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Research article

Regional differences of high-quality development level for manufacturing industry in China

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Abstract: The development of China's manufacturing industry is still facing the challenge of regional imbalance. To solve the problem of development imbalance, it is necessary to realize regional development. First, we must analyze the development characteristics of different regions. To this end, we consider the requirements of the new development era and design an evaluation index system for the high-quality development level of the manufacturing industry from the dimensions of innovation, green, and efficiency. Then construct a novel hybrid model which combines the grey incidence clustering model and AP algorithm for panel data in this paper. According to the statistical data from 2014 to 2018, we find out the high-quality development of China's manufacturing industry is characterized by obvious regional differences, different development stages and different constraints.

Keywords: high-quality; development level; difference; panel data; grey incidence

1. Introduction

The development level of the manufacturing industry can show one country's economic strength. It's also the foundation to realize industrialization and modernization. Promoting the high-quality development of the manufacturing industry is an important part to build the modern economic system. Many scholars have carried out related research. Yang [1] analyzed the influencing factors and development trends of the transformation and upgrading of the manufacturing industry in the Guangdong-Hong Kong-Macao Greater Bay Area. Through these works, we find that the development scale, quality and efficiency performance of the manufacturing industry vary a lot from region to region. There are still many problems in the high-quality development of China's manufacturing industry, such as the high proportion of low-end capacity and the weak competitiveness in the high-end industry. For example, Fu [2] found that regional innovation capability has a significant spatial correlation with green technology manufacturing efficiency, and the manufacturing industry in the eastern region is most vulnerable to the positive impact of innovation capability. Li [3] also proved that the green development of high-end manufacturing in China exists Regional heterogeneity. The development scale, quality and efficiency performance of the manufacturing industry vary a lot from region to region. This phenomenon of regional development imbalance is common in China, and at the same time seriously affects the development of high-quality economic and hinders the implementation of national strategies. To solve this problem, it is necessary to promote the improvement of the development level of the regional manufacturing industry in a targeted manner. Therefore, grasping the status and level of high-quality development of manufacturing in China and exploring the regional differences in high-quality development of manufacturing have great practical significance. It's also good for upgrading the industrial structure, and enhancing the core competitiveness of the country.

In view of this, we design an evaluation index system from the dimensions of innovation, green, and efficiency, and propose an improved grey incidence clustering model based on panel data to measure the high-quality development level of the manufacturing industry. Our study is based on the data from the manufacturing statistical yearbooks of 30 provinces in China from 2014 to 2018.

The rest of this paper is organized as follows. In Section 2, we provide a brief review of related works. In Section 3, we design an evaluation index system that fully considers the special requirements for high-quality development of the manufacturing industry. In Section 4, we proposed an improved grey incidence clustering model. Based on Section 3 and Section 4, we measure and analyze the high-quality development level and regional differences of the country's manufacturing industry in Section 5. In Section 6, we conclude this paper with some remarks and provide some suggestions.

2. Related literatures

Promoting the high-quality development of the manufacturing industry has important practical significance for upgrading the industrial structure and enhancing the country's core competitiveness. Scholars at home and abroad actively carry out theoretical and practical explorations. After combing the relevant literature, we can see that the current works on the high-quality development level of the manufacturing industry mainly focus on three main aspects. They are the identification of influencing factors, the design of the index system and the construction of measurement methods. In terms of the analysis of factors that affect the high-quality development of the manufacturing industry, domestic and foreign scholars mainly discuss the impacts of scientific research and innovation personnel [4–6], capital investment [7,8] and patent output capacity [9–11]. Peng Li studies the nonlinear impact of technical change on green productivity in China [12]. Li [13] studies the influence of product profitability, environmental regulations [14–16] and enterprise-scale [17–19], etc. Roper also analyzes the effect caused by factors such as the openness of innovation [20], the quality of labor [21]. Li considers the import trade and export trade [22], and quality management [23] as impact factors as well.

In the design of an index system of the high-quality development level of the manufacturing industry, domestic and foreign scholars mainly focus on the perspective of manufacturing production input and output. They use factors related to the technology R&D (research and development) expenditure, R&D personnel [24,25], patent output [26–28], green technology innovation [29], and new product revenue [25,30]as key indexes to construct an index system to measure the high-quality development level of the manufacturing industry. Some scholars focus on the industry characteristics of high-quality development of the manufacturing industry, considering domestic ， foreign market shares and competitiveness, international trade barriers, economic performance and social benefits, innovation and resource allocation efficiency, to build an index system for measuring the high-quality development level of manufacturing [31–35]. Previous manufacturing evaluation researches pay more attention to the economic performance of the manufacturing industry, and lack discussions on factors of high-quality development such as the transformation of energy structure, product export competitiveness, and social benefits created by the manufacturing industry.

