

Research Article

Analysis of China's Regional Economic Competitiveness, Regionalization, and Spatial Aggregation Characteristics Based on Density Clustering Algorithm

Jinglin He ¹ and Rixing Liu²

¹College of Economics and Management, Hubei University of Automotive Technology, Shiyan, Hubei 442002, China

²Western Jiangxi Regional Economic and Social Development Research Center of Yichun University, Yichun University, Yichun, Jiangxi 336000, China

Correspondence should be addressed to Jinglin He; 20190013@huat.edu.cn

Received 25 May 2022; Revised 16 June 2022; Accepted 27 June 2022; Published 3 August 2022

Academic Editor: Kai Guo

Copyright © 2022 Jinglin He and Rixing Liu. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Regional development disparities, especially in developing countries, have traditionally been one of the central issues of empirical research in regional economics. However, this rapid change is accompanied by profound changes in the spatial distribution of economic activities in China, the formation of regional economic “blocks,” the widening of regional disparities, and the geographical concentration of economic growth efficiency are important issues highlighted in this change. Therefore, it is important to explore the spatial clustering characteristics and patterns of regional economic growth to provide a scientific basis for relevant government departments to formulate reasonable regional development strategies and promote the balanced and stable development of economic growth. Clustering analysis is an important research topic in the field of data mining, which is used to discover unknown object classes in large-scale data sets. This paper proposes a density-clustering algorithm based on the regional economic competitiveness of China and analyzes its spatial aggregation characteristics. From the perspective of spatial structure theory, economic development is a dynamic process, and to optimize the spatial pattern of China's regional economic development and improve the efficiency of economic interaction between regions, it is necessary to fully exploit the diffusion and trickle-down effects of important growth poles in the region to the surrounding areas. The experimental results show that the error rate of KSNM is very small, and the error rate of K-means and PSO has increased to a certain extent. Therefore, it can be obtained that the density-clustering algorithm based on the regional economic competitiveness zoning method in China can find out the correct clustering results without the given clustering individual cases. Thus, it is important to grasp the current situation of regional economic agglomeration and reveal the driving factors of agglomeration formation to promote the coordinated development of regional economy and guide the spatial layout of economic development.

1. Introduction

Regional economic activities will produce agglomeration within a certain range due to the flow of production factors; otherwise, they will be increasingly fragmented [1]. In a market economy, a country, an industry, and a region face a competitive environment [2]. The country has to participate in competition, the industry has to participate in competition, and the region also has to participate in competition [3]. The development of market economy system and

industrial structure adjustment is uneven, while the eastern region is gradually converging with the international standards, the central and western regions are slow in adjusting their ownership structure and industrial structure [4]. When decomposing the composition and sources of regional differences, we only examined the impact of the three major zones and interprovincial differences on the overall regional differences in China, but failed to refine them to the level of intraprovincial differences, ignoring the unevenness of regional economies within provinces [5].

Economic growth refers to the sustainable growth of national wealth or social wealth, which is generally expressed as the growth of gross domestic product (GDP) [6]. To solve the problem of regional equity, it is necessary to accelerate the pace of economic development while needing to simultaneously take into account the coordinated relationship between developed and less-developed regions [7]. The earlier hierarchical and mesh database systems have failed to meet the market demand, and the research and development of relational database systems have led to a new era of database systems [8]. At the same time, the development of data modeling tools and indexing and access methods have further driven the progress of database systems [9]. Under the impetus of knowledge-based economy, especially in the context of the bottleneck of global manufacturing development, the world economy, especially developing countries and regional economies, needs to change the economic growth mode and upgrade the industrial structure [10]. The density-clustering algorithm makes it easier to understand why things happen and find out the difference between whether (good and bad) history repeats itself [11]. Because trends are now changing very fast, automatic analysis and specialized algorithms that identify trends, identify anomalies, and predict the future also make the difference between winning and just competing [12].

Two significant features of the globalized world economy are the global flow of resources, and the global market economy. When external disturbances occur, Chinese provinces differ in their industrial structure, economic openness, and flexibility in adjusting their economic activities due to the differences [13]. Provinces face different combinations of unemployment-inflationary pressures and have widely varying states of economic performance [14]. Factors such as slow economic development and unbalanced regional economic development have seriously constrained China's economic construction [15]. Thus, it is necessary to adhere to the principle of practical approach, analyze in depth the historical process and current situation of economic development of each region, and implement the principle of adapting to the time and place. Therefore, it is important for governments to consider how to improve the competitiveness of national regions, create regional advantages, and strengthen their attractiveness to global resources. Due to the long-standing deep-seated structural contradictions and the unconventional mode of economic growth, institutional, institutional, and legal barriers to land management still exist. The formulation of policies to enhance the competitiveness of national regions has become an important part of the strategies and policy systems of regional governments.

The innovative points of this paper are as follows:

- (1) The article applies competitiveness zoning and spatial aggregation characteristics to regional economic analysis, which intuitively and quantitatively realizes regional economic analysis in a spatial manner.
- (2) In view of the deficiency that the density-clustering algorithm relies on the decision map generated in the

algorithm when the clustering centers are selected, which is difficult to accurately determine the clustering centers, the spatial aggregation feature analysis is proposed.

- (3) The dynamics of the spatial clustering characteristics of regional economic growth is explored and applied to a multiregional and multiscale empirical study.

The research framework of this paper contains five major parts, which are organized as follows:

The first part of this paper introduces the research background and significance, and then introduces the main work of this paper. The second part imports the work related to regional economic competitiveness zoning and spatial aggregation characteristics of China, and density-clustering algorithm. In the third part, we present an overview of economic growth efficiency measurement methods and regional economic competitiveness zoning methods so that the readers of this paper can have a more comprehensive understanding of China's regional economic competitiveness zoning methods based on density-clustering algorithm. The fourth part is the core of the thesis, which completes the description of the spatial aggregation analysis based on density-clustering algorithm and spatial aggregation feature analysis. The last part of the paper is the summary of the whole work.

