones is essential for understanding their innovation potential. As innovation hubs, high-tech zones have been extensively studied domestically and internationally.

Bruno and Tyebjee (1982) were pioneers in researching the evaluation index system for science and technology parks, developing a system comprising 12 factors significantly impacting companies [1]. Makecki (1987, 1988) assessed the innovation capability of high-tech zones from eight perspectives, including government support strength, capital flow speed, and personnel mobility [2, 3]. Chung (2004) applied the AHP method to evaluate companies in Taiwan's science and technology parks, identifying seven factors closely tied to the high-tech industry: consumption effect, industry relevance, and government influence [4]. Zeng (2010) posited that the innovation capability of high-tech zones can be evaluated based on the innovation environment, innovation promotion, and innovation organization [5].

Since 1993, the Chinese Ministry of Science and Technology has revised the National Indicator System for evaluating high-tech zones four times, integrating various innovation directions. Xu Guanhua (2006) identified six factors, such as innovation environment and technological innovation, as crucial to innovation capability [6]. Recent studies have applied diverse methods: Zhang Jixin (2022) used the entropy value and catastrophe progression method [7]; Zhang (2022) used the effectiveness coefficient method in Shandong[8]; Guo Yanqing (2022) applied factor analysis to 44 zones in central China [9]; Ren Fei (2020) used DEMATEL-ANP for 25 enterprises in Zhengzhou [10]; Ding Qingqing (2019) applied the DEA Malmquist index to 54 zones [11]; and Su Chenqing (2018) used the catastrophe progression method for 14 zones in the Yangtze River urban cluster [12].

However, existing research on high-tech zones faces several problems: firstly, there is no consensus on the evaluation index system for high-tech zones, and relatively few studies focus on unique indicators; secondly, most existing evaluation methods rely on linear models, which makes it challenging to analyze empirical objects with nonlinear relationships effectively. Additionally, there is a lack of comprehensive spatial variation analysis of the innovation capability of high-tech zones, which is crucial for identifying regional differences and formulating targeted policies [13].

In summary, this study aims to construct an appropriate innovation capability evaluation index system and apply the entropy weight method and the catastrophe series method to evaluate the innovation capability of the country's national high-tech zones to ensure the accuracy of the measurement and priority of the innovation capability of high-tech zones. The research conclusions of this paper can not only identify the spatial differences in the innovation capability of high-tech zones but also provide valuable insights for policymakers and stakeholders to promote the sustainable development and competitive advantage of high-tech industries [14, 15].

Materials and Methods

This study constructs a comprehensive and multidimensional indicator system to assess the innovation capability of China's national high-tech zones. The system is based on scientificity, comprehensiveness, operability, systematicity, and objectivity. It incorporates the framework of cybernetic theory and information theory, referencing existing research results domestically and internationally and considering the actual situation of China's high-tech zones. The secondary indicators include innovation input, innovation output, innovation environment, and organizational operation.

By applying the Catastrophe Progression Method (CPM) and the Entropy Weight Method (EWM), the study first determines the indicators for the catastrophe evaluation system. Then, the weights of the indicators are calculated using the EWM. Finally, it comprehensively evaluates the innovation capability using a normalization formula. Additionally, the study utilizes Geographic Information System (GIS) tools for data analysis, visually representing the spatial variation in innovation capability among the high-tech zones and revealing the strengths and weaknesses across different regions.

Construction of the Index System

A comprehensive and multidimensional indicator system is constructed to assess the innovation capacity of China's national high-tech zones. The system is based on scientificity, comprehensiveness, operability, systematicity, and objectivity. It is designed to address the framework of cybernetic theory and information theory, as well as existing research results at home and abroad, in light of the actual situation of China's hi-tech zones. When establishing the evaluation indicator system for the innovation capability of high-tech zones, the selection of innovation input, innovation output, innovation environment, and organizational operation as the four secondary indicators are based on the following reasons:

Theoretical Foundation

According to cybernetic information theory, regional innovation systems can be seen as dynamic and complex systems. This theory emphasizes the interaction of the system's information, material, and energy flows. Inputs, outputs, environment, and operation in the innovation system are crucial factors for ensuring its stability and sustained innovation capability. A comprehensive evaluation of these four aspects can fully reflect the innovation capability of high-tech zones.

Characteristics of High-Tech Zone Innovation Systems

High-tech zones concentrate many technological resources and high-tech enterprises, serving as vital carriers for technological innovation and industrial upgrading. The characteristics of their innovation systems necessitate a multi-dimensional comprehensive evaluation to ensure coordinated development across various aspects and maximize innovation efficiency. Innovation activities in high-tech zones require substantial resource input, efficient organizational operations, and a favorable external environment. These four aspects cover these critical factors comprehensively.

Evaluation Objectives

The core objective of evaluating the innovation capability of high-tech zones is to promote comprehensive enhancement of their innovation capabilities, optimize the allocation of innovation resources, and drive the transformation of scientific and technological achievements. Therefore, it is essential to detail the evaluation indicators from various dimensions to ensure a comprehensive and scientific reflection of the innovation capability level. A multi-perspective evaluation can more accurately identify the strengths and weaknesses of high-tech zones in the innovation process, enabling the development of targeted improvement strategies.

Reference to Existing Successful Experiences

Numerous studies and practical experiences indicate that evaluating innovation systems must comprehensively consider input, output, environment, and operation. For example, research by Fu and Liu (2020) demonstrates that the eastern region excels in innovation input and output, while Hu and Shi (2023) point out that the central region shows significant innovation potential with policy support and resource investment. These findings provide essential references for constructing a scientific and rational evaluation system, ensuring the selected indicators' practical significance and scientific rigor.

The reason for selecting these four secondary indicators is their comprehensive coverage of the critical elements of high-tech zone innovation capability. This allows for a scientific and systematic reflection of the innovation capability and its improvement paths. Such a multi-dimensional evaluation system can reveal the current status of innovation capability and provide directional guidance for future development, ensuring that high-tech zones maintain their innovative vitality in a competitive environment. Through the design of this indicator system, strong decision-making support can be provided to policymakers and managers, promoting the high-quality development of high-tech zones. The indicator system consists of four first-level indicators: innovation input, innovation output, organizational operation, and environmental support. The first-level indicators are further divided into eight second-level indicators and 28 third-level indicators to ensure the accuracy and comprehensiveness of the evaluation. As shown in Table 1.