Scholars have a wealth of options when evaluating manufacturing development. Many scholars mainly use methods such as DEA (data envelopment analysis) [36–38], total factor productivity [39], clustering analysis [40], stochastic frontier model [41], the spatial autoregressive model [26], system GMM (Gaussian Mixture Model) regression model [24,42] to measure manufacturing high-quality development level. Buesa uses factor analysis to explore the regional systems of innovation and the knowledge production function [43]. Luo uses principal component analysis to analyze the regional disparity of China’s industrial companies [44]. Each method has its own advantages and disadvantages. For example, the DEA method is the most commonly used method to measure manufacturing efficiency, but it can’t help us to fully explain the regional difference. Peng [12] construct a novel TODIM (an Interactive multi-criteria decision-making method) method and use it to solve a venture investment problem in which the decision matrix is characterized by general grey numbers. Jing [45] considers both economic and environmental criteria and uses a comprehensive weighted grey incidence decision approach to make evaluation and select green supplier in a process industry. Tang [46] constructs a grey clustering evaluation model to evaluate the tourism development potential of tea intangible cultural heritage. Zeng [47,48] studies the production trends of coalbed methane and other multi-energy gases with the grey forecasting methods, and provides suggestions for energy policy formulation. The above research proves that the grey theory has a good application effect in dealing with the decision-making evaluation problem in the economic field. Grey clustering is also a method suitable for studying the influence of regional differences on measurement results. But in an application, grey models rely on subjective experience in parameter setting, and have defects such as the inability to achieve automatically cluster. According to the above analysis and discussion, we know that many scholars have studied the high-quality development level of the manufacturing industry and have achieved a lot of results, but there are still some problems to be improved in the existing research. (1) The index system of the high-quality development level of the manufacturing industry should be updated. The existing measurement index system for the high-quality development level of the manufacturing industry focuses on economic benefits like input and output, while ignoring the development efficiency, green development, and social benefits of the manufacturing industry. Regional differences are not fully analyzed. (2) The method for measuring the high-quality development level of the manufacturing industry needs to be improved. The measurement indexes of the high-quality development level of the manufacturing industry present positive and negative characteristics of development. It’s necessary to construct a measurement method suitable for this characteristic.

In view of this, we design an evaluation index system from the dimensions of innovation, green, and efficiency to measure the high-quality development level of the manufacturing industry. We also construct a grey incidence clustering method which combines the advantages of grey incidence method and the AP (affinity propagation) clustering algorithm to deal with panel data. This method is used to measure the high-quality development level of manufacturing of 30 provinces in China and analysis its regional differences. Compared with the traditional evaluation method, the advantage of our proposed model is as follows. On the one hand, the model is based on the grey incidence analysis, so it can be used for evaluation with grey numbers and fuzzy data. On the other hand, the model can realize automatic clustering and calculate the best cluster center at the same time.

3. An index system of the high-quality development level for manufacturing industry

The high-quality development has important strategic significance for the optimization and upgrading of the industrial structure and the enhancement of the country's core competitiveness. The high-quality development of the manufacturing industry is affected and restricted by many factors such as technology innovation, energy consumption, environmental performance, production efficiency, economic performance, social benefits, and products' market competitiveness. Among them, technological innovation is a key factor restricting high-quality development [49]. Energy consumption and environmental performance [50] are two important bottlenecks restricting the current sustainable development of the economy in China's society. Efficiency is the key task of resource allocation for manufacturing development [51,52], and green development is the inevitable trend of manufacturing development [53]. Considering the influence of these factors, formulate a scientific and reasonable evaluation index system for the evaluation of high-quality development of the manufacturing industry, and recognize key problems are important. Based on the research results of Rusinko [54] and others, we design an index system from the three dimensions of innovation, greenness, and efficiency, which is shown in Table 1.

(1) In terms of innovation, innovative R&D intensity and innovative R&D capabilities are the most important factors. In terms of innovative R&D intensity, R&D personnel, number of R&D industrial enterprises, innovation R&D funding expenditure [55,56], the number of new product development projects, and new product development funding [57] are commonly used indexes to measure manufacturing innovation R&D level. Taking regional differences into account, we use the proportion of R&D personnel and the proportion of R&D activity industrial enterprises to measure the popularity and importance of R&D activities of manufacturing enterprises in various regions. At the same time, referring to the evaluation index system of enterprise innovation capability issued by the Ministry of Science and Technology, the contribution of industrial enterprise R&D expenditures to main business income is selected to measure the innovation expenditure input.

Different from the existing research, we subdivide technological innovation into technology introduction and independent research. In terms of innovative R&D capabilities, considering that technology import is a short path for the development of new technology. Independent R&D, especially the independent R&D of core technologies, is a key factor that determines the future high-quality development of an enterprise. We select the number of effective invention patents and the proportion of invention patents, technology import funds and industrial enterprise R&D funds, and the ratio of technology digestion and absorption funds to technology import funds to measure the ability of innovation resource introduction and innovation resource integration.

(2) In terms of green, energy input and pollutant emissions [58] and governance capabilities can better reflect the friendliness of environmental protection and the degree of green, and represent the attitude of local governments and enterprises towards environmental issues over a period. At present, the green development of the manufacturing industry is mainly measured by energy consumption and pollutant emissions.

Creatively， we consider the transformation of energy structure, and select evaluation indexes from traditional energy and new energy respectively. First, coal is the most used energy source of China's manufacturing enterprises. It's reasonable to use coal consumption per unit of industrial added value to reflect the utilization rate of traditional energy in the industrial production process and the degree of contribution to the output value. At the same time, referring to the proportion of energy resources of industrial enterprises in the statistical yearbook, electricity is also the main new energy resource of China's manufacturing industry. Therefore, we choose the consumption of electricity per unit of industrial added value to measure the new energy consumption of manufacturing enterprises.

From the perspective of pollutant emissions, undesired output such as pollutant emissions caused by manufacturing production is an important factor affecting the level of green development. Scholars mainly use the discharge of wastewater and waste gas and the comprehensive utilization rate of solid waste to measure the pollutant discharge situation [59]. Considering the regional differences of economic development, we choose the main pollutants in the waste gas per unit of industrial added value and the discharge of main pollutants in wastewater per unit of industrial added value to reflect the negative impact of industrial production activities on the environment.

From the perspective of environmental governance, the solid waste utilization rate is generally used to evaluate the solid waste treatment capacity. In addition, the local capital investment to control the pollutant output can directly reflect the attitude of the government to environmental governance. We call this indicator the completed investment in industrial pollution treatment. (3) In terms of efficiency, the development level of the manufacturing industry is generally measured from the dimensions of economic performance, social benefits and product competitiveness. In terms of economic performance, the three major indexes are capital output efficiency, total labor productivity, and sales profit rate [60]. Capital-output efficiency mainly reflects the ability of assets to increase in value. Total labor productivity reflects the added value of the industry due to the labor of the workers. The sales profit rate reflects the profitability of the manufacturing industry, which is a comprehensive measure of the economic benefits of enterprises.