2. Related Work

2.1. Regional Economic Competitiveness Division and Spatial Agglomeration Characteristics in China. The research on regional development disparities in China consists of two aspects: first, an empirical study on the change of the East–West gap, mainly using economic statistical indicators to examine the current situation and dynamic trajectory of the gap between regions in China; second, an explanation of the causes of the gap formation. On the one hand, regional economic growth depends on regional human capital, natural resources, capital stock, and the level of regional science and technology and the speed of technological progress. On the other hand, regional economic growth is closely related to regional industrial agglomeration. By analyzing the spatial pattern of regional economic growth and spatial agglomeration results in different time periods, we analyze the spatial agglomeration pattern of regional economic growth, and then provide theoretical basis and important support for the spatial restructuring of economic growth and policy formulation in the country and five regions.

Deng et al. started to apply a new approach to decompose the composition and sources of regional differences in order to reveal some of the main factors that cause the variation of regional differences [16]. Based on the understanding that the technology spillover effect decreases gradually with geographical distance and thus technology spillover is localized, Chen et al. theoretically concluded that spatial agglomeration drives regional economic growth through technology spillover [17]. Obomeghie and Ugbohmhe decomposed the Gini coefficient to analyze the differences in the income of the population between rural areas [18]. A study on the dynamics of spatial agglomeration

characteristics and regional comparisons of regional economic growth in multiple study areas was conducted to explain the spatial differences in regional economic growth in China. Goli and Joksimovi used spatial density to represent agglomeration and argued that agglomeration affects labor productivity in US states through three ways: transportation costs, externalities from knowledge spillovers, and pecuniary externalities [19]. The empirical results found that employment density and labor productivity and the Bai et al. used a weighted coefficient of variation to decompose the industrial or sectoral composition of regional differences [20].

Based on this reviewing of the theoretical and empirical studies on regional disparities and China's regional disparities under the framework of economic growth theory, spatial economics, and the combination of both, the characteristics, progress, and further issues to be addressed in these studies are analyzed and summarized.

2.2. Density-Clustering Algorithm. We adopt different management strategies and methods for regional economies at different stages of development. We can correctly grasp the law of China's economic development, identify the weak points of economic development and the unbalanced areas of economic development, and give macroscopic inclined policy regulation to promote China's rapid economic development. The current domestic research focuses more on the difference of development level and less on the difference of regional economic development status. Density-clustering algorithm is to solve this problem, and the maturity of database technology and the development of artificial intelligence technology provides the basis for the research of density-clustering algorithm, and the researchers from various disciplines came together to study the density-clustering algorithm technology.

Chen et al. proposed a hybrid genetic clustering algorithm by using K-means operator instead of crossover operator in genetic operator [21]. Kumar and Kumar introduced the improved idea of having the distance from the sample point of density maximum to the sample point of density minimum as the truncated reference value [22]. Ma et al. adopted the floating point encoding of clustering center and designed the floating-point crossover and variation algorithm [23]. Gungor and Ozmen obtained the I-DBSCAN adaptive clustering algorithm with the help of two main factors in discriminating the clustering results, the trend of the number of clusters and the trend of the number of noise points [24]. Lu and Zhu proposed a K-means clustering algorithm using particle swarm optimization algorithm. It improves the global search capability of K-means and also has local search capability [25].

Density clustering algorithm brings together researchers from different fields, especially scholars and engineers in database, artificial intelligence, mathematical statistics, visualization, parallel computing, etc. Therefore, density-clustering algorithms are a broad interdisciplinary discipline involving various technologies such as artificial intelligence techniques, statistical techniques, and database techniques.

3. Regional Economic Competitiveness Division Method of China Based on Density-Clustering Algorithm

3.1. Measurement Method of Economic Growth Efficiency. For the country, the relational database formed by the data information accumulated in its daily business is an important data source for intelligence mining, so it is especially important to choose a good clustering algorithm to get a good clustering effect and find out the hidden valuable information [26]. As a result, the country is facing a series of economic and social development problems, and the issue of regional economic disparities in China has thus increasingly become one of the central issues of empirical research in regional economics [27]. Regional economic disparities are mainly measured by comparing GDP or national income in a per capita sense across geographic regions [28]. Division of labor is the source of economic agglomeration, while externalities and increasing payoffs have to be the link between the role of division of labor and economic agglomeration. Based on this, the path of economic growth efficiency agglomeration formation can be summarized in Figure 1.

First, the frontier surface of production is derived by data envelopment analysis. Since the results of spatial exploratory data analysis of the regional economy are related to the scale of the regional study unit, the spatial agglomeration of regional economic growth will be influenced by both spatial and temporal scales [29]. Therefore, its simulation process is based on random numbers, which are generated mainly by using random sampling data tables, by using physical methods, and by using data methods to generate pseudorandom numbers. Column j in matrix U is sample X_j , which is relative to the membership function of C subset, so the hard partition space of X is

$$M_{be} = \{U \in R^{cn} | \mu_{ik} \in \{0, 1\}, \forall i, k; \forall k\}. \quad (1)$$

Therefore, a country should pay attention to study the essential characteristics of these four different stages and formulate corresponding development countermeasures in order to maintain a sustainable competitive advantage. Each productivity change requires solving four linear programs including two current environmental technical efficiencies and two mixed environmental technical efficiencies. The spatial weight matrix is introduced to estimate the parameters of the regional spatiotemporal process model more effectively. The objective is to search for the cluster centers with the best clustering partitioning effect, even though the criterion function is minimal, so the fitness function should be taken as $1/E$, i.e. the fitness function:

$$f(x) = \frac{1}{E} = \frac{1}{\sum_{i=1}^K \sum_{x \in C_i} |x - c_i|^2}. \quad (2)$$