Evaluation objectives	***Level 1 Indicators***	***Level 2 Indicators***	***Level 3 Indicators***	***Indicator Description***	***Unit***
High-tech Zone Innovation Capability	Innovation Input Capability	Intellectual input	R&D personnel	Number of R&D Personnel	Persons
			Scientific and technological activity personnel	Number of technologically active personnel	Persons
			R&D Personnel Full-time Equivalent	Full-time equivalent of R&D personnel	Persons/year
			The density of middle and senior title personnel	Number of middle and senior title personnel/number of employees at the end of the year	%
		Financial input	Funds for scientific and technological activities	Internal Expenditure on S&T Activities	Thousands of Yuan
			R&D Expend	Internal Expenditure on R&D	Thousands of Yuan
			The intensity of Expenditure on Scientific and Technological Activities	Internal Expenditure on S&T Activities/Total Income	%
			R&D Expenditure Intensity	Internal Expenditure of R&D Funds/ Total Income	%
	Innovation Output Capability	Scale of output	The scale of technology income	Amount of technology income	Thousands of Yuan
			Annual Increase of High-tech Enterprises	Growth of high-tech enterprises	per unit
			The scale of export earnings	Export earnings amount	Thousands of Yuan
		Output efficiency	Profitability	Enterprise net profit ratio	%
			Return rate of R&D investment	Technology Income/R&D Expenditure	%
			Technology Income Creation per Unit of R&D Personnel	Technology Income/R&D Personnel	Thousand Yuan/person
	Environmental Support Capability	Hard environment	Enterprise size	Total revenue/number of enterprises	Thousand Yuan/Each
			Employee Size	Number of employees at the end of the year	persons
			Capital Operation Status	Year-end assets/year-end liabilities	%
			Total number of technology business incubators	Number of incubators	per unit
		Soft environment	Policy Support	Measured according to the policy introduction of each high-tech zone	Level
			Institutional Mechanism Innovation	Measured according to the operation and management of each high-tech zone	Level
			Basic Supporting Environment	Measured by the infrastructure of each high-tech zone	Level
			Financial Support	Measured by financial services of each hi-tech zone	Level

	Organization Operation Capability	Innovation main body capability	The scale of high-tech enterprises	Number of high-tech enterprises	per unit
			Number of Universities and R&D Institutions	Number of universities and R&D institutions	per unit
			Number of Innovation Service Organizations	Number of Innovation Service Organizations	per unit
		Organization and coordination capability	Number of National University Science Parks	Number of National University Science Parks	per unit
			Number of Innovative Industrial Clusters	Number of Innovative Industrial Clusters	per unit
			Number of Productivity Promotion Centers	Number of Productivity Promotion Centers	per unit

Table 1: Evaluation Indicators System of Innovation Capability of High-tech Zone.

Evaluation of Innovation Capability: Entropy Weight Method and Catastrophe Progression Method

The Catastrophe Progression Method (CPM), founded by Rene Thom in 1972, is based on mutation theory and uses topological dynamics and singularity theory for state evaluation and change trend analysis. Known as a "revolution in mathematics," CPM is applied to multi-criteria decision problems by decomposing the evaluation objective into multiple levels, using a mutation fuzzy membership function, and normalizing the data to produce a single parameter for comprehensive evaluation results.

Step 1: Determine the index system for mutation evaluation

When determining mutation evaluation indexes, the process begins with the overall index and decomposes it step by step into two or more indexes to better represent the evaluation object. Typically, the mutation system contains no more than four control variables, so each level of decomposition does not exceed four indicators. This hierarchical breakdown ensures that each indicator can be effectively evaluated, as shown in Table 3.

Step 2: Determine the weights of the indicators --EWM

In the catastrophe progression method, indicator weights are not used in calculations but are needed to establish the mutation level indicator system. Weights determine the relative importance of each indicator, with higher weights ranked first. This study uses the entropy weight method to minimize subjectivity in index sorting, an objective approach to weight assignment. Before calculating weights, the original data must be standardized. Y_{ij} Indicates indicate the j sample of the i indicator. All of them are standardized data.

Firstly, the weight of the j sample of the i indicator is $p_{ij} = y_{ij} \Big/ \sum_{j=1}^{n} y_{ij} \quad (i = 1, 2, \cdots, m; j = 1, 2, \cdots, n)$;

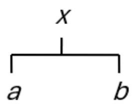
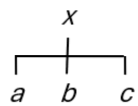
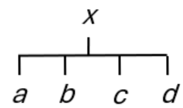
Secondly, the entropy value of the i indicator $e_i = -1 \Big/ \ln n \sum_{j=1}^{n} (p_{ij} \ln p_{ij})$;

Finally, according to the utility value of the indicator $d_i = 1 - e_i$, the weight of the i indicator is obtained $\omega_i = d_i \Big/ \sum_{i=1}^{m} d_i$.

If the evaluation index system is a multi-layer structure, then according to the additivity of entropy, the utility value of the indicators of the lower structure can be summed up to get the utility value of each type of indicator in the upper layer D_k. Thus, the weight of the corresponding upper indicator can be obtained $W_k = D_k \Big/ \sum_{k=1}^{s} D_k \quad (k = 1, 2, \cdots, s)$.

Step 3: Determine the type of mutation

In general, the mutation system will have no more than four control variables, so there will be at most seven forms of mutation: cusp mutation, dovetail mutation, butterfly mutation, fold mutation, hyperbolic umbilical point mutation, elliptical umbilical point mutation, parabolic umbilical point mutation. Only three types are generally expected when using the catastrophe progression method, as shown in Table 2.

Type	***Spike mutation system***	***Swallowtail mutation system***	***Butterfly mutation system***
System model	$f(x)=x^4+ax^2+bx$	$f(x)=\frac{1}{5}x^5+\frac{1}{3}ax^3+\frac{1}{2}bx^2+cx$	$f(x)=\frac{1}{6}x^6+\frac{1}{4}ax^4+\frac{1}{3}bx^3+\frac{1}{2}cx^2+dx$
Control variable	*a*, *b*	*a*, *b*, *c*	*a*, *b*, *c*, *d*
Divergence point equation	a=-6x^2, b=8x^3	a=-6x^2, b=8x^3, c=-3x^4	a=-10x^2, b=20x^3, c=-15x^4, d=5x^5
Normalization formula	$x_a=\sqrt{a}, x_b=\sqrt[3]{b}$	$x_a=\sqrt{a}, x_b=\sqrt[3]{b}, x_c=\sqrt[4]{c}$	$x_a=\sqrt{a}, x_b=\sqrt[3]{b}, x_c=\sqrt[4]{c}, x_d=\sqrt[5]{d}$
Diagram			

Remark: Using the diagrams, we can determine the type of each mutation, i.e., “one change two” for the spike mutation, “one change three” for the swallowtail mutation, and “one change four” for the butterfly mutation.