We also consider social benefits created by manufacturing industry in this paper. We choose the contribution rate of industry to employment and the average annual income of employed employees to measure the role of manufacturing industry in alleviating employment pressure and the life quality of manufacturing workers respectively. Considering the availability of data, we use the proportion of employed persons in urban units of manufacturing industry to represent the contribution rate of industry to employment. At the same time, we use the average wage of employed persons in urban units of manufacturing industry to represent the average annual income of employed persons in urban units of manufacturing industry.

Researches on the market competitiveness of manufacturing products are mostly qualitative research. We try to make a quantitative analysis by considering the following factors. We hold that the export of new products, the contribution of R&D and innovation, the efficiency of technology transformation and the quality of products can reflect the competitiveness of manufacturing products from different dimensions. Therefore, we choose five indexes including international competitiveness of new products, contribution of R&D input and output, output value rate of new products, input-output efficiency of technological innovation, and quality efficiency. Our country is in transition from "Made in China" to "Create in China", the competitiveness of the products in the market, especially the competitiveness of the new products in the international market should be valued.

Table 1. Evaluation index system and calculation formula.

I Indexes/ II Indexes	Ⅲ Indexes	Index Description	Index Symbol
Innovation			
Innovative R&D efforts	Proportion of personnel participating in R&D activities	R&D personnel of industrial enterprises above designated size equivalent to full-time equivalent/Average number of workers	X11
	Proportion of industrial companies with R&D activities	Number of companies with R&D activities/Number of industrial companies	X12
	R&D expenditure input intensity	R&D expenditure of industrial enterprises above designated size/Main business income of industrial enterprises above designated size	X13
	Number of new product development projects	Number of new product projects of industrial enterprises above designated size (item)	X14
	Expenditures for new product development	Expenditures for new product development by industrial enterprises above designated size (ten thousand yuan)	X15
Innovative R&D capability	Innovative resource introduction capability	Technology introduction funding/R&D funding of industrial enterprises above designated size	X21
	Innovative resource integration capability	Enterprise technology digestion and absorption funds/Enterprise technology introduction funds	X22
	Technical innovation output level	Number of effective invention patents (items)	X23
	Technical innovation output level	Proportion of invention patents Invention patent applications/Patent applications	X24
Green			
Energy consumption	Coal consumption	Coal consumption per unit of industrial added value (10,000 tons/10,000 yuan)	Y11
	Electricity consumption	Electricity consumption per unit of industrial added value (100 million kilowatts/hour)	Y12
Emission	Discharge Waste water	Discharge of main pollutants in wastewater per unit of industrial added value (10,000 tons)	Y21
	Waste gas unit industrial added value	Emissions of main pollutants in exhaust gas (10,000 tons)	Y22

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I Indexes/ II Indexes	Ⅲ Indexes	Index Description	Index Symbol
Governance intensity	Solid waste utilization situation	General industrial solid waste comprehensive utilization/general industrial solid waste generation	Y23
	Industrial pollution control intensity	Industrial pollution control completed investment (ten thousand yuan)	Y31
Efficiency			
Economic and social value	Economic and social value	Capital output efficiency Main business income realized per hundred yuan of assets (yuan)	Z11
	Total labor productivity	Industrial added value/average number of workers	Z12
	Sales profit margin	Operating profit of industrial enterprises above designated size/Main business income of industrial enterprises above designated size	Z13
	Contribution rate of industry to employment	Employment in manufacturing urban units/employed in urban units	Z14
	Average annual income of employed employees	Average salary of employed employees in manufacturing urban units (yuan)	Z15
Product competitiveness	Product competitiveness International competitiveness of new products	Export sales income of new products of industrial enterprises above designated size / Sales income of new products of industrial enterprises above designated size	Z21
	R&D input-output contribution rate	R&D expenditure of industrial enterprises above designated size/Industrial added value	Z22
	New product output value rate	New product sales revenue of industrial enterprises above designated size/Main business income of industrial enterprises above designated size	Z23
	Input-output efficiency of technological innovation	Sales revenue of new products of industrial enterprises above designated size/Development expenditure of new products of manufacturing industry	Z24
	Quality efficiency	Product quality superior product rate	Z25

4. Research methods

We can represent the manufacturing data of each province in the form of panel data, and calculate its grey incidence degree accordingly. Then we use the grey incidence degree to characterize the distance of high-quality development among the manufacturing industry in different provinces. The higher the grey incidence degree is, the smaller the development gap is. Through multiple experiments, we can use the AP algorithm to divide all provinces into three classes: excellent, qualified, and poor. The specific steps are as follows.

4.1. Calculate the grey incidence degree matrix for panel data

Panel data is a data set composed of multiple index values of multiple samples at different time points, including information on three dimensions: time dimension, object dimension, and index dimension. We can map the observation values of various indexes in each sample at different time points to points in three-dimensional space.

Assume that there are N research objects, each research object has M research indexes, and the observation time length is T. X is a panel data, which can be expressed as $X=\{X_1(m,t),X_2(m,t),...,X_N(m,t)\}$, $m=1,2,...M$; $t=1,2,...,T$. Let X_i indicate the behavior matrix of the object $i(i=1,2,...,n)$, and $x_i(m,t)$ stands for the value of the index m of the object i at time t, and $x_i(m,t)>0$, $i=1,2,3,...,N; m=1,2,3,...,M; t=1,2,3,...T$. We can define the time matrix and index matrix of the object i similarly. If the dimensions of the indexes are different or the range of value is too large, we should initialize the original data matrix. Let d_{ik}^C denote the grey incidence degree of decision object i and k over the spatiotemporal characteristic attribute set C.