Economic growth and regional disparity, simultaneously as products in development, are interdependent and mutually transformed in the presence of a critical point of efficiency agglomeration. However, in

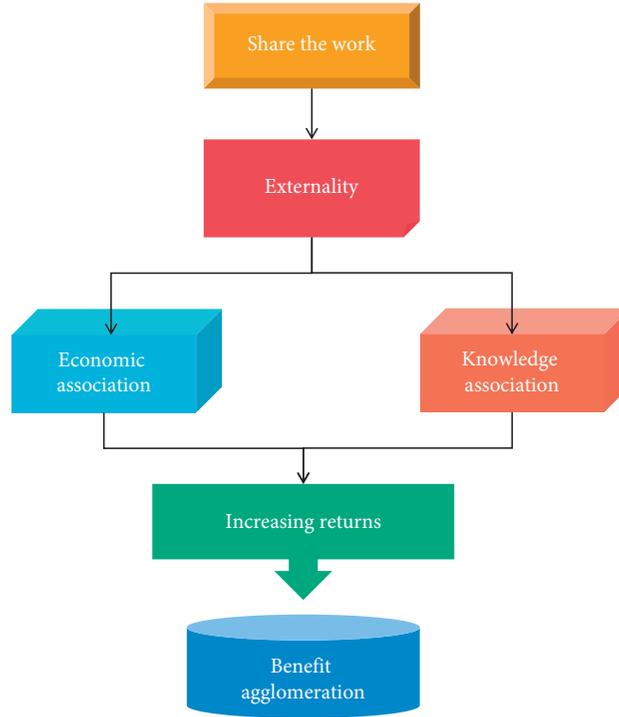


FIGURE 1: The formation path of long-term economic efficiency agglomeration.

order for the transformation to be successfully completed, attention must be paid to the satisfaction of the corresponding transformation conditions. Therefore, the impact and mechanism of efficiency agglomeration on economic growth and regional disparity can be shown in Figure 2.

Second, technical efficiency and productivity are measured by directional distance functions. Monte Carlo simulation analysis is used to test the local spatial autocorrelation indicators and obtain the empirical pseudosignificance level. Thus, it is determined whether the observations of a spatial target are arranged in the overall region with significant local correlation, and the specific pattern of regional economic growth spatial agglomeration is analyzed. In order to facilitate a convenient and rational analysis, the various categories of the country can be classified into several strategic business units according to their strategic relevance. Classification is built by providing a training data set with labels, acquiring data features through pretraining, and then using the model to predict data categories. To measure the quality of the clusters, an error sum of squares reference function is used, defined as follows:

$$E = \sum_{i=1}^k \sum_{x \in C_i} \|x - \bar{x}_i\|^2. \quad (3)$$

\bar{x}_i —The average value of the cluster, that is, the cluster center.

Since the regional economic information and analysis model is based on polygons such as counties and cities, provinces and countries, we have to try to generate the

spatial weight matrix of spatial polygons. The prefecture-level cities are selected as the basic research unit, with moderate geographical area and large enough cities, especially the central cities are mostly large- and medium-sized cities, which can become the growth poles with strong ability to gather and diffuse economic factors. If the variance of the cost function is negative, the original center of mass is replaced by the noncentral center of mass at the current location; otherwise, the center of mass remains unchanged. The degree of adaptation is appropriately extended by the simulated annealing algorithm, and the degree of adaptation stretching method is as follows:

$$f_i = \frac{e^{f_i/T}}{\sum_{i=1}^M e^{f_i/T}}. \quad (4)$$

f_i —Adaptation of the i th individual.

However, not all methods can satisfy the monotonicity requirement due to the different types of clustering methods chosen. In this paper, the correlation coefficient is calculated based on the Euclidean distance using the variational method with the following recursive expressions:

$$D_{kr}^2 = \frac{1+\beta}{2} [D_{kp}^2 + D_{kq}^2] + \beta D_{pq}, G_r = \{G_r, G_q\}. \quad (5)$$

Finally, the further decomposition of ML index can obtain the situation of technological progress, technical efficiency, and scale effect. According to the factors influencing regional economic spatial agglomeration, combined with the existing research results, it can be

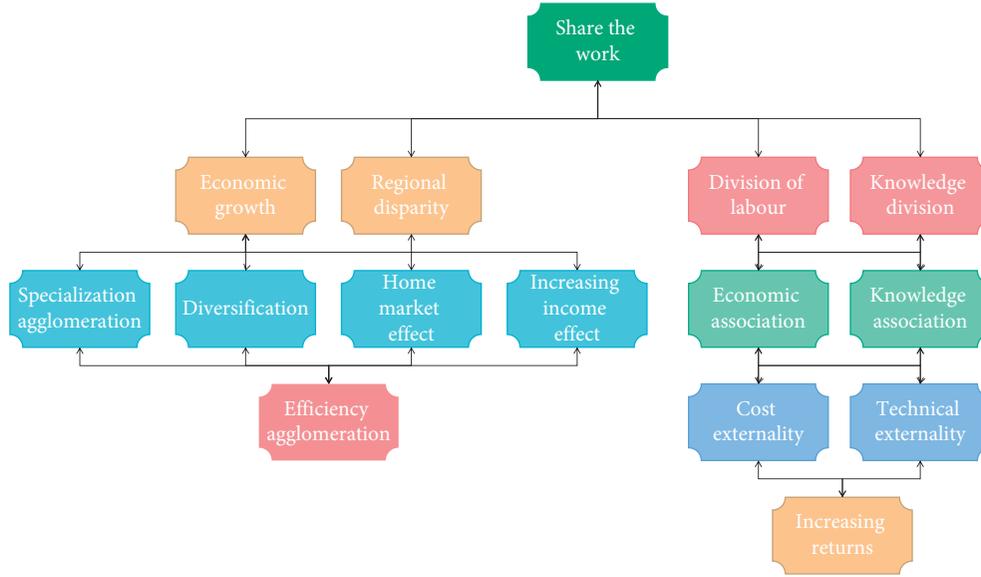


FIGURE 2: Origin, formation, and influence of efficiency agglomeration.

seen that the index system is mainly constructed from several aspects, such as factor endowment, human resources, transportation cost, knowledge, and capital. These indicators mainly reflect the economic correlation between a certain region and other regions, and the strength of the connection between the region and other regions. The distance-based spatial weight matrix assumes that the strength of spatial interactions is determined by the distance between regions in the center of mass or the distance between the locations of regional administrative centers. Exploratory spatial data analysis is often the first step in spatial analysis. It is a method that integrates GIS, graphics, and statistics to describe the spatial distribution of study objects and geographic units, thereby revealing spatial connections, agglomerative properties, identifying singular observations, and discovering other consistent features.