Table 2: Mutation level system model and diagrams.

Table 2 models the potential function of a state variable x of the mutation system. The coefficients of x, a, b, c, and d denote the control variables of the state variable. The state variable and the control variable of the potential function of the system are two opposing aspects. If an indicator is decomposed into two sub-indicators, the system can be regarded as a hump mutation system; if an indicator is decomposed into three sub-indicators, the system can be considered as a dovetail mutation system; if an indicator is decomposed into four sub-indicators, the system can be regarded as a butterfly mutation system.

Step 4: Derive the normalization formula from the divergence equation

According to the mutation theory, divergence point set equations cannot be directly analyzed and evaluated because the range of values of the state and control variables is not uniform, nor can it be consistent with the range of values of fuzzy affiliation numbers 0 to 1. Thus, limiting the range of state and control variable values in each mutation model to 0 to 1, i.e., normalization is necessary. The divergence point equations are obtained by taking the potential function’s first-order derivatives, and the mutation system’s set of singularities is obtained by taking the second-order derivatives $f''(x)=0$. By $f'(x)=0$ $f''(x)=0$ eliminating x, the divergence point set equation of the mutation system is obtained, i.e., the equilibrium surface formed by the set of all critical points. The divergence point set equation indicates that the system mutates when each control variable satisfies this equation. The normalization formula can be derived by decomposing the form of the divergence point set equation. The normalization formula indicates $x_i(i=a,b,c,d)$ the number of mutation levels corresponding to the control variable i. The normalization formula is a multidimensional fuzzy affiliation function in the mutation-level system.

Step 5: Comprehensive evaluation using the normalization formula

The normalization formula transforms the different qualitative states of each control variable in the system into the same qualitative state, i.e., the control variables are unified into the qualitative state expressed by the state variables. Control variables in the use of the normalization formula to calculate the value of each state variable, if there is no apparent correlation between the control variables of the system, the object of the control scalar for the “non-complementary,” following the principle of “taking the smallest out of the big," let $\min\{x_a, x_b, x_c, x_d\}$ to be the x value of the entire system; If there is evident interrelatedness between the control variables of the system, then the control variables of the object are called "complementary," and let $\frac{1}{m}\sum_{i=1}^{m} x_i$ to be the x value of the entire system; which is the only way to meet the requirement of qualitative change of the divergence equation. Finally, the evaluation objects are ranked according to their total evaluation index scores regarding their advantages and disadvantages.

Data Analysis

The data analysis involves descriptive statistics to provide an overview of the data, followed by the application of EWM and CPM to evaluate the innovation capabilities of high-tech zones. The spatial variation of innovation capabilities is then analyzed using geographic information system (GIS) tools to visualize the regional disparities and identify areas for improvement.

Results and Discussion

Determination of samples and data

The research sample of this dissertation is 169 national high-tech zones in China. Since the data come from many sources and statistical yearbooks, as of April 2024, taking into account the release of all the data of all national government departments, only the data for 2021 is complete; the data for 2022 is missing, and some governmental units have not yet released the data for 2022, and the data for 2023 is missing even more. Therefore, this research takes the data related to the 169 national hi-tech zones for 2021 as the object of study. The data involved herein are all derived from the Annual Statistical Survey of National Hi-Tech Zones, which was approved by the National Bureau of Statistics and organized by the Torch Center (the most recent data in this report is the year's data for 2021.

Quantitative indicators in the evaluation index of innovation capability of high-tech zones R&D personnel, scientific and technological activity personnel, R&D personnel full-time equivalent, the density of personnel with middle and senior titles, scientific and technological activity funding, R&D funding, expenditure intensity of scientific and technological activity funding, expenditure intensity of R&D funding, the scale of technological income, the annual increment of high-tech enterprises, the scale of foreign exchange earnings from exports, profitability, the rate of return on investment in R&D funding, the number of units of R&D personnel The data for 22 indicators were obtained from China Torch Statistical Yearbook (2021-2022), China Science and Technology Statistical Yearbook (2022), and China High-Tech Industry Statistical Yearbook (2022). and China High-Tech Industry Statistical Yearbook 2022; data for universities and R&D organizations from China Urban Statistical Yearbook 2022; and data for innovation service organizations from National High-Tech Zone Comprehensive Development and Data Analysis Report 2022. In addition, the four qualitative indicators, including policy support, institutional mechanism innovation, essential supporting environment, and financial support, are obtained according to the binary relative comparison method, i.e., based on the square table of the binary relative comparison indicators, 15 experts compare the scores based on their experience and subjective judgment and then sum up the scores of the indicators.

This research's data is from 2021, during or just before the COVID-19 pandemic. The pandemic has profoundly impacted the global economy and social activities, which may have also affected the innovation capabilities of high-tech zones. Therefore, the 2021 data might reflect the impact of the pandemic on innovation input, output, environment, and organizational operations. When interpreting the research results, this specific context should be considered to understand the innovation capabilities and trends in high-tech zones comprehensively.

Calculation of indicator weights

After the evaluation indicators are determined, the evaluator can determine the importance of each indicator based on statistical data (quantitative) and experience (qualitative). Among the indicators of the same attribute and level, those with relatively large importance are placed in the front, and those with relatively small importance are placed in the back. To overcome the subjective factors in the ordering of the indicators at each level, this research selects the entropy weight method to calculate the size of the weight of each indicator to rank it, which is a relatively accurate and objective assignment method, thus ensuring the consistency of the order of each indicator with the corresponding degree of importance. The process of determining weights by entropy weight method is as follows:

Data standardization

This research adopts deviation standardization to standardize the original data. After the deviation standardization, the numerical range of the observed values of various variables will be between [0, 1], and the standardized data are pure quantities without units. Discrepancy standardization is the simplest way to eliminate the effects of the effect of the scale (unit) and the impact of the variance size factor. The specific method is shown below.