Let H_i, $C_i(t)$ respectively denote the slope function of X_i in the index and time dimensions and the average value of the absolute slope value of the index dimension of object i at time t [61]. Then let $U_i(m,t)$ represent the average of the slope of object i from index $m-1$ to index m at time t.

$$U_i(m,t)=\frac{H_i(m,t)}{C_i(t)},i=1,2,...,N,m=2,3,...,M,t=1,2,...,T \tag{1}$$

$U_i(m,t)$ stands for the result of standardization. It shows the similarity of the relative change trend of the sequence curve. The closer slopes equal to the larger grey incidence degrees. When $|U_i(m,t)|$ and $|U_j(m,t)|$ are closer to each other, the grey incidence degree between the panel data X_i and X_j from the index $m-1$ to the index m is larger.

We use $l_{ij}^H(m,t)(m=2,3,...,M,t=1,2,3...,T)$ to measure the grey incidence coefficient of X_i and X_j in the index dimension [61]. Here l represents the grey incidence measure operator.

If $U_i(m,t)$ and $U_j(m,t)$ are not 0 at the same time, we let

$$l_{ij}^H(m,t)=\frac{\operatorname{sgn}(U_i(m,t)\times U_j(m,t))}{[1+\frac{1}{2}\left\|U_i(m,t)\right|-\left|U_j(m,t)\right\|+\frac{1}{2}(1-\frac{\min(\left|U_i(m,t)\right|,\left|U_j(m,t)\right|)}{\max(\left|U_i(m,t)\right|,\left|U_j(m,t)\right|)})]} \tag{2}$$

If $U_i(m,t)$ and $U_j(m,t)$ are both 0, then let $l_{ij}^H(m,t)=1$, then we can have

$$\operatorname{sgn}(U_i(m,t)\times U_j(m,t))=\begin{cases}1, & U_i(m,t)\times U_j(m,t)\geq 0;\\ -1, & U_i(m,t)\times U_j(m,t)<0.\end{cases} \tag{3}$$

Let $\left|\gamma_{ij}^H\right|$ stand for the grey incidence degree in the index dimension, for panel data X_i and X_j, we can obtain γ_{ij}^H as follows:

$$\gamma_{ij}^{H}=\frac{\sum_{m=2}^{M}\sum_{t=1}^{T}l_{ij}^{H}(m,t)}{T(M-1)} \tag{4}$$

Similarly, we can calculate the grey incidence degree in the time dimension $\left|\gamma_{ij}^{W}\right|$.

We calculate the arithmetic mean γ_{ij} of the absolute value of the grey incidence degree in the index dimension and the time dimension as the grey incidence degree of X_i and X_j, where $\gamma_{ij}=\frac{1}{2}(\left|\gamma_{ij}^{H}\right|+\left|\gamma_{ij}^{W}\right|)$. The larger the value of γ_{ij} is, the larger the grey incidence degree between the panel data is. Then, we have the grey incidence matrix of panel data, which can be denoted as
$$Y=\begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1j} & \cdots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2j} & \cdots & \gamma_{2n} \\ \vdots & \ldots & \vdots & \ldots & \vdots \\ \gamma_{i1} & \gamma_{i2} & \cdots & \gamma_{ij} & \cdots & \gamma_{in} \\ \vdots & \ldots & \vdots & \ldots & \vdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nj} & \cdots & \gamma_{nn} \end{bmatrix}.$$

4.2. Cluster analysis based on AP clustering algorithm

Although the traditional grey relational analysis method can also achieve cluster analysis, the setting of the likelihood function is often disturbed by empirical data. AP clustering algorithm, namely attractor propagation clustering, is a clustering algorithm based on “information transfer” between data points [62]. It can realize automatic clustering according to the distance between the research objects, which can effectively improve the objectivity of decision-making results. We don't need to specify the number of clusters in advance, which can improve decision-making efficiency. Furthermore, it can well solve non-Euclidean space problems and large-scale sparse matrix calculation problems which we may face when using the grey incidence clustering method only.

Let the development gap matrix S represent the development distance between different regions, we can obtain it through the transformation of the grey incidence matrix, where $S=Y\text{-}\mathrm{E}$. (where E is the identity matrix). Smaller distance means higher similarity of the two regions' development level.

The AP algorithm takes the sample similarity matrix S as an input variable. P is the bias parameter used to reflect the probability of becoming a representative point of the class. Generally, the bias parameter P of each sample is the same, and its value can be determined by prior knowledge. Let R and A denote the attractiveness matrix and the attribution matrix, respectively. Assume that $r(i,j)$ stands for the attractiveness of the sample x_j to the sample x_i, which is used to describe the degree of the suitability of the sample x_j as a class representative of the sample x_i, and the propagation direction is $i \to j$. Assume that $a(i,j)$ stands for the attribution degree of the sample x_i to the sample x_j, which is used to describe the suitability of the sample x_j selected as its class representative, and propagation direction is $j \to i$. The greater the sum of attractiveness and attribution is, the more likely the sample x_j will be the final cluster center. After multiple iterations, the cluster center and the relationship between each sample and the cluster center are output. The specific iteration rules are as follows:

Step 1. Initialize the degree of attractiveness and attribution, let $a(i,k)=0$, $r(i,k)=0$.