3.2. Regional Economic Competitiveness Zoning Method. The indicators of the delineated residential, commercial, and industrial functional areas are consistent with the principles of functional area delineation and can be used as an object for evaluating the level of intensive use within Chinese cities [30]. Different data types of data sets require different types of clustering algorithms for calculation. Density-clustering algorithms usually involve more complex mathematical methods and information technology, and in order to facilitate users to understand and use such techniques, it is necessary to instruct the operation, guide the mining, and express the results, etc., figuratively with the help of graphics, images, animations, etc., otherwise, it is difficult to promote the popularization of density-clustering algorithms. Therefore, it is not only necessary to study numerical data but also requires the method of cluster analysis to be adapted to the change of data types. The natural conditions mainly consider the slope and topographic relief in the region, while the

natural resources mainly consider the distribution of water resources and mineral resources in the region. The flow chart of the locational directional model is shown in Figure 3 below.

First, statistical data can be spatialized through spatial analysis methods. The project goals and requirements are understood from a business perspective, converted into a problem definition of a density-clustering algorithm, and an initial plan to reach the goals is designed. Commonly used criterion functions are the error sum-of-squares criterion and the weighted average sum-of-squares distance criterion. Call the whole C fuzzy division space of X . If it contains degenerate division, then it is called degenerate C fuzzy division space. Let

$$V = i \frac{\sum_{j=1}^n (u_{ij})^m x_j}{\sum_{j=1}^n (u_{ij})^m}. \quad (6)$$

In the division of functional areas, there are three types of functional areas: residential, commercial, and industrial, so it is necessary to classify the land-use types of residential, commercial, and industrial land. We use data range normalization here. The method is to first find the range of each variable and then calculate the mean of each variable:

$$X = \frac{X_{ij}' \overline{X_j'}}{\text{mix}\{X_{ij}'\} - \text{mix}\{X_j'\}}. \quad (7)$$

The initial point has a large influence on it, and it is even difficult to achieve the global optimum, furthermore, it can only dispose of the clustering cases where hyperspherical cluster structures exist, and it does not have the ability to identify the clustering structures of arbitrary shapes. Therefore, in the actual cluster analysis, different types of attributes are combined in the same difference degree matrix for calculation. Data

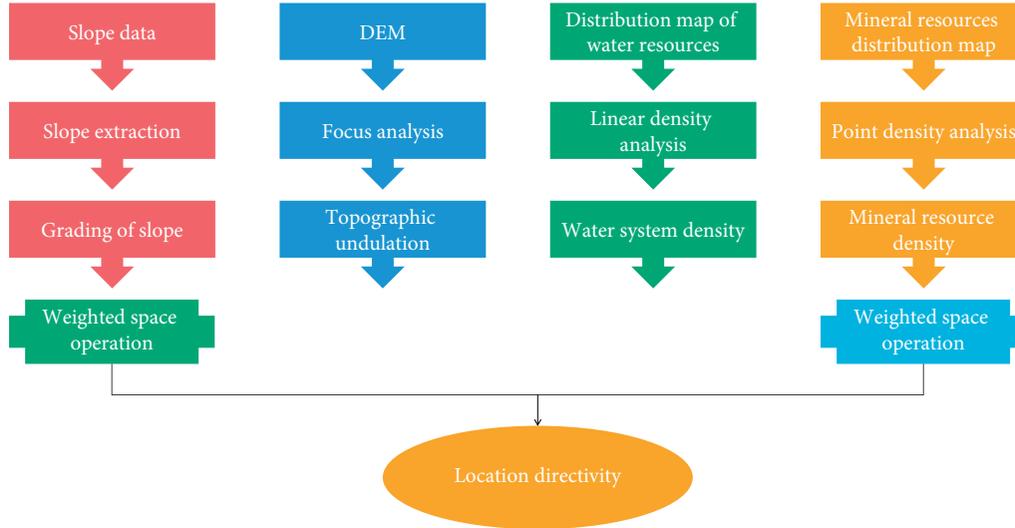


FIGURE 3: Flow chart of location directivity model.

preprocessing techniques as a step in knowledge discovery can improve the quality of data, and thus can enhance the accuracy and quality of the density clustering algorithm process. When the absolute value of the data is compared with the specified threshold, the soft threshold noise is removed because the part less than or equal to the threshold is zero and the part greater than or equal to the threshold is the difference from the specified threshold, with the following equation:

$$\omega\lambda = \begin{cases} [\text{sign}(\omega)](|\omega| - \lambda), & |\omega| \geq \lambda, \\ 0, & |\omega| < \lambda. \end{cases} \quad (8)$$

Second, overlay analysis is applied to reflect the combined effects of various factors on economic spatial agglomeration from a spatial perspective and to explain the occurrence of spatial agglomeration. The initial raw data are constructed into a data set that is eventually suitable for processing by modeling tools. Urban single residential land and urban mixed residential land are all residential type land, while commercial land, financial and insurance land, supplementary business and financial, restaurant and hotel land, and supplementary wholesale and retail land are commercial type land. Therefore, it is necessary to preprocess the data before density clustering and transform the data into suitable data for mining. Assume a mixed data $X(k)$, which consists of m dimensional observation signal vectors:

$$x(k) = [x_1(k), x_2(k), \dots, x_m(k)]^T. \quad (9)$$

A similarity measure of the gaps is defined for the actual problem, and then certain objects are assigned to belong to a certain cluster according to the nearest neighbor rule. The results of economic region classification are shown in Table 1.

