8

APPLICATION OF FUZZY C-MEANS CLUSTERING ALGORITHM FOR SPATIAL STRATIFIED HETEROGENEITY OF INNOVATION CAPABILITY OF NATIONAL HIGH-TECH ZONES IN CHINA

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Chenqing Su[1],
Noppadol Amdee[1*] and Adisak Sangsongfa[1]
[1]Faculty of Industrial Technology, Muban Chombueng Rajabhat University, Ratchaburi, Thailand
*Corresponding author e-mail: nopadolamd@mcru.ac.th

Abstract

The objectives of the study were to construct a comprehensive and scientific evaluation index system to assess the innovation capabilities of 169 national high-tech zones in China, analyze the spatial stratified heterogeneity of innovation capabilities across 34 provinces, and visualize and analyze innovation capabilities' spatial distribution and disparities. The research adopted a multi-method approach, including the entropy weight method, catastrophe progression method, weighted average method, and fuzzy c-means clustering algorithm, supplemented by data visualization using Python-based tools. The results showed that the evaluation index system consisted of four levels and 28 indicators, effectively quantifying the innovation performance. Catastrophe progression results indicated that Beijing Zhongguancun (0.9725), Shanghai (0.9531), and Shenzhen (0.9472) rank highest, while Rongchang (0.7810), Huainan (0.7947), and Qianjiang (0.7968) rank lowest. The fuzzy c-means clustering analysis classified provinces into six distinct categories of innovation capability, revealing a pronounced "strong East, weak West" spatial pattern. The findings offered spatially grounded policy insights that was to bridge regional innovation gaps, China should enhance R&D investment, optimize resource allocation, promote innovation output conversion, and strengthen inter-regional cooperation, particularly in less developed regions. These measures supported the goal of achieving balanced regional innovation and sustainable national development.

Keywords: Innovation capability, Spatial stratified heterogeneity, Fuzzy C-mean Clustering Algorithm, National high-tech zones in China

Introduction

National High-tech Industrial Development Zones (hereafter "High-tech Zones") in China are key drivers of regional innovation, significantly impacting regional innovation capacity. With the "Innovative Country" strategy, emphasis has shifted towards building regional innovation systems that leverage local strengths. High-tech industries, as vital pillars of economic growth, reflect a nation's comprehensive power and competitiveness. Therefore, enhancing the innovation capacity of these zones is essential for advancing high-tech industries and fostering an innovative nation.

Bruno and Tyebjee (1982) laid the groundwork for evaluating science and technology parks by identifying 12 critical factors influencing companies. Malecki (1987, p.205) and Malecki and Nijkamp (1988, p. 383) expanded this by assessing innovation capabilities across eight dimensions, including government support and personnel mobility. Chen and Huang (2004, p.839) applied the AHP method to Taiwan's science parks, highlighting seven key factors, including industry relevance and government influence. Zeng et al. (2010, p.402) focused on the role of the innovation environment and organizational structure in evaluating high-tech zones. Since 1993, China's Ministry of Science and Technology has repeatedly updated the national evaluation system for high-tech zones. Xu (2006, p.3) pinpointed six essential factors: environment and technological innovation. Recent studies have utilized various methods. For example, Zhang and Chen (2022, p.60) employed the entropy weight and catastrophe progression methods. Zhang et al, (2022, p.88) used the effectiveness coefficient method; Guo and Wang (2022, p.155) applied factor analysis in central China; Ren (2020, p.25) used DEMATEL-ANP; Ding (2019, p.11) utilized the DEA Malmquist index; Su et al., (2018, p.235) applied the catastrophe progression method to the Yangtze river urban cluster.

Current research on high-tech zones faced some challenges, including the lack of a unified evaluation standard and the limitations of linear models in addressing complex, nonlinear systems. Moreover, spatial variation in innovation capabilities is underexplored, which is crucial for identifying regional disparities and developing effective policies. This research focused on 169 national high-tech zones in China to address these gaps, constructing a comprehensive evaluation system. The research revealed significant regional disparities by applying the entropy weight and catastrophe progression methods alongside the fuzzy c-means (FCM) clustering algorithm. The findings highlighted the innovation strengths of eastern coastal regions and the challenges in central and western areas, offering policymakers actionable insights for promoting balanced regional development and sustainable growth in China's high-tech industries.