Step 2. Update the attractiveness matrix R, and then update the attribution matrix A.

$$a(i,k)=\begin{cases}\min\{0,r(k,k)+\sum\limits_{i',s.t.i'\notin\{i,k\}}\max\{0,r(i',k)\}\},\ i\neq k,\\ \sum\limits_{i',s.t.i'\neq k}\max\{0,r(i',k)\}\},i=k,\end{cases} \tag{5}$$

$$r(i,k)=s(i,k)\text{-}\max_{k's.t.k'\neq k}-\max_{k's.t.k'\neq k}\{a(i,k')+s(i,k')\} \tag{6}$$

To avoid model oscillation during iteration, introduce a damping factor $\lambda\in[0,1)$ in the information update process, generally λ=0.5.

$$r(i,k)^{(t+1)}=\lambda r(i,k)^{(t)}+(1-\lambda)r(i,k)^{(t-1)} \tag{7}$$

$$a(i,k)^{(t+1)}=\lambda a(i,k)^{(t)}+(1-\lambda)a(i,k)^{(t-1)} \tag{8}$$

Step 3. Calculate the sum of attribution and attractiveness of all sample points.

$$\arg\max_{k}(a(i,k)+r(i,k)) \tag{9}$$

In AP clustering algorithm, we only need to determine the maximum number of iterations and bias parameters before experiments. Generally speaking, the size of the bias parameter will affect the number of clusters. Reducing the value P will reduce the number of classes, and increasing the value P will increase the number of classes. In the application, we need to set the corresponding bias parameters according to the analysis needs of different problems. When the cluster center is stable or reaches the maximum number of iterations, the optimal class representative point and the membership relationship between the sample point and the class representative point are obtained.

5. Empirical analysis

5.1. Research object and data

In this paper, we select 30 provinces in Mainland China (Hong Kong, Macau, Tibet, and Taiwan are not within the scope of this research due to data reasons). According to the relevant statistical yearbook from 2014 to 2018 such as China Science and Technology Statistical Yearbook, China Statistical Yearbook, and China Industrial Statistical Yearbook, and statistical yearbooks of various provinces, we acquire the data from 2013 to 2017 to build the index system, and then we can use them to measure the high-quality development level for the manufacturing industry in each province and analyze their regional differences.

5.2. Measurement of the high-quality development level for the manufacturing industry

5.2.1. The high-quality development level of each province

The symmetric matrix Y represents the grey incidence matrix calculated by each province, reflecting the similarity of the high-quality development level of manufacturing between every two regions. The higher the value, the higher the similarity is. Then let $S = Y - E$. The size of the value P affects the number of clusters. Under the condition of ensuring that the overall network similarity is as large as possible, we can determine the values of P through multiple experiments. In experiments, according to the AP clustering algorithm, we calculate the similarity of the network with different cluster numbers. The values of P in innovation, green and efficiency dimensions are as follows: $P_{in} = 0.39$, $P_{gr} = 0.58$, $P_{ef} = 0.43$. Under the condition that the similarity is reasonable, three levels are set for the convenience of analysis and discussion. That is the thirty provinces are divided into three levels, respectively recorded as excellent, qualified, and poor. Then, set an optimal reference matrix S_0, where $S_0(m,t)$ represents the optimal value of the index m in the year t. We can obtain the grey incidence degrees between each province and the annual optimal value from 2013 to 2017, and use it as the high-quality development level of the manufacturing industry in each province. Table 2 shows the manufacturing industry's high-quality development level and clustering results in different regions from the perspectives of innovation, green and efficiency.

Table 2. The results of the high-quality development level in each province.

Area	Innovation		Green		Efficiency	
	Degree	Cluster Center	Degree	Cluster Center	Level	Cluster Center
Entire Country	0.7131	/	0.6701	/	0.7269	/
East Area	0.7115	/	0.6595	/	0.7155	/
Central Area	0.6843	/	0.6926	/	0.7014	/
West Area	0.6635	/	0.6638	/	0.6971	/
North-East Area	0.634	/	0.6224	/	0.6908	/
Beijing (BJ)	0.4288	poor	0.4961	poor	0.6906	excellent
Tianjin (TJ)	0.6283	excellent	0.7846	excellent	0.6838	qualified
Hebei (HE)	0.4355	poor	0.4718	poor	0.7061	excellent
Shanxi (SX)	0.6281	qualified	0.4531	poor	0.6719	excellent
Inner Mongolia (NM)	0.4326	poor	0.422	poor	0.6903	qualified
Liaoning (LN)	0.6254	qualified	0.6392	qualified	0.6906	qualified
Jilin (JL)	0.6354	qualified	0.6751	qualified	0.6746	excellent
Heilongjiang (HLJ)	0.6192	excellent	0.6514	qualified	0.6862	qualified
Shanghai (SH)	0.6358	excellent	0.7085	excellent	0.7059	qualified
Jiangsu (JS)	0.6793	excellent	0.7195	excellent	0.6963	qualified
Zhejiang (ZJ)	0.4728	poor	0.7234	excellent	0.6883	qualified
Anhui (AH)	0.6836	qualified	0.7154	excellent	0.6759	qualified
Fujian (FJ)	0.6404	excellent	0.7026	qualified	0.506	poor
Jiangxi (JX)	0.6473	qualified	0.4462	poor	0.4845	poor
Shandong (SD)	0.4568	poor	0.7059	excellent	0.6961	qualified