Finally, the impact of various factors on locational directionality is considered, and then the relative

magnitude of the factors' influence is simulated. The model is evaluated more thoroughly and each step of constructing the model is checked to confirm whether it actually achieves the intended business purpose. The commonly used Hemming distance between fuzzy sets, let A and B be two fuzzy subsets of $U = \{u_1, u_2, \dots, u_n\}$, is found as follows:

$$D(A, B) = \frac{1}{n} \sum_{i=1}^n |\mu_A(u_i) - \mu_B(u_i)|. \quad (10)$$

Since clustering is the combination of objects for classification to maximize the separability of categories, the clustering criterion should be a function reflecting the similarity or dissimilarity between categories. It seeks the optimal combination and relative position of various economic objects in space from their clustering degree in space and their interaction relationship, and examines the dynamic change law of them in interaction over time. Spatial correlation is multidimensional, so when measuring spatial correlation, it is necessary to judge the expression of geographic space, indicating the neighboring relationship of each unit, thus introducing the spatial weight matrix to quantify the position of each unit as a prerequisite for spatial measurement analysis. The contradiction between the demand for differentiated macrocontrol policies and the uniform supply of central macrocontrol policies is more prominent in each province, and it is necessary to implement differentiated macrocontrol.

4. Analysis of Spatial Aggregation Characteristics Based on Density-Clustering Algorithm

4.1. Analysis of Density-Clustering Algorithm. The density-clustering algorithm has the advantage of automatically discovering the class cluster centers of dataset samples and can satisfy the efficient clustering of arbitrarily shaped

TABLE 1: Division results of economic regions.

Name of economic zone	North economic zone	Yangtze river basin economic zone	Southeast economic zone	Southwest corner economic zone	Northwest economic region
Provinces included	Beijing, Tianjin, Hebei, ...	Shanghai, Jiangsu, Anhui, ...	Guangdong, Guangxi, Hainan, ...	Chongqing, Sichuan, Yunnan, ...	Gansu, Ningxia, Xinjiang, ...
Number of provinces	10	7	5	4	4

dataset samples. Spatial clustering refers to the study area's economy exhibiting specific spatial patterns, and the economic effects in this paper emphasize the externalities that clustered areas have on the economic development of other regions. The density-clustering algorithm has a high density in the center, surrounded by neighbors whose densities are below it, and the density of surrounding data points continuously decreases. The error rates of KSNM, K-means, and PSO algorithms are compared using the public data set iris, and the results are shown in Figures 4 and 5.

The error rate of KSNM is very small, and the error rate of K-means and PSO has increased to a certain extent. Therefore, it can be concluded that the density-clustering algorithm is based on China's regional economic competitiveness zoning method can find the correct clustering results without the given clustering individual cases.

First, the clustering centers are established based on the present-day characteristics of the class centers. This can be determined by regression, inference-based tools using Bayesian formalism, or decision tree induction. Gini coefficient calculations by population groups are performed on sample data to examine the status of per capita income differences between and within groups, and also to examine the degree of per capita income crossover between groups. The purpose is to analyze the neighboring spatial clustering relationships, spatial instability, and spatial structural framework of the values taken by a certain spatial object, especially when the global correlation analysis is not able to detect the spatial distribution patterns within the region. This type of clustering is often called minimum variance partitioning, and it is suitable for situations where the classes of objects are dense and similar in number, while the objects between the different classes are clearly separated. For each object that constitutes a cluster, there must be no less than a given value, that is, the density of its domain must be no less than a certain threshold. The clustering continues as long as the number of density samples in the adjacent regions exceeds a certain threshold value. The interclass priority and intraclass priority can be obtained using the method of authority value and hub value used by hits algorithm. KSNM and SNN, respectively, are calculated for the above three data sets to obtain the values of J_c . Table 2 shows the results of comparing the convergence ability of KSNM with SNN.

Second, the other data points are drawn to the class of data points with the smallest proximity and higher density than their current class. The smoothed data are

obtained by examining the "near neighbors" of the data, and the smoothed values include box mean, box median, and box boundary, etc. The larger the box width, the better the smoothing effect. Based on the results, the spatial distribution of the coordination between economic development and resources and environment in each region of China is analyzed and based on this, and the relevant influencing factors of economic growth efficiency are proposed from the perspective of spatial economics, and the strength and mode of action of these factors are further examined. That is, for each sample in a given cluster, at least a certain number of samples must be included in a given range of regions. The nodes are ranked using the authority values to generate intracluster priorities and intercluster priorities, which are analyzed separately. Local spatial correlation analysis can effectively detect the spatial differences caused by spatial correlation, determine the spatial hotspot areas, or high incidence areas of spatial object attribute values, and thus make up for the shortcomings of global spatial correlation analysis.

Finally, the decision diagram of sample distance relative to sample density is established to achieve the effect of presenting the class cluster center of arbitrary dimensional data set through two-dimensional plane, thus completing the clustering analysis of arbitrary dimensional data. The data attributes are divided into intervals by equal distance, and then the data falling within the intervals are mapped to equal discrete values. Using priority as the similarity measure can effectively avoid the effect of distance vector failure in clustering of high-dimensional data sets. Using provinces as the study unit will lead to the failure to truly reflect the spatial clustering characteristics and changes of economic growth within the study unit, while using counties as the study unit will compare urban areas with counties on the same scale.