Suppose k indicators X_1, X_2,...X_k are given, where Xi = {x_1, x_2,...x_n}. Assume that the standardized data for each indicator refers to Y_1, Y_2,..., Y_k, then

$$Y_{ij} = \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (1)$$

Calculation of information entropy of indicators

According to the formula of information entropy $e_i = -1 \Big/ \ln n \sum_{j=1}^{n} (p_{ij} \ln p_{ij})$, the information entropy of 28 indicators can be calculated, as shown in Table 5.

Determination of indicator weights

According to the utility value of the indicator $d_i = 1 - e_i$, its weight is obtained $\omega_i = d_i \Big/ \sum_{i=1}^{m} d_i$. The weights of 28 indicators are shown in Table 3.

The data was calculated using IBM SPSS 27 software to arrive at the following conclusions.

Indicators	***R&D personnel***	***Scientific and technological activity personnel***	***R&D Personnel Full-time Equivalent***	***Density of middle and senior title personnel***	***Funds for scientific and technological activities***	***R&D Expend***	***Intensity of Expenditure on Scientific and Technological Activities***
Weights	0.0462	0.0569	0.0474	0.0048	0.0619	0.0540	0.0062
Indicators	R&D Expenditure Intensity	The scale of technology income	Annual Increase of High-tech Enterprises	The scale of export earnings	Profitability	Return rate of R&D investment	Technology Income Creation per Unit of R&D Personnel
Weights	0.0089	0.0927	0.0430	0.0481	0.0068	0.0387	0.0367
Indicators	Enterprise size	Employee Size	Capital Operation Status	Total number of technology business incubators	Policy Support	Institutional Mechanism Innovation	Basic Supporting Environment
Weights	0.0127	0.0355	0.0085	0.0354	0.0430	0.0619	0.0230
Indicators	Financial Support	The scale of high-tech enterprises	Number of Universities and R&D Institutions	Number of Innovation Service Organizations	Number of National University Science Parks	Number of Innovative Industrial Clusters	Number of Productivity Promotion Centers
Weights	0.0089	0.0494	0.0201	0.0354	0.0607	0.0198	0.0335

Table 3: Weights for 28 indicators.

Determination of mutation types

After determining the indicators' weights, this research reorders them according to their weight size. It determines the types of mutation system layers according to the mutation level system model and diagram in Table 2. The final innovation capability evaluation indicator system and mutation types are shown in Table 4.

Evaluation objective	***Level 1 indicator***	***Mutation types***	***Level 2 indicator***	***Mutation types***	***Marker***	***Level 3 indicator***
Innovation capability of high-tech zones (Butterfly mutation system)	Innovation Output Capability A_1	Spike mutation system	The scale of output B_1	Swallowtail mutation system	C_1	Annual Increase of High-tech Enterprises
					C_2	The scale of technology income
					C_3	The scale of export earnings
			Output efficiency B_2	Swallowtail mutation system	C_4	Return rate of R&D investment
					C_5	Technology Income Creation per Unit of R&D Personnel
					C_6	Profitability
	Organization Operation Capability A_2	Spike mutation system	Organization and coordination capability B_3	Swallowtail mutation system	C_7	Number of National University Science Parks
					C_8	Number of Productivity Promotion Centers
					C_9	Number of Innovative Industrial Clusters
			Innovation main body capability B_4	Swallowtail mutation system	C_{10}	The scale of high-tech enterprises
					C_{11}	Number of Innovation Service Organizations
					C_{12}	Number of Universities and R&D Institutions
	Innovation Input Capability A_3	Spike mutation system	Intellectual input B_5	Butterfly mutation system	C_{13}	Scientific and technological activity personnel
					C_{14}	R&D Personnel Full-time Equivalent
					C_{15}	R&D personnel
					C_{16}	Density of middle and senior title personnel
			Financial input B_6	Butterfly mutation system	C_{17}	Funds for scientific and technological activities
					C_{18}	R&D Expend
					C_{19}	R&D Expenditure Intensity
					C_{20}	Intensity of Expenditure on Scientific and Technological Activities

	Environmental Support Capability A_4	Spike mutation system	Hard environment B_7	Butterfly mutation system	C_{21}	Total number of technology business incubators
					C_{22}	Employee Size
					C_{23}	Capital Operation Status
					C_{24}	Enterprise size
			Soft environment B_8	Butterfly mutation system	C_{25}	Financial Support
					C_{26}	Basic Supporting Environment
					C_{27}	Policy Support
					C_{28}	Institutional Mechanism Innovation

Table 4: Innovation capability evaluation index system and mutation types.

According to the basic principle of the Catastrophe Progression Method, the type of mutation system for each level of the evaluation index system is given in order from bottom to top, and the type of system mutation for each level is shown in Table 4.

Tertiary indicator system

Output scale belongs to swallow-tail mutation and the control variables are marked as C1, C2, and C3; output efficiency belongs to swallow-tail mutation, and the control variables are marked as C4, C5, and C6; organizational coordination capability belongs to swallow-tail mutation and the control variables are marked as C7, C8, and C9; innovation primary body capability belongs to swallow-tail mutation and the control scalars are marked as C10, C11, and C12; and intellectual input belongs to butterfly mutation, and the control scalars are markers C13, C14, C15, C16; financial input belongs to butterfly mutation and the control variables are labeled as C17, C18, C19, C20; complex environment belongs to butterfly mutation and the control scalars are labeled as C21, C22, C23, C24; and soft environment belongs to butterfly mutation and the control variables are labeled as C25, C26, C27, C28.

Second-level indicator system

Two secondary indicators are decomposed under the first-level indicators of innovation output capability, organizational operation capability, innovation input capability, and environmental support capability, all of which belong to cusp mutation, and the control variables are marked as B1, B2, B3, B4, B5, B6, B7, and B8, respectively.

First-level indicator system

The total innovation capability indicator of the high-tech zone is decomposed into four indicators: innovation output capability, organizational operation capability, innovation input capability, and environmental support capability. These indicators belong to butterfly mutation, and the control variables are marked as A1, A2, A3, and A4.