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Area	Innovation		Green		Efficiency	
	Degree	Cluster Center	Degree	Cluster Center	Level	Cluster Center
Henan (HN)	0.6569	qualified	0.6896	qualified	0.6975	qualified
Hubei (HB)	0.6122	excellent	0.6833	qualified	0.6839	qualified
Hunan (HU)	0.6573	qualified	0.6705	qualified	0.6771	qualified
Guangdong (GD)	0.6703	excellent	0.5112	poor	0.7254	qualified
Guangxi (GX)	0.637	qualified	0.6623	qualified	0.7025	excellent
Hainan (HA)	0.6428	qualified	0.433	poor	0.4768	poor
Chongqing (CQ)	0.6424	excellent	0.5257	poor	0.6905	qualified
Sichuan (SC)	0.6343	qualified	0.4386	poor	0.6871	excellent
Guizhou (GZ)	0.4581	poor	0.6514	qualified	0.7146	qualified
Yunnan (YN)	0.6478	qualified	0.6467	qualified	0.6897	excellent
Shaanxi (SA)	0.4447	poor	0.6611	qualified	0.7191	excellent
Gansu (GS)	0.4496	poor	0.6295	qualified	0.4711	poor
Qinghai (QH)	0.621	excellent	0.6335	qualified	0.6704	excellent
Ningxia (NX)	0.6557	qualified	0.6421	qualified	0.7013	excellent
Xinjiang (XJ)	0.4705	poor	0.6671	qualified	0.6745	excellent

Note: Because of the different magnitudes, this paper does not include the eastern, middle, western and northeastern regions in the cluster analysis, and the regional analysis mainly considers the overall state, so there is no cluster center city and it is represented by "/". According to the index data values of the three dimensions of innovation, green, and efficiency, we can obtain the high-quality development levels and clustering results of the manufacturing industry, as shown in Figure 1. The darker color in the figure means the city has a better comprehensive high-quality development trend of the manufacturing industry. The regions with the same color are in the same class. In general, the comprehensive level of high-quality development of China's manufacturing industry is high. Among them, there are sixteen provinces at the excellent level, and their cluster center is Guangdong. Ten provinces are at the qualified level, and their cluster center is Shandong. Four provinces are at the poor level, and their cluster center is Fujian.

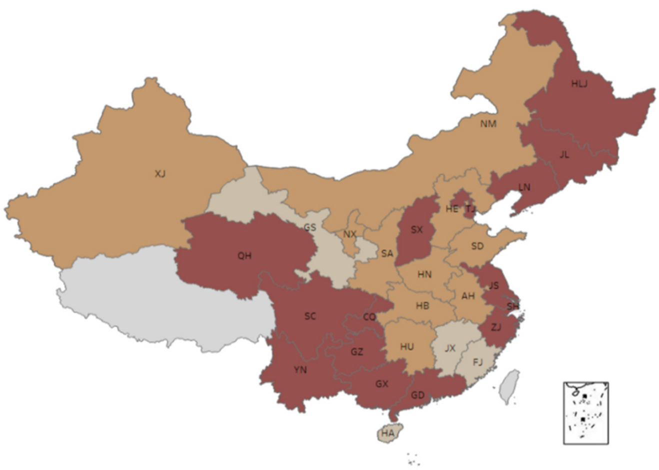

Figure 1. Comprehensive clustering results of the innovation, green and efficiency dimensions.

The clustering results in the innovation dimension are shown in Figure 2. The lighter color of the region means the city has a higher development level in the innovation dimension. There are 9 regions at the excellent level, and the cluster center is Shanghai with innovation degree 0.636. There are 12 regions at the qualified level, the cluster center is Sichuan with innovation degree 0.634. There are 9 regions at the poor level, and the cluster center is Shandong with innovation degree 0.457. According to Figure 2, the overall level of innovation dimension in the country is great, most provinces are at the excellent and qualified level. The gap between excellent and qualified regions is small, but the regions at the poor level lag far behind.

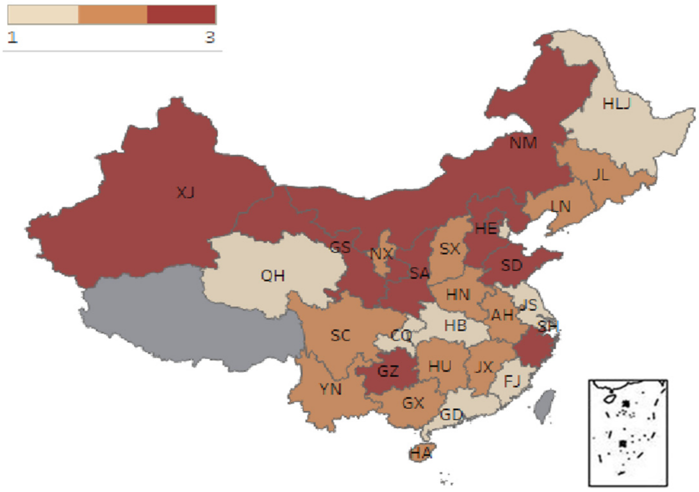

Figure 2. Clustering results of innovation dimensions from 2013 to 2017.

The clustering results in the green dimension are shown in Figure 3. The lighter color of the region means the city has a higher development level in the green dimension. There are 6 regions at excellent level, the cluster center is Hebei with green degree 0.706. There are 15 regions at the qualified level, the cluster center is Zhejiang with green degree 0.688. There are 9 regions at the poor level, and the cluster center is Hubei with green degree 0.683. Different regions perform similarly in the green dimension. The gap between the regions of excellent, qualified and poor level is small. The southeast coastal area shows obvious regional advantages and rank high in green development.

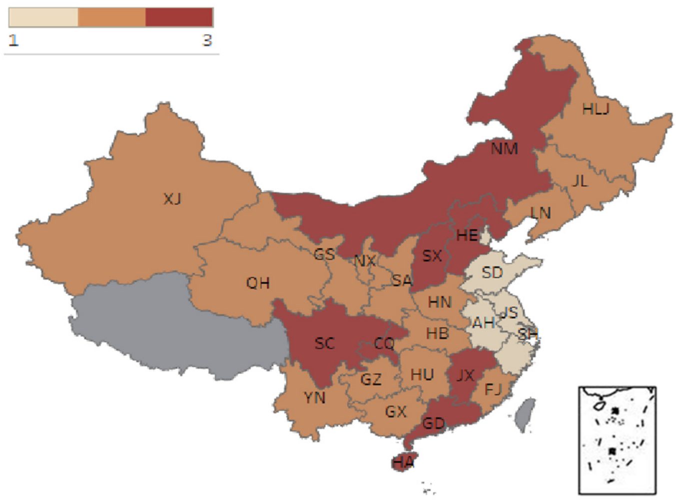

Figure 3. Green dimension clustering results from 2013 to 2017.