Research Objective

1. To evaluate the innovation capabilities of 169 national high-tech zones in China using a scientifically constructed and comprehensive evaluation index system.

2. To analyze the spatial stratified heterogeneity of innovation capabilities of national high-tech zones across the 34 provinces in China.

3. To visualize and analyze the spatial distribution and disparities of innovation capabilities across high-tech zones in different provinces of China

Research Methodology

This research systematically evaluated the spatial differences in innovation capabilities across 169 national high-tech industrial development zones in China. To ensure objectivity and accuracy, the research employed a combination of methods, including the entropy weight method, catastrophe progression method, weighted average method, and fuzzy c-means clustering algorithm. Data visualization techniques were also used to intuitively display the spatial distribution of innovation capabilities across provinces. The following sections provided a detailed overview of the methodologies and their application (Su et al., 2024).

1. Evaluation of innovation capability: Entropy weight method and catastrophe progression method

The Catastrophe Progression Method (CPM), originating from mutation theory, integrates topological dynamics with singularity theory to conduct state assessments and trend evaluations. Recognized as a "mathematical breakthrough," CPM tackles multi-criteria decision-making by hierarchically decomposing evaluation objectives, applying a fuzzy mutation membership function, and standardizing data to derive a unified parameter for overall assessment.

Step 1: Construction of the indicator system

This research developed a multi-dimensional indicator system to assess the innovation capacity of China's national high-tech zones, emphasizing scientific rigor, coverage, applicability, and system coherence, based on cybernetic information theory and adapted to national conditions (Su et al., 2023, p.52). The selection of four key secondary dimensions—innovation input, output, environment, and organizational operation—was informed by several factors: the importance of flows of information, materials, and energy in maintaining system stability; the need for multi-level evaluation to enhance development efficiency; and the necessity of detailed indicators to identify strengths, gaps, and improvement directions. These indicators were supported by empirical evidence and practical experience, ensuring validity and contextual relevance (Su et al., 2024, p.8). The catastrophe progression evaluation framework identified core innovation dimensions and refined them into specific indicators. Consistent with catastrophe theory, the model restricted control variables to four to ensure feasibility and representativeness. It included four primary dimensions—innovation input, output, organizational operation, and environmental support—divided into eight secondary and 28 tertiary indicators, as presented in table 1.

Table 1 Innovation capability evaluation index system and mutation types

Evaluation objective	Level 1 indicator	Mutation types	Level 2 indicator	Mutation types	Weight	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	0.0430	Annual Increase of High-tech Enterprises
					0.0927	The scale of technology income
					0.0481	The scale of export earnings
			Output efficiency B_2	Swallowtail mutation system	0.0387	Return rate of R&D investment
					0.0367	Technology Income Creation per Unit of R&D Personnel
					0.0068	Profitability
	Organization Operation Capability A_2	Spike mutation system	Organization and coordination capability B_3	Swallowtail mutation system	0.0607	Number of National University Science Parks
					0.0335	Number of Productivity Promotion Centers
					0.0198	Number of Innovative Industrial Clusters
			Innovation main body capability B_4	Swallowtail mutation system	0.0494	The scale of high-tech enterprises
					0.0354	Number of Innovation Service Organizations
					0.0201	Number of Universities and R&D Institutions
	Innovation Input Capability A_3	Spike mutation system	Intellectual input B_5	Butterfly mutation system	0.0569	Scientific and technological activity personnel
					0.0474	R&D Personnel Full-time Equivalent
					0.0462	R&D personnel
					0.0048	Density of middle and senior title personnel
			Financial input B_6	Butterfly mutation system	0.0619	Funds for scientific and technological activities
					0.0540	R&D Expend
					0.0089	R&D Expenditure Intensity
					0.0062	Intensity of Expenditure on Scientific and Technological Activities
	Environmental Support Capability A_4	Spike mutation system	Hard environment B_7	Butterfly mutation system	0.0354	Total number of technology business incubators
					0.0355	Employee Size
					0.0085	Capital Operation Status
					0.0127	Enterprise size
			Soft environment B_8	Butterfly mutation system	0.0089	Financial Support
					0.0230	Basic Supporting Environment
					0.0430	Policy Support
					0.0619	Institutional Mechanism Innovation

Remark: Due to space constraints, this table includes the indicator system and incorporates content required for subsequent sections.