The location of economic activities is mainly influenced by natural conditions and distribution of natural resources and tends to be more spatially distributed in places with better natural conditions and more concentrated natural resources. Therefore, the factor analysis method was applied to measure the scores of each factor and the overall competitiveness score of high-tech service industry in each province and city. The global type is mainly used to judge whether there are clustering characteristics of the whole regional economic phenomenon, and it does not reflect the specific places where the clusters are located, while the factor analysis can point out the range of clusters.

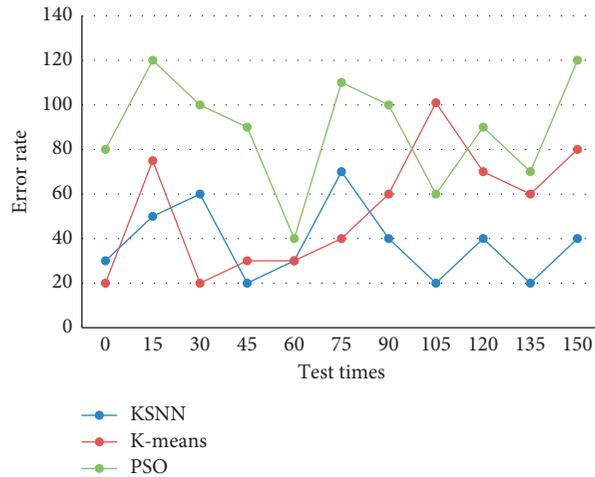


FIGURE 4: Comparison of error rates of KSNN, K-means, and PSO.

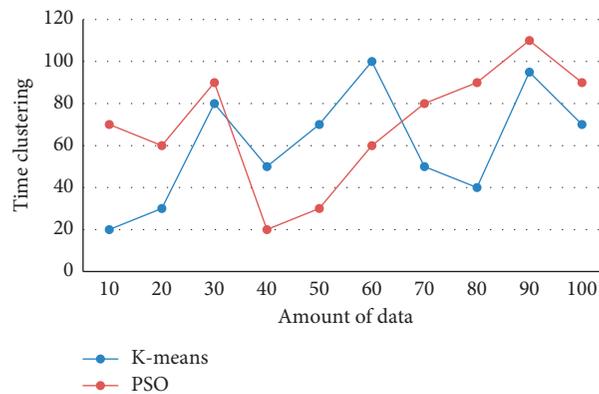


FIGURE 5: Performance analysis of K-means and PSO algorithms.

4.2. Analysis of Spatial Aggregation Characteristics.

Although the high-, medium-, and low-economic growth efficiencies do not correspond exactly to the zoning structure of East, Central, and West. However, most of the regions with high environmental technical efficiency, i.e. high-economic growth efficiency, are indeed concentrated in the eastern regions of China, while most of the regions with low-environmental technical efficiency are concentrated in the western regions of China. The absorption of labor from other regions by developed regions is selective, and developed regions need a large amount of higher-quality labor such as skills and talents, skilled labor, and entrepreneurs, rather than general labor. It is difficult to discover potential local spatial association patterns by applying global indicators, and when global statistics cannot provide evidence of global spatial association, it is more necessary to use local indicators to discover potential locally significant spatial association. The comparison of priorities among nodes in the dataset at $k = 10$, and $k = 20$, respectively, was utilized. The comparison results are shown in Figure 6.

First of all, the central city has strong agglomeration power. Indicators and methods to measure the degree of spatial agglomeration of a regional economy are concentration rate, geographic linkage rate, and locational entropy method. Under the conditions of modern market economy, economic growth depends on the degree of possession of resources and markets; therefore, the competition for resources and markets is the main expression of competition, which is the soul of market economy. Concentration index is the proportion of the population of the area where half of a geographical factor is concentrated to the total population, reflecting the degree of concentration of the geographical factor in the area. The core objects will be increasing in this process, and the unprocessed objects are kept in the memory. If there are huge clusters in the database, a large amount of memory will be required to store the core object information, and its demand is unpredictable. Since the fusion operation is performed only for one convex hull functional area range at a time, and the distance between polygons in that range is not

TABLE 2: Comparison of convergence ability between KSNM and SNN.

J_c	KSNM	SNN
Fac	769.25	885.62
Iris	42.87	47.91
Artificial data set	673.95	681.83

too large, a larger distance is sufficient for the built-in distance parameter here. The density ratio determines the size of the clusters expanded from the centroid, and when the density ratio is larger, the class is expanded only to the relatively denser regions in the cluster, making the less-dense regions separated out, so the results of the impact of density radius change on the clustering results are shown in Figure 7.

Second, the economic volume of the border areas is small. The geographical linkage rate index mainly reflects the geographical distribution of the two factors in the region. To achieve the goal of coordinated regional economic development, a reasonable division of economic regions is a prerequisite. For the clustering operation of the dataset, the correlation between the nodes in different clusters is weak, and even there is no dependency between the nodes in the clusters. The radius ratio restricts the search from the core point to the ratio of the core point to its nearest neighbor distance, but it also causes the elimination of candidate core points, which affects the clustering accuracy. The effects of different radius ratio variations on clustering results are shown in Figure 8.

Meanwhile, any kind of changes in GDP growth rate and inflation rate can be attributed to the effects of external supply disturbances and external demand disturbances. Because of the possible crossover between the convex hull functional areas, the unwanted convex hull functional areas can be removed by the delete operation function. However, the algorithm has obvious limitations, namely, it is sensitive to the user-defined parameters, and subtle differences may lead to widely varying results, while the selection of parameters is irregular and can only be determined empirically.