Empirical calculation results

According to the high-tech zone innovation ability evaluation index system and mutation type in Table 4, based on the statistical data of 169 national high-tech zones in 2021, the normalization formula to gradually synthesize from the bottom to the top until the evaluation results of the highest level of total indexes are derived, and MATLAB 7.0 software is used to program and calculate to get the evaluation results of 169 national high-tech zones' innovation ability and the ranking of innovation ability. as shown in Table 5.

Name of High-Tech Zone	*Innovation Input Capability*	*Innovation Output Capability*	*Environmental Support Capability*	*Organization Operation Capability*	*Innovation capability*	*Ranking*
Beijing Zhonggu-ancun	0.9743	0.8326	0.8671	0.9867	0.9725	1
Shanghai Zhang-jiang	0.9049	0.8439	0.8401	0.8096	0.9531	2
Shenzhen	0.9244	0.8181	0.8032	0.7545	0.9472	3
Wuhan	0.8704	0.7761	0.8222	0.8823	0.9449	4
Hangzhou	0.8484	0.7868	0.8064	0.8186	0.9382	5
Xi'an	0.8587	0.7630	0.8157	0.8147	0.9377	6
Guangzhou	0.8519	0.7538	0.7877	0.8576	0.9362	7
Chengdu	0.8354	0.7807	0.8017	0.8266	0.9359	8
Nanjing	0.8571	0.7315	0.7717	0.8655	0.9339	9
Hefei	0.8220	0.7433	0.7722	0.7752	0.9251	10
Suzhou	0.7782	0.7586	0.7915	0.8053	0.9238	11
Suzhou Industrial Park	0.8529	0.7043	0.7697	0.6945	0.9199	12
Changsha	0.7876	0.7256	0.7467	0.8080	0.9185	13
Tianjin Binhai	0.7621	0.7289	0.7503	0.8579	0.9184	14
Jinan	0.8107	0.6805	0.7705	0.7926	0.9179	15
Chongqing	0.7532	0.7183	0.7671	0.8649	0.9177	16
Ningbo	0.7846	0.7333	0.7671	0.7430	0.9164	17
Qingdao	0.7844	0.7054	0.7574	0.8010	0.9163	18
Foshan	0.7894	0.6994	0.7626	0.7580	0.9142	19
Xiamen	0.7850	0.6814	0.7310	0.7646	0.9096	20
Shenyang	0.7675	0.6701	0.7343	0.7992	0.9083	21
Dalian	0.7434	0.7034	0.7373	0.7778	0.9073	22
Fuzhou	0.7644	0.6828	0.7371	0.7389	0.9057	23
Changzhou	0.7405	0.6764	0.7618	0.7740	0.9057	24
Zhengzhou	0.7531	0.6652	0.7073	0.7943	0.9032	25
Huizhou	0.7438	0.7038	0.7543	0.6900	0.9031	26
Wuxi	0.7584	0.6449	0.7483	0.7579	0.9027	27
Nanchang	0.7645	0.6266	0.7549	0.7672	0.9027	28
Dongguan	0.7280	0.7019	0.7520	0.7099	0.9017	29
Shijiazhuang	0.7576	0.6914	0.6951	0.7292	0.9016	30
Zhuhai	0.7793	0.6345	0.7445	0.6506	0.8971	31
Xiangyang	0.7298	0.6581	0.7350	0.6990	0.8952	32
Guiyang	0.7179	0.6603	0.7122	0.7353	0.8943	33
Nanning	0.7147	0.6891	0.6996	0.6949	0.8933	34
Nantong	0.7059	0.6775	0.7461	0.6746	0.8930	35
Zibo	0.7369	0.6339	0.7414	0.6739	0.8924	36
Xuzhou	0.7168	0.6016	0.7441	0.7635	0.8918	37
Weifang	0.7436	0.6225	0.7597	0.6435	0.8913	38
Luoyang	0.7603	0.5544	0.7352	0.7337	0.8899	39

Lianyungang	0.7522	0.6158	0.7392	0.6306	0.8893	40
Yantai	0.6996	0.6633	0.7002	0.7101	0.8893	41
Shanghai Zizhu	0.7079	0.7268	0.6864	0.6100	0.8891	42
Harbin	0.6937	0.6240	0.6927	0.7881	0.8883	43
Zhongshan	0.6815	0.6278	0.7202	0.7554	0.8871	44
Yangzhou	0.7135	0.6148	0.7084	0.7045	0.8862	45
Changchun	0.6927	0.6151	0.7038	0.7501	0.8857	46
Kunshan	0.7336	0.6329	0.7306	0.5986	0.8855	47
Xiangtan	0.6961	0.6517	0.6949	0.6755	0.8847	48
Wenzhou	0.7094	0.6396	0.7109	0.6380	0.8840	49
Ma'anshan Cihu	0.7053	0.6205	0.7109	0.6605	0.8828	50
Weihai	0.6920	0.5970	0.7365	0.6969	0.8826	51
Lanzhou	0.6588	0.6416	0.6886	0.7556	0.8826	52
Taiyuan	0.6932	0.6149	0.6616	0.7541	0.8825	53
Zhuzhou	0.7474	0.5538	0.7387	0.6478	0.8824	54
Wuhu	0.7193	0.5522	0.7267	0.7039	0.8810	55
Shaoxing	0.7096	0.6537	0.6912	0.5934	0.8807	56
Anshan	0.7145	0.6164	0.6770	0.6519	0.8803	57
Jilin	0.6993	0.5538	0.7078	0.7589	0.8803	58
Jiaxing	0.6843	0.6414	0.7142	0.6302	0.8802	59
Baotou	0.7225	0.5816	0.7051	0.6521	0.8798	60
Baoding	0.7479	0.5578	0.6965	0.6438	0.8793	61
Changshu	0.7015	0.5588	0.7179	0.7133	0.8791	62
Kunming	0.6691	0.5899	0.7044	0.7445	0.8789	63
Xianyang	0.6774	0.6248	0.6947	0.6678	0.8783	64
Wujin	0.7227	0.6026	0.7070	0.5896	0.8779	65
Mianyang	0.7134	0.5307	0.7259	0.7060	0.8775	66
Quanzhou	0.6768	0.6119	0.6773	0.6833	0.8764	67
Xinjiang Corps	0.6525	0.6024	0.7187	0.7035	0.8763	68
Jiangyin	0.7362	0.5857	0.7179	0.5555	0.8761	69
Jiangmen	0.7060	0.5908	0.6954	0.6285	0.8760	70
Nanyang	0.7010	0.6142	0.6710	0.6074	0.8744	71
Jining	0.6741	0.5777	0.7252	0.6601	0.8742	72
Guilin	0.6651	0.6407	0.6669	0.6265	0.8730	73
Xiaoshan Linjiang	0.7328	0.6013	0.7147	0.4997	0.8725	74
ZhenJiang	0.6919	0.5632	0.6944	0.6490	0.8719	75
Baoji	0.7198	0.5176	0.6910	0.6731	0.8717	76
Yancheng	0.6715	0.5817	0.6665	0.6803	0.8709	77
Jingmen	0.6925	0.5822	0.6981	0.5848	0.8699	78
Taizhou	0.6744	0.5640	0.6843	0.6583	0.8692	79
Tangshan	0.6701	0.6352	0.6394	0.5947	0.8684	80
Ankang	0.6208	0.6562	0.6658	0.6334	0.8682	81
Zhaoqing	0.6798	0.5543	0.6914	0.6350	0.8678	82