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

Once the evaluation indicators were defined, their relative importance was assessed using statistical data and expert input. Indicators sharing the same type and hierarchical level were prioritized by significance, with the most influential placed first. To minimize subjectivity, the entropy weight method was utilized to assign weights, ensuring that the rankings objectively reflect actual relevance. The steps for calculating weights via the entropy weight method were as follows:

1) Data standardization

This research processed the raw data using deviation-based normalization. After transformation, all variable values fell within the range of [0, 1], and the resulting standardized values were unit-free quantities. This method was straightforward and eliminated differences in scale and mitigated the influence of varying variances. The specific formula was presented below, as equation (1).

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

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

2) Calculation of information entropy of indicators

According to the formula of information entropy $e_i = -1/In\, n \sum_{j=1}^{n}\left(p_{ij} In\, p_{ij}\right)$, the information entropy of 28 indicators could be calculated.

3) Determination of indicator weights

According to the utility value of the indicator $d_i = 1 - e_i$, its weight was obtained $\omega_i = d_i / \sum_{i=1}^{m} d_i$.

Step 3: Determine the type of mutation.

A typical mutation system involved up to four control variables, which corresponded to seven distinct mutation types: cusp, dovetail, butterfly, fold, hyperbolic umbilical, elliptical umbilical, and parabolic umbilical. However, the catastrophe progression method primarily emphasized three types, as illustrated in Table 2. The same table also presented the potential function for a state variable x, with the parameters a, b, c, and d serving as control variables. These parameters captured the conflicting dimensions within the system. When an indicator was divided into two, three, or four sub-indicators, it formed a hump, dovetail, or butterfly mutation system, respectively.

Step 4: Derive the normalization formula from the divergence equation.

According to the mutation theory, divergence point set equations could not be directly analyzed and evaluated because the range of values of the state and control variables was not uniform, nor could 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 was necessary. The divergence point equations were obtained by taking the potential function's first-order derivatives, and the mutation system's set of singularities was 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 was obtained, i.e., the equilibrium surface formed by the set of all critical points. The divergence point set equation indicated that the system mutated when each control variable satisfies this equation. The normalization formula could be derived by decomposing the form of the divergence point set equation. The normalization formula indicated $x_i(i = a, b, c, d)$ the number of mutation levels corresponding to the control variable i. In the mutation-level system, the normalization formula was a multidimensional fuzzy affiliation function.

Table 2 Mutation level system model and diagrams

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	x a b	x a b c	x a b c d

Remark: The diagrams helped identify each mutation type: "one change two" for the spike, "one change three" for swallowtail, and "one change four" for butterfly mutations.

Step 5: Comprehensive evaluation using the normalization formula

The normalization formula transformed the different qualitative states of each control variable in the system into the same qualitative state, i.e., the control variables were 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 was 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 were ranked according to their total evaluation index scores regarding their advantages and disadvantages.

2. Weighted Average Method

The weighted average method derived a composite score by allocating weights to individual indicators according to their relative significance or influence. In this research, the method was employed to evaluate the innovation capacity of high-tech zones at the provincial level. Each zone's output value was initially used to establish its proportional weight within its respective province. These weights were subsequently aggregated to compute the overall innovation performance of each province, producing a set of comprehensive innovation capability scores for high-tech zones throughout China.

3. Fuzzy C-means Clustering Method

The fuzzy c-means (FCM) clustering method was a soft clustering approach that permitted data points to be associated with multiple clusters by minimizing the weighted sum of squared deviations, effectively managing uncertainty and data ambiguity. In this research, FCM was utilized to classify the innovation capabilities of provincial high-tech zones. Based on results from the weighted average method, the calculated innovation scores were fed into the FCM algorithm, where the number of clusters (c) and the fuzziness parameter (m) were predefined. The algorithm grouped the zones through an iterative refinement process, revealing commonalities and distinctions in their innovation performance.