Finally, the economic support of coastal areas is weak. The GDP growth rate and inflation rate are directly observable, and the supply disturbance and demand disturbance exist only in theoretical assumptions and are unobservable, but they are the main basis for implementing regulatory policies. Therefore, the priority within different clusters is greatly influenced by the nodes within this cluster and little influenced by the nodes within other clusters, or even not influenced by any nodes from other clusters. The coastal areas should develop high precision industries, speed up the construction of coastal ports, and energy development in areas with better resources, and vigorously develop agriculture, while the inland areas should speed up the construction of energy, transportation, and raw material

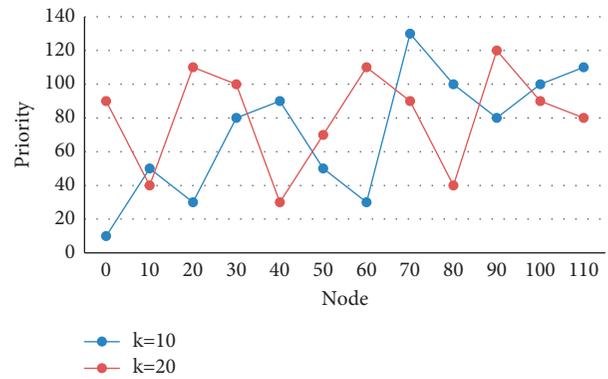


FIGURE 6: Priority comparison among data set nodes.

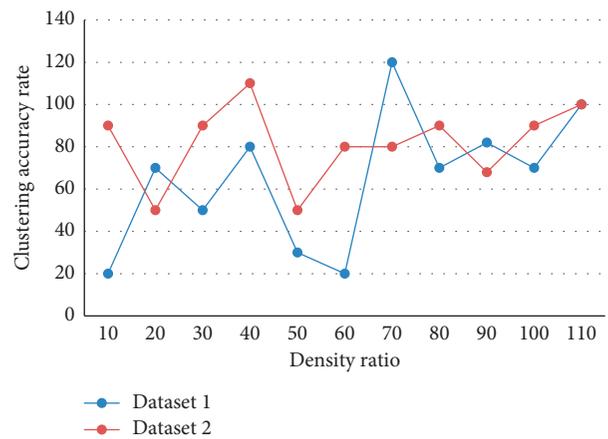


FIGURE 7: Influence of density radius change on clustering results.

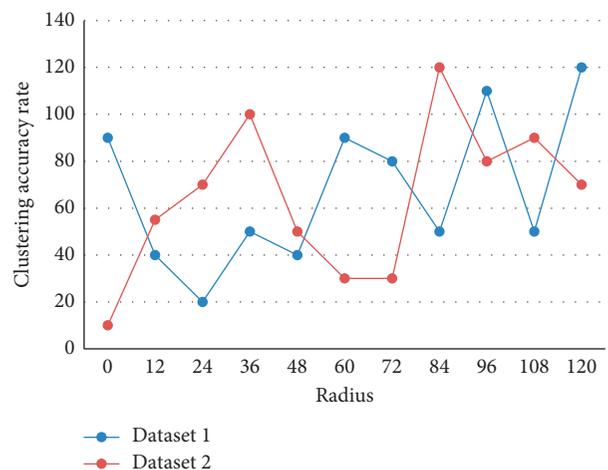


FIGURE 8: Influence of radius ratio change on clustering results.

industries, adjust and transform the existing machinery industry, develop consumer goods industries in a planned manner, and give full play to the potential of agricultural production.

5. Conclusions

In recent years, China's economy has been growing rapidly at nearly double-digit rates, and the economic and social landscapes have been greatly transformed, a phenomenon that academics at home and abroad call the "Chinese miracle." Although the results of interprovincial analysis show the changes in the regional economic landscape better, there is still the drawback of too large a spatial unit of analysis. The agglomeration of economic growth is very obvious in the historical process of economic development of industrialized countries. The analysis of this huge amount of information has become a difficult problem for national economic competition. Traditional methods of regional economic analysis assume that regions are independent of each other, while in reality, regions are interconnected as well as influenced by each other, and different regional environments have different effects on the economy. Density-clustering algorithm is a technique to mine knowledge and intelligence from massive digital information, so using density-clustering technology can improve the depth of intelligence analysis and the efficiency of national economic competition. In this paper, we propose a density clustering algorithm-based zoning method for China's regional economic competitiveness and analyze the spatial aggregation characteristics in detail to reveal the spatial autocorrelation and spatial heterogeneity of the economic development level of each province and region in China and its spatial dynamic evolution pattern. This provides favorable conditions for the creation of "growth poles" in the inland areas; the creation of "dual growth poles" in the eastern coastal growth poles and inland areas not only has a realistic basis but also has important practical significance for the improvement of the pace of regional gap reduction. It is also possible to incorporate geographic spatial effects into the model framework to detect and measure the impact of economic growth spillover from spatially adjacent regions on regional economic growth.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the Science and Technology Research Project of Hubei Education Department (Grant no. D20201801) and the Doctoral Scientific Research Foundation of Hubei University of Automotive Technology (Grant no. BK201907).