The clustering results in the efficiency dimension are shown in Figure 4. The lighter color of the region means the city has a higher development level in efficiency dimension. There are 11 regions at the excellent level, and the cluster center is Beijing with efficiency level 0.703. There are 15 regions at the qualified level, the cluster center is Tianjin with efficiency level 0.676. There are 4 regions at the poor level, and the cluster center is Jiangxi with efficiency level 0.485. In terms of efficiency, most regions are at the excellent and qualified levels. But there is a clear gap between each two of the three levels, the gap between excellent regions and poor regions is greater than 0.2.

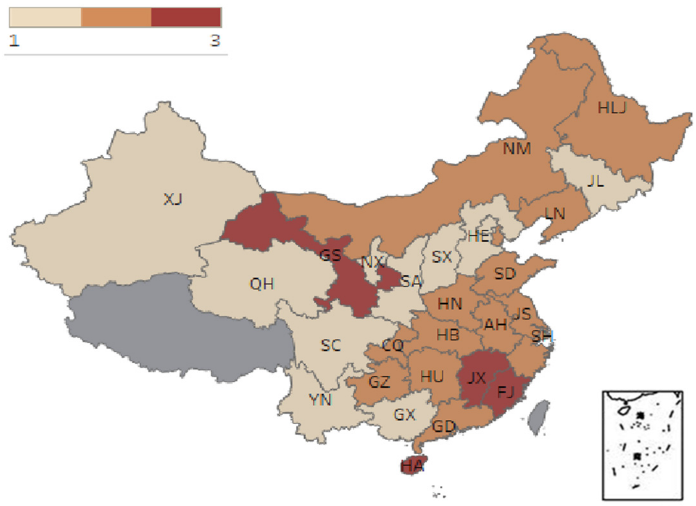

Figure 4. Efficiency dimension clustering results from 2013 to 2017.

5.2.2. The high-quality development level by year

Without considering the time dimension, we calculate the grey incidence degrees of each province and region on different dimensions separately by year. The specific analysis is as follows:

(1) The high-quality development degree in the innovation dimension by year

By calculating the innovation degrees of the manufacturing industry's high-quality development during the period from 2013 to 2017, we can obtain the results shown in Table 3. The degrees are in the range of [0.44, 0.73]. From Figure 5, the innovation level is good in the year 2014, 2016 and 2017. But most regions neglect innovation development in 2015. The innovation degrees of Xinjiang and Jilin decline in 2017 compared with 2016, which requires the attention of regional governments. The government need to analyze the policy and environment changes to find out the reasons for the reduction in innovation. From the perspective of time, the development fluctuation of innovation dimension is fierce, and the variation range of each year is large. And then, to ensure the sustainable development of innovation dimension, it's necessary to continuously and steadily increase the intensity of innovation input and strengthen the transformation from innovation to technological achievements.

(2) The high-quality development level in green dimension by year

By calculating the green degrees of the manufacturing industry's high-quality development during the period from 2013 to 2017, we can obtain the results shown in Table 4. The degrees are in the range of [0.45, 0.87]. According to Figure 6, in terms of the green dimension, many regions show a worsening trend year by year.

Table 3. Innovation degrees of high-quality development in various regions from 2013 to 2017.

Area	High-quality development level of manufacturing industry in innovation				
	2013	2014	2015	2016	2017
Entire Country	0.6718	0.6497	0.662	0.6073	0.6266
East Area	0.6576	0.5975	0.6545	0.6806	0.6188
Central Area	0.6469	0.6045	0.7091	0.5359	0.5884
West Area	0.6198	0.5308	0.6275	0.5053	0.5605
North-East Area	0.6131	0.539	0.5874	0.5291	0.5526
Beijing (BJ)	0.5972	0.5382	0.6221	0.525	0.4967
Tianjin (TJ)	0.5775	0.5622	0.6261	0.518	0.5203
Hebei (HE)	0.5964	0.6001	0.6366	0.5174	0.4713
Shanxi (SX)	0.6082	0.5435	0.5972	0.5153	0.4998
Inner Mongolia (NM)	0.6456	0.5492	0.6041	0.5116	0.5249
Liaoning (LN)	0.6389	0.5297	0.6221	0.5048	0.4933
Jilin (JL)	0.6109	0.5225	0.6396	0.5566	0.605
Heilongjiang (HLJ)	0.5653	0.4987	0.6187	0.4898	0.4661
Shanghai (SH)	0.6029	0.5371	0.5751	0.5134	0.4944
Jiangsu (JS)	0.5921	0.6766	0.629	0.5211	0.5522
Zhejiang (ZJ)	0.5598	0.5324	0.6048	0.5894	0.55
Anhui (AH)	0.6419	0.5359	0.6547	0.5202	0.5116
Fujian (FJ)	0.6333	0.5415	0.5426	0.5805	0.5105
Jiangxi (JX)	0.6404	0.6516	0.621	0.4849	0.4453
Shandong (SD)	0.6554	0.6004	0.6397	0.5643	0.5187
Henan (HN)	0.6048	0.6811	0.612	0.5215	0.5164
Hubei (HB)	0.6022	0.5066	0.5708	0.4928	0.4941
Hunan (HU)	0.6311	0.684	0.6328	0.5592	0.5587
Guangdong (GD)	0.6435	0.5759	0.6165	0.5375	0.5475
Guangxi (GX)	0.6292	0.5657	0.6465	0.5599	0.552
Hainan (HA)	0.579	0.7017	0.6167	0.5008	0.4893
Chongqing (CQ)	0.6083	0.5715	0.6192	0.5721	0.535
Sichuan (SC)	0.6476	0.5683	0.6286	0.5276	0.4828
Guizhou (GZ)	0.6801	0.5352	0.6645	0.5935	0.4809
Yunnan (YN)	0.6181	0.5248	0.6912	0.5042	0.4608
Shanxi (SA)	0.5965	0.5294	0.658	0.5487	0.5093
Gansu (GS)	0.62	0.6789	0.6402	0.6335	0.648
Qinghai (QH)	0.5647	0.5405	0.6003	0.501	0.4865
Ningxia (NX)	0.599	0.6652	0.5694	0.5125	0.4881
Xinjiang (XJ)	0.6459	0.6466	0.6616	0.5017	0.6004