The FCM algorithm began by randomly initializing the number of clusters (K) and the initial cluster centers and membership grades for all data points. Membership degrees were then computed by measuring the relative distance between data points and cluster centroids, indicating the strength of association with each group. Cluster centers were updated as the weighted mean of data points, where the weights corresponded to membership degrees. This process—membership evaluation and centroid adjustment—is repeated until a stopping condition was satisfied, such as reaching the maximum iteration limit or when centroid changes fell below a threshold. Upon convergence, the algorithm produced final cluster centers and membership values, enabling the assignment of data points and supporting the interpretation of the clustering outcome.

4. Data Visualization

Data visualization, utilizing tools like Python and libraries like Matplotlib, Seaborn, and Geopandas, enabled researchers to explore complex datasets more intuitively by uncovering underlying trends, distributions, and anomalies. In this research, a range of visualization methods-including scatter plots, heatmaps, and geographic maps-were applied to improve the interpretability of the data. The clustering outcomes related to innovation capability were displayed on a map of China, clearly depicting the provincial-level spatial patterns.

Research Results

1. Data Sources

The research drew upon a sample of 169 national high-tech zones across China, with primary data from the 2021 annual statistical survey of national hi-tech zones, officially authorized by the national bureau of statistics and compiled by the Torch center. As complete datasets for 2022 and 2023 were not yet available, the analysis in this research was based solely on the comprehensive data from 2021.

2. Evaluation of Innovation Capability

The entropy weight method was used to determine the relative importance of each indicator, ensuring the evaluation system remained objective and scientifically sound. This method identified key factors influencing innovation capacity, providing a reliable basis for assessing and comparing performance among high-tech zones. The resulting weights were shown in table 1. Next, the catastrophe progression method was applied to calculate the overall innovation capability of 169 national high-tech zones. By integrating the weights from the entropy method, a composite index was generated and used to rank each zone. These results revealed regional differences in innovation capacity and support further clustering analysis. Based on the evaluation system, mutation types, and weights from table 1, MATLAB 7.0 was used to compute innovation scores and rankings for all 169 zones using 2021 data, as shown in table 3.

Table 3 Evaluation results of innovation Capability ranking of 169 national high-tech zones

Name of High-Tech Zone	Innovation Input Capability	Innovation Output Capability	Environmental Support Capability	Organization Operation Capability	Innovation capability	Ranking
Beijing Zhongguancun	0.9743	0.8326	0.8671	0.9867	0.9725	1
Shanghai Zhangjiang	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
...	...	...	...	...	...	...
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

Remark: Given the extensive data from 169 high-tech zones, only the top 10 and bottom 10 zones in innovation capability were shown here due to space constraints.

3. Clustering Analysis of Innovation Capability of High-Tech Zones Across Provinces

To represent the results of innovation capability, map-based visualization techniques were employed to depict spatial variations among China's national high-tech zones. Since provincial-level maps did not support the pinpointing of specific zone locations, we first computed the weighted average innovation capacity across 34 provinces encompassing the 169 zones, excluding Taiwan, Xizang, Hong

Kong, and Macao, which lack such zones. This yielded data from 30 provinces. The weighting was based on each zone's output value; the results were presented in table 4.

Subsequently, the fuzzy c-means (FCM) clustering algorithm was used to group provinces by innovation performance. The procedure involved feeding the weighted capacity values into the FCM model, assigning six clusters (c = 6) and a fuzziness index of 1.5 (m = 1.5). The choice of six clusters followed the categorization approach of Xie et al. (2011, p.105), while the parameter m = 1.5 was confirmed through repeated testing as the most suitable for reflecting data complexity. The clustering process iteratively refined the centers and membership values, classifying provincial innovation capacities into distinct categories. All calculations were conducted using MATLAB, which produced the final clustering outcomes, highlighting interregional commonalities and disparities in innovation strength and offering a foundation for subsequent spatial research.