Urumqi	0.6030	0.6811	0.6816	0.6051	0.8673	83
Xinxiang	0.6827	0.5772	0.6932	0.5839	0.8673	84
Jiaozuo	0.6711	0.5874	0.6778	0.6075	0.8673	85
Linyi	0.6806	0.5804	0.6857	0.5638	0.8652	86
Daqing	0.6021	0.6251	0.6689	0.6785	0.8652	87
Anyang	0.6828	0.5476	0.6674	0.6258	0.8647	88
Shantou	0.6704	0.5944	0.6649	0.5715	0.8642	89
Haikou	0.6366	0.6762	0.6634	0.5207	0.8639	90
Huangshi Dayehu	0.6790	0.5431	0.6514	0.6500	0.8639	91
Liuzhou	0.6875	0.5054	0.6800	0.6589	0.8634	92
Luzhou	0.6462	0.5828	0.6908	0.5921	0.8628	93
Weinan	0.6544	0.5496	0.6682	0.6404	0.8617	94
Erdos	0.6569	0.6106	0.6782	0.5268	0.8615	95
Fuzhou	0.6754	0.5799	0.6787	0.5342	0.8614	96
Yingkou	0.6613	0.5617	0.6684	0.5931	0.8608	97
Hohhot	0.6024	0.5932	0.7058	0.6146	0.8600	98
Yichang	0.7229	0.6205	0.7373	0.3493	0.8600	99
Beihai	0.6068	0.6567	0.6646	0.5542	0.8599	100
Jingdezhen	0.6862	0.5634	0.6659	0.5318	0.8597	101
Xianning	0.6766	0.5893	0.6535	0.5202	0.8594	102
Huaian	0.6794	0.4998	0.6889	0.6180	0.8593	103
Hengyang	0.6757	0.6192	0.6352	0.4928	0.8588	104
Pingdingshan	0.6483	0.5744	0.6658	0.5679	0.8582	105
Changchun Jingyue	0.6579	0.6412	0.6193	0.5044	0.8581	106
Yulin	0.6131	0.6097	0.6551	0.5951	0.8580	107
Ganzhou	0.6452	0.5697	0.6722	0.5671	0.8576	108
Suizhou	0.6341	0.5851	0.6840	0.5525	0.8576	109
Bengbu	0.6705	0.5473	0.6756	0.5470	0.8574	110
Yangling	0.5944	0.6171	0.6221	0.6420	0.8564	111
Xinyu	0.6560	0.5538	0.7003	0.5242	0.8562	112
Deyang	0.6448	0.5418	0.6504	0.6168	0.8560	113
Qingyuan	0.6509	0.5672	0.6562	0.5546	0.8558	114
Xiaogan	0.6698	0.5791	0.6315	0.5270	0.8558	115
Qinghai	0.6161	0.5638	0.6308	0.6620	0.8558	116
Changzhi	0.6770	0.4867	0.6673	0.6195	0.8555	117
Zaozhuang	0.6372	0.6065	0.5822	0.5662	0.8527	118
Bishan	0.6974	0.5582	0.5860	0.5181	0.8525	119
Chengde	0.6161	0.5788	0.6164	0.6069	0.8523	120
Changde	0.6443	0.5453	0.6674	0.5429	0.8521	121
Tongling Shizis-han	0.6332	0.5329	0.6648	0.5699	0.8508	122
Laiwu	0.6800	0.5022	0.6841	0.5104	0.8508	123

Jinzhou	0.6300	0.5059	0.6623	0.6179	0.8502	124
Jingzhou	0.6192	0.5591	0.6318	0.5835	0.8500	125
Suqian	0.6741	0.5712	0.6178	0.4742	0.8497	126
Yuxi	0.6257	0.5314	0.7150	0.5144	0.8490	127
Zigong	0.6493	0.5074	0.6590	0.5579	0.8486	128
Yongchuan	0.6518	0.5718	0.6374	0.4785	0.8485	129
Dezhou	0.6198	0.5635	0.6295	0.5562	0.8483	130
Yanjiao	0.6424	0.5456	0.6135	0.5436	0.8472	131
Tai’an	0.7054	0.6086	0.7110	0.2945	0.8472	132
Qiqihar	0.6227	0.5559	0.6361	0.5238	0.8458	133
Ji’an	0.6743	0.5536	0.6217	0.4481	0.8455	134
Changji	0.5895	0.5424	0.6235	0.6197	0.8452	135
Moganshan	0.6909	0.6181	0.7061	0.2800	0.8437	136
Yichun Fengc-heng	0.6332	0.5697	0.6259	0.4625	0.8428	137
Fuxin	0.6488	0.5260	0.6345	0.4784	0.8420	138
Huanggang	0.6627	0.6286	0.6650	0.3145	0.8418	139
Yinchuan	0.6360	0.5520	0.5943	0.4993	0.8415	140
Panzhihua	0.6150	0.5378	0.6391	0.5077	0.8412	141
Chenzhou	0.6268	0.5672	0.5984	0.4400	0.8369	142
Xiantao	0.6261	0.4911	0.6166	0.5263	0.8365	143
Anshun	0.6612	0.4917	0.5720	0.5044	0.8361	144
Zhanjiang	0.6438	0.6211	0.6875	0.2740	0.8345	145
Tonghua	0.6363	0.4304	0.6383	0.5371	0.8324	146
Baiyin	0.6257	0.4287	0.6418	0.5471	0.8316	147
Benxi	0.6351	0.4969	0.5521	0.5086	0.8311	148
Sanming	0.6139	0.4946	0.5939	0.4823	0.8291	149
Longyan	0.6299	0.6201	0.6395	0.2743	0.8282	150
Jiujiang Gongqing City	0.6207	0.6217	0.6593	0.2557	0.8259	151
Liaoyang	0.5885	0.4602	0.6111	0.5217	0.8253	152
Chuxiong	0.6281	0.4748	0.5751	0.4510	0.8241	153
Leshan	0.6346	0.5360	0.6693	0.2856	0.8229	154
Yuancheng	0.6560	0.5327	0.6554	0.2694	0.8224	155
Yingtan	0.6585	0.5338	0.6891	0.2391	0.8212	156
Yiyang	0.6886	0.6007	0.6481	0.1813	0.8204	157
Maoming	0.6423	0.5377	0.6681	0.2553	0.8199	158
Neijiang	0.6377	0.5498	0.6564	0.2502	0.8190	159
Shizuishan	0.6480	0.5117	0.6467	0.2459	0.8142	160
Quzhou	0.6729	0.5521	0.6580	0.1847	0.8136	161
Zhangzhou	0.5822	0.5947	0.6544	0.2316	0.8124	162
Huaihua	0.6202	0.5392	0.6221	0.2494	0.8118	163
Yanji	0.4804	0.5923	0.5090	0.3540	0.7975	164