References

- [1] J. Jiang, D. Hao, Y. Chen, M. Parmar, and K. Li, "GDPC: gravitation-based density peaks clustering algorithm," *Physica A: Statistical Mechanics and Its Applications*, vol. 502, Article ID S0378437118301705, 2018.
- [2] Z. Xue and H. Wang, "Effective density-based clustering algorithms for incomplete data," *Big data mining and analysis*, no. 3, p. 12, 2021.
- [3] Z. Xue and H. Wang, "Effective density-based clustering algorithms for incomplete data," *Big Data Mining and Analytics*, vol. 4, no. 3, pp. 183–194, 2021.
- [4] Y. Zhou and Z. Lu, "Research on evaluation of regional economic competitiveness based on fuzzy analytic hierarchy process," *Region - Educational Research and Reviews*, vol. 1, no. 2, p. 24, 2020.
- [5] X. Cheng, R. Long, H. Chen, and Q. Li, "Coupling coordination degree and spatial dynamic evolution of a regional green competitiveness system – a case study from China," *Ecological Indicators*, vol. 104, no. SEP, pp. 489–500, 2019.
- [6] E. Kot, T. Kruzhkova, O. Rushitskaya, A. Ruchkin, and V. Kukhar, "The problem of improving the competitiveness of enterprises in the system of socio-economic relations," *IOP Conference Series: Earth and Environmental Science*, vol. 699, no. 1, Article ID 012058, 2021.
- [7] D. Zhao, Z. Zhao, and Z. Chen, "Construction of regional economic vitality model," *Journal of Economic Science Research*, vol. 3, no. 2, p. 5, 2020.
- [8] X. Wang, "Comprehensive evaluation on regional economic competitiveness of suzhou, wuxi and changzhou in jiangsu province," *Statistics and Applications*, vol. 09, no. 3, pp. 386–392, 2020.
- [9] I. Triyani, K. Adam, and D. Kristina, "Strengthening rural and regional economic competitiveness triggering purworejo reGENCY economic growth through tourism-based kutoarjo transit node development," *The Indonesian Journal of Planning and Development*, vol. 4, no. 1, p. 19, 2019.
- [10] L. Nazarova, "The development of the regional economic system competitiveness policy," *Modern Economics*, vol. 20, no. 1, pp. 162–166, 2020.
- [11] D. Novita, M. Asaad, L. Tanjung, D. Hendrawan, and A. Hasibuan, "The regional investment competitiveness in binjai city," *International Journal of Pure and Applied Mathematics*, vol. 119, no. 17, p. 1983, 2020.
- [12] Y. A. Fridman, G. N. Rechko, and A. G. Pimonov, "Competitive positions of a region in innovative economic development," *Regional Research of Russia*, vol. 7, no. 4, pp. 333–341, 2017.
- [13] D. D. Burkaltseva, I. N. Voronin, and A. M. Lisitsky, "Assessing the effects of investments into innovative activity as a regional competitiveness factor," *International Journal of Applied Business and Economic Research*, vol. 15, no. 8, pp. 11–27, 2017.
- [14] S. T. Okutayeva, M. S. Bauer, A. K. Jussibaliyeva, and K. Bodaughan, "Development of regional livestock cluster in Kazakhstan as a method to improve competitiveness," *International Journal of Economic Research*, vol. 14, no. 7, pp. 223–237, 2017.
- [15] H. Dawid, P. Harting, and M. Neugart, "Fiscal transfers and regional economic growth," *Review of International Economics*, vol. 26, no. 3, pp. 651–671, 2017.
- [16] C. Deng, J. Song, R. Sun, S. Cai, and Y. Shi, "GRIDEN: an effective grid-based and density-based spatial clustering

- algorithm to support parallel computing,” *Pattern Recognition Letters*, vol. 109, no. JUL.15, pp. 81–88, 2018.
- [17] X. Chen, X. Wang, and H. K. Chan, “Manufacturer and retailer coordination for environmental and economic competitiveness: a power perspective,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 97, no. JAN, pp. 268–281, 2017.
- [18] M. A. Obomeghie and U. O. Ugbomhe, “Globalization and its brunt on Nigeria global economic competitiveness: the need for holistic and dynamic strategies,” *International Journal of Social Sciences and Economic Review*, pp. 1–06, 2021.
- [19] R. Goli and M. Joksimovi, “Regionalization of Serbia as an instrument of balanced regional development and reduction of regional inequalities,” *Zbornik radova - Geografski fakultet Univerziteta u Beogradu*, vol. 2017, no. 65-1a, pp. 209–226, 2017.
- [20] L. Bai, X. Cheng, J. Liang, H. Shen, and Y. Guo, “Fast density clustering strategies based on the k-means algorithm,” *Pattern Recognition*, vol. 71, pp. 375–386, 2017.
- [21] J. Chen, H. He, J. Chen, S. Yu, and Z. Shi, “Fast density clustering algorithm for numerical data and categorical data,” *Mathematical Problems in Engineering*, vol. 2017, Article ID 6393652, 15 pages, 2017.
- [22] A. Kumar and S. Kumar, “Density based initialization method for K-means clustering algorithm,” *International Journal of Intelligent Systems and Applications*, vol. 9, no. 10, pp. 40–48, 2017.
- [23] J. Ma, X. Jiang, and M. Gong, “Two-phase clustering algorithm with density exploring distance measure,” *CAAI Transactions on Intelligence Technology*, vol. 3, no. 1, pp. 59–64, 2018.
- [24] E. Gungor and A. Ozmen, “Distance and density based clustering algorithm using Gaussian kernel,” *Expert Systems with Applications*, vol. 69, no. mar, pp. 10–20, 2017.
- [25] J. Lu and Q. Zhu, “An effective algorithm based on density clustering framework,” *IEEE Access*, vol. 5, pp. 4991–5000, 2017.
- [26] J. Xu, L. C. Fang, M. Gen, and S. E. Ahmed, “Proceedings of the twelfth international conference on management science and engineering management,” in *Proceedings of the International Conference on Management Science and Engineering*, Phuket Thailand, May 2019.
- [27] B. J. Lakshmi, K. B. Madhuri, and M. Shashi, “An efficient algorithm for density based subspace clustering with dynamic parameter setting,” *International Journal of Information Technology and Computer Science*, vol. 9, no. 6, pp. 27–33, 2017.
- [28] G. Pistilli, A. Campagna, L. Persia, and M. R. Saporito, “Regionalization of Ports as a strategic leverage to improve competitiveness: a study on central Italy ports and related hinterland,” *International Journal of Transport Development and Integration*, vol. 4, no. 1, pp. 51–61, 2020.
- [29] V. Bondarenko, O. Kurey, E. Derdi, and O. Butusov, “Monitoring of a region’s competitiveness as a mechanism of a state regional policy implementation,” *Regional Economy*, vol. 2, no. 2(96), pp. 33–43, 2020.
- [30] J. M. C. Díaz, L. Martínez-Bernabéu, and F. Flórez-Revuelta, “Automatic parameter tuning for functional regionalisation methods,” *Papers in Regional Science*, vol. 96, no. 4, pp. 859–879, 2017.