Table 4 Value of innovation capability of national high-tech zones in each province

Province	Innovation capability value	Cluster	Province	Innovation capability value	Cluster
Beijing	0.9725	6	Henan	0.8852	3
Shanghai	0.9514	6	Hebei	0.8835	3
Guangdong	0.9208	5	Shanxi	0.8794	3
Tianjin	0.9184	5	Jilin	0.8793	3
Shaanxi	0.9109	5	Guangxi	0.8760	3
Jiangsu	0.9055	4	Heilongjiang	0.8755	3
Sichuan	0.9047	4	Fujian	0.8752	3
Zhejiang	0.9033	4	Neimenggu	0.8709	2
Anhui	0.9018	4	Jiangxi	0.8702	2
Hubei	0.8996	4	Yunnan	0.8684	2
Shandong	0.8952	4	Xinjiang	0.8674	2
Guizhou	0.8895	3	Gansu	0.8644	2
Liaoning	0.8892	3	Hainan	0.8639	2
Hunan	0.8873	3	Qinghai	0.8558	2
Chongqing	0.8872	3	Ningxia	0.8274	1

4. Data Visualization

This research employed a color-coded scheme to differentiate regions based on innovation capacity: red for high, orange for medium, and blue for low levels. Within each category, darker shades indicated relatively higher or lower innovation strength. The visualization of China's map was created using Python libraries such as Geopandas and Matplotlib. To ensure precision, we first aligned the clustering outcomes with the corresponding geographic data for each province. A range of color gradients was then applied to visually present the clustering results and overall innovation capacities. Lastly, visual elements such as legends and labels were refined to enhance readability, producing final maps that clearly illustrate the spatial distribution of innovation capabilities across Chinese provinces, as depicted in figures 1 and 2.