Qianjiang	0.6281	0.5399	0.5889	0.1734	0.7968	165
Putian	0.6097	0.5449	0.6265	0.1651	0.7962	166
Huanghe Delta	0.3155	0.5870	0.6200	0.5850	0.7962	167
Huainan	0.6215	0.5319	0.5692	0.1825	0.7947	168
Rongchang	0.6542	0.5395	0.6357	0.0832	0.7810	169

Table 5: Evaluation results of innovation Capability ranking of 169 national high-tech zones.

This research comprehensively evaluates the innovation capability of 169 national high-tech zones in China, ranking them based on four primary indicators: innovation input, innovation output, environmental support, and organizational operation. The results reveal significant disparities in innovation capabilities across different regions, providing scientific evidence for policy formulation and resource allocation.

Advantages of the Eastern Coastal Regions

Beijing Zhongguancun (0.9725), Shanghai Zhangjiang (0.9531), and Shenzhen High-Tech Zone (0.9472) rank at the top in terms of innovation capability. These high-tech zones excel in all four aspects: innovation input, innovation output, environmental support, and organizational operation. Zhongguancun stands out in innovation input (0.9743) and organizational operation (0.9867), Zhangjiang excels in innovation output (0.8439), and Shenzhen shows strong performance in innovation input (0.9244). Their advantages stem from a robust economic foundation, abundant research resources, and comprehensive policy support. The concentration of high-level research personnel and enterprises fosters a highly integrated innovation ecosystem, promoting rapid transformation and application of scientific and technological achievements.

Innovation Potential in the Central Regions

High-tech zones in central regions such as Wuhan (0.9449) and Hangzhou (0.9382) demonstrate considerable innovation potential. Wuhan performs exceptionally in innovation input (0.8704) and organizational operation (0.8823), benefiting from its rich academic and research resources. Hangzhou excels in innovation output (0.7868) and organizational operation (0.8186), reflecting its favorable innovation environment and strong industrial base. The central regions are undergoing industrial restructuring and upgrading, and increased policy support and resource investment will further enhance their innovation capabilities.

Challenges in the Less Developed Western and Central Regions

Less developed western and central regions, such as Xinjiang High-Tech Zone (ranked 83, 0.8673) and Qinghai High-Tech Zone (ranked 116, 0.8558), face significant challenges in improving their innovation capabilities. These areas are relatively weak in innovation input and environmental support; Xinjiang struggles with innovation input (0.6030) and organizational operation (0.6051), while Qinghai lags in innovation input (0.6161) and environmental support (0.6308). The lack of research resources and a weak economic foundation limit their innovation development. Although the government has introduced supportive policies, effective implementation needs to be strengthened to ensure these policies' full impact.

Through a systematic evaluation of the innovation capabilities of 169 national high-tech zones in China, this research highlights the significant advantages of the eastern coastal regions, the innovation potential of the central regions, and the challenges faced by the less developed western and central regions. To address these disparities, the government should enhance policy support and resource investment in underdeveloped areas, optimize the allocation of research resources, and improve the management and organizational capabilities of high-tech zones. These measures aim to achieve balanced regional development and overall enhancement of innovation capabilities, driving the sustainable development of China's high-tech industry.

Analysis of Empirical calculation results

After conducting a comprehensive evaluation of the innovation capability of 169 national high-tech zones, this research delves into the key indicators that determine innovation capability. These indicators reflect the performance of each high-tech zone in terms of innovation input, innovation output, environmental support, and organizational operation, revealing how these factors collectively influence the overall innovation capability. Through a detailed analysis of these indicators, we can better understand the disparities in innovation capability among different high-tech zones and provide a scientific basis for enhancing overall innovation capability. Through the comprehensive evaluation of the innovation capability of 169 national high-tech zones, this research identified the following key indicators that significantly determine the innovation capability of high-tech zones.

Innovation Input Capability

Data indicates that R&D expenditure and the number of technological personnel are among the most critical factors determining the innovation capability of high-tech zones. For instance, Beijing Zhongguancun (0.9743) and Shanghai Zhangjiang (0.9049) have high R&D expenditure, which is directly reflected in their innovation capability scores. This finding is consistent with existing literature, which emphasizes R&D investment as a core driver of innovation capability. Additionally, the number of technological personnel also directly impacts innovation capability. Beijing Zhongguancun and Shenzhen's high investment in this area (0.8326 and 0.8181, respectively) ensures the smooth conduct of R&D activities, enhancing overall innovation levels.