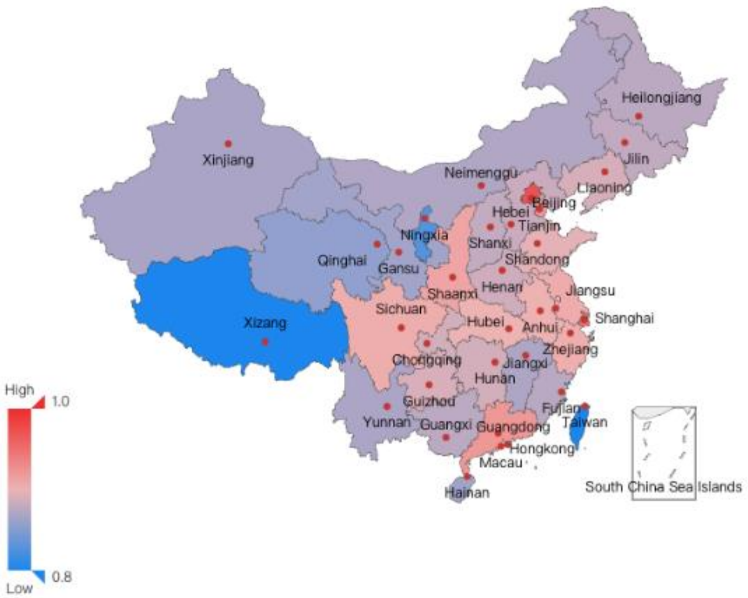

Figure 1 Visualization of the value of innovation capability

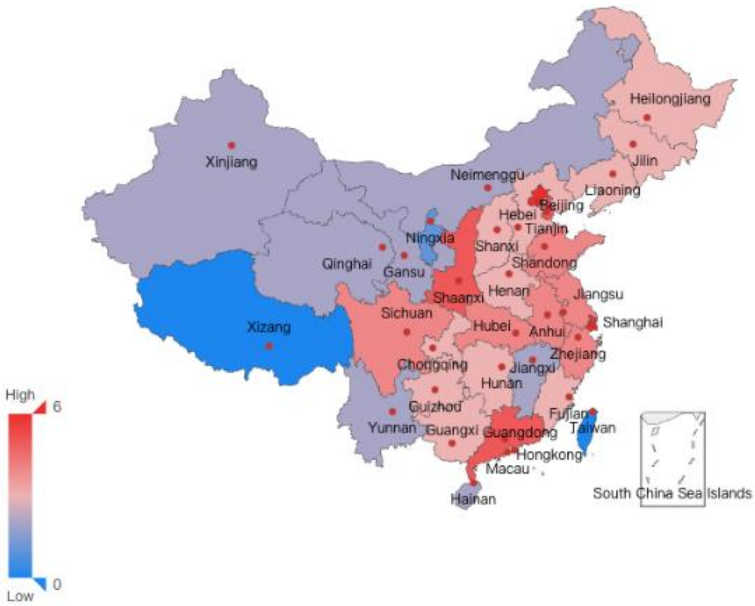

Figure 2 Visualization of clustered values of innovation capability

This research utilized the fuzzy c-means clustering technique to examine the innovation performance of 169 national high-tech zones across China, uncovering a distinct regional imbalance characterized by a "strong East, weak West" pattern. Innovation leadership was concentrated in eastern coastal areas such as Beijing, Shanghai, and Guangdong, where plentiful R&D investment, mature institutions, and robust policy backing contributed to high innovation levels, visually represented in dark red on the map. Provinces in central China, including Hubei and Hunan, exhibited moderate innovation performance but still fell behind the eastern region, indicating the need for improved innovation ecosystems and stronger governmental support. Western provinces like Qinghai, Ningxia, and Xinjiang demonstrated low innovation potential, depicted in blue, mainly due to limited resources and underdeveloped infrastructure.

The geographic layout of innovation capacity underscored stark regional differences influenced by disparities in economic conditions, governmental incentives, and access to innovation resources. Addressing these imbalances required redistributing resources more equitably and enhancing the innovation climate in central and western provinces. This would thereby support coordinated regional growth and advance China's innovation competitiveness on the global stage.

Discussions

This research provided new empirical evidence on the spatial differentiation of innovation capabilities among China's national high-tech zones, offering theoretical insights into regional innovation dynamics. Constructing a multidimensional evaluation system effectively captured key components such as innovation input, output, organizational operation, and environmental support, contributing to a more nuanced understanding of regional innovation performance. The clustering results derived from the fuzzy c-means algorithm highlighted persistent spatial stratification, particularly the concentration of high-performing zones in eastern provinces and lagging innovation capabilities in central and western regions. These findings were consistent with earlier research (Zhang & Chen, 2022) but extended the analysis by introducing cluster-based heterogeneity, which better explained the structural complexity across regions. Furthermore, the spatial visualization of innovation capabilities enhanced data interpretability and clarified where disparities were most severe. These results underscored the importance of considering geographic, economic, and institutional contexts when assessing innovation development. The research also contributed methodologically by integrating entropy weighting, catastrophe progression, and clustering techniques in a spatial framework, offering a replicable model for evaluating innovation capacity in other national or regional settings.

Conclusions and Suggestions

This research systematically addressed its three core objectives by developing an integrated evaluation index system, applying spatial clustering analysis, and visualizing the distribution of innovation capabilities across 169 national high-tech zones in China. The results revealed pronounced regional disparities, with innovation concentrated in eastern coastal regions. This highlights the urgent need for differentiated innovation strategies across provinces.

Recommendation for using to benefit

1. National policymakers should strengthen R&D infrastructure in underdeveloped regions, create innovation-friendly environments, and attract high-quality talent.
2. There should be establishment of a national resource-sharing platform to promote resource integration and collaboration, particularly in areas with weaker innovation capacity.
3. High-tech zone management should be addressed to improve organizational efficiency and fosters collaboration with universities, industries, and research institutions to accelerate innovation commercialization.
4. Spatial distribution can be optimized by implementing targeted innovation policies for underdeveloped areas, balancing the allocation of innovation resources, and promoting nationwide equitable innovation development.

Recommendation for future research

1. Adopt advanced analytical methods.
2. Expand the dataset.
3. Deepen the research of policy impacts.

This research also provided Thailand with a model for addressing regional innovation disparities through policy support, infrastructure improvement, and collaborative initiatives, fostering balanced and sustainable development.

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