Innovation Output Capability

The number of patents and new product development are essential indicators of innovation outcomes. High-tech zones such as Shanghai Zhangjiang and Shenzhen, with outstanding performance in patent numbers (0.8439 and 0.8181, respectively), significantly enhance their innovation capability. Moreover, the number of new product developments directly reflects the innovation vitality of high-tech zones. Wuhan (0.7761) and Hangzhou (0.7868) have notable achievements in new product development, boosting their overall innovation capability.

Innovation Environment Support Capability

Research infrastructure and policy support are crucial to ensuring the innovation capability of high-tech zones. Excellent research infrastructure is a significant factor for high-tech zones like Beijing Zhongguancun and Shanghai Zhangjiang, with scores of 0.8671 and 0.8401, respectively. This demonstrates the critical role of a conducive research environment in innovation capability. Strong policy support is another critical factor in enhancing innovation capability. Data shows that high-tech zones with robust government and local policy support, such as Beijing Zhongguancun and Guangzhou (0.7877), generally perform well regarding innovation capability.

Organizational Operation Capability

Efficient management levels and the degree of collaboration with universities and research institutions are vital for enhancing innovation capability. High-tech zones with high management levels, such as Beijing Zhongguancun (0.9867) and Shanghai Zhangjiang (0.8096), have higher innovation capability scores. Additionally, the degree of collaboration with universities and research institutions is an important indicator. High-tech zones with close collaborations can better translate research outcomes into practical applications, enhancing innovation capability. For example, Nanjing (0.8655) excels in this aspect.

Through an in-depth analysis of the critical indicators mentioned above, we can identify the factors that most significantly impact the innovation capability of high-tech zones. These indicators include R&D expenditure, technological personnel, patents, new product development, research infrastructure, policy support, management levels, and industry-university-research collaboration. The research results indicate that improving these key indicators can significantly enhance the innovation capability of high-tech zones. This analysis provides a scientific basis for subsequent discussions and recommendations, helping to formulate targeted strategies and measures to achieve overall enhancement and balanced development of innovation capability in high-tech zones.

Data visualizations

To visualize the results of innovation capabilities, we use map visualization tools to mark and present the spatial variations in innovation capabilities of high-tech zones on the map of China. However, since the map can only be displayed by provinces and cannot show the actual location of high-tech zones, we first calculate the weighted average value of innovation capacity of 30 provinces where 169 high-tech zones are located (there are 34 provincial administrative units in China, but there are no high-tech zones in Taiwan, Xizang, Hong Kong, and Macao, and the relevant value is 0. Therefore, here are 30 provinces). Using the output value of the parks as the source of the weight, the results are shown in Table 6.

Province	*Innovation capability value*	*Rankings*	*Province*	*Innovation capability value*	*Rankings*
Beijing	0.9725	1	Henan	0.8852	16
Shanghai	0.9514	2	Hebei	0.8835	17
Guangdong	0.9208	3	Shanxi	0.8794	18
Tianjin	0.9184	4	Jilin	0.8793	19
Shaanxi	0.9109	5	Guangxi	0.8760	20
Jiangsu	0.9055	6	Heilongjiang	0.8755	21
Sichuan	0.9047	7	Fujian	0.8752	22
Zhejiang	0.9033	8	Neimenggu	0.8709	23
Anhui	0.9018	9	Jiangxi	0.8702	24
Hubei	0.8996	10	Yunnan	0.8684	25
Shandong	0.8952	11	Xinjiang	0.8674	26
Guizhou	0.8895	12	Gansu	0.8644	27
Liaoning	0.8892	13	Hainan	0.8639	28
Hunan	0.8873	14	Qinghai	0.8558	29
Chongqing	0.8872	15	Ningxia	0.8274	30

Table 6: Value of innovation capability of national high-tech zones in each province.

Through carefully designed color schemes, different colors are used to represent and facilitate differentiation and recognition. Red indicates high, and the thicker the red, the higher the innovation ability; Blue indicates low, and the darker the blue, the lower the innovation capability. The results of the innovation capability of the high-tech zones in each province are reflected on the map of China, as shown in Figure 1.

Using geographic information system (GIS) tools to analyze the spatial variation of innovation capabilities among high-tech zones, the results indicate that the eastern regions of China (e.g., Beijing, Shanghai, Guangdong) exhibit significantly higher innovation capabilities than the central and western regions. This is primarily due to richer resources, advanced infrastructure, and strong policy support. The central areas (e.g., Wuhan, Hefei) have achieved high innovation capabilities through recent investments in innovation infrastructure and increased government support. In contrast, the western regions generally have lower innovation capabilities, highlighting the need for further improvements in infrastructure, increased investment, and enhanced policy support to bolster their innovation ecosystems.

The findings of this study suggest that the regional disparities in innovation capabilities necessitate targeted support and investment in less developed regions to balance the innovation landscape. Strengthening innovation infrastructure, such as R&D facilities and innovation service organizations, can significantly enhance the innovation capabilities of high-tech zones. Furthermore, continuous policy support and institutional innovation are crucial for maintaining and improving the innovation ecosystems within these zones, which will help promote sustainable development and enhance the competitive advantages of high-tech industries.

Figure 1: Visualization of the value of innovation capability.

Conclusion

This study constructed an innovation capability evaluation index system. It employed the Catastrophe Progression Method (CPM) to comprehensively evaluate and analyze the spatial variation of innovation capabilities in 169 national high-tech zones in China. The results show that the high-tech zones in eastern China, such as Beijing, Shanghai, and Guangdong, exhibit significantly higher innovation capabilities due to richer resources, advanced infrastructure, and strong policy support. The central regions, including zones in Wuhan and Hefei, also demonstrate high innovation capabilities due to recent investments in innovation infrastructure and increased government support. In contrast, the western regions generally have lower innovation capabilities, indicating a need for improved infrastructure, increased investment, and enhanced policy support to boost their innovation ecosystems.

The findings of this study reveal the strengths and weaknesses of different high-tech zones and provide a detailed analysis of regional innovation capability disparities. This offers valuable insights for policymakers and stakeholders, highlighting the areas that require priority support and development, thereby aiding in formulating more effective policies and strategies. By strengthening innovation infrastructure and policy support in less developed regions, the overall innovation capability and competitiveness of high-tech zones across the country can be enhanced. In summary, this study provides a new perspective on understanding the innovation capabilities and spatial variation of China's national high-tech zones, offering practical, theoretical support and guidance for promoting sustainable development and technological innovation in these zones.

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