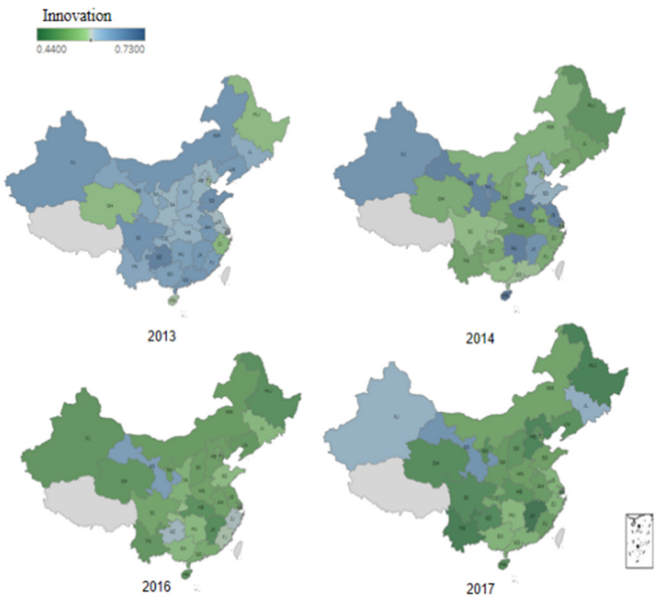

Figure 5. The changing trend in innovation dimension from 2013 to 2017.

The level of green development is weak in north China, especially in northwest China. And the trend of deterioration can't be ignored. Except for 2014, the southeast coastal areas are at the leading level of green development in China during the period. In the green dimension, the development levels change significantly over time, but the development trend doesn't change a lot. This fact indicates that the annual investment affects the evaluation results in a long period of time. Therefore, all regions need to pay close attention to the status and trend of the green development of the manufacturing industry. We should carefully change the production layout, implement the concept of sustainable development, firmly disseminate the awareness that clear water and green mountains are gold and silver mountains, and avoid the development of the manufacturing industry at the cost of sacrificing the environment.

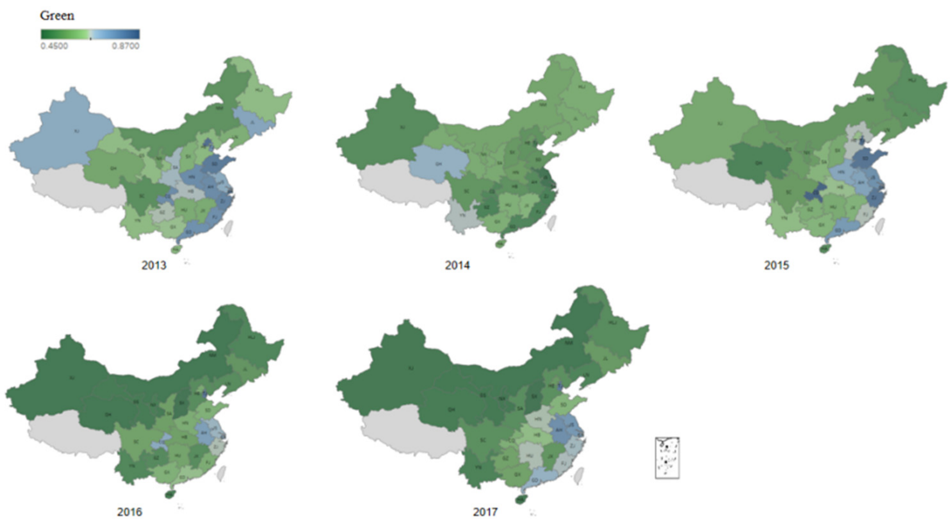

Figure 6. The changing trend in green dimension from 2013 to 2017.

Table 4. Green degrees of high-quality manufacturing development in various regions from 2013 to 2017.

Area	High-quality development level of manufacturing industry in green				
	2013	2014	2015	2016	2017
Entire Country	0.6135	0.589	0.607	0.5702	0.5148
East Area	0.5861	0.5505	0.6361	0.582	0.6035
Central Area	0.6829	0.5521	0.5922	0.5813	0.5822
West Area	0.6336	0.5774	0.5241	0.5453	0.5501
North-East Area	0.5995	0.6029	0.5004	0.4951	0.5221
Beijing (BJ)	0.841	0.556	0.642	0.5921	0.5521
Tianjin (TJ)	0.7537	0.4863	0.8545	0.8209	0.8079
Hebei (HE)	0.6259	0.5352	0.6601	0.5155	0.525
Shanxi (SX)	0.605	0.5488	0.5885	0.459	0.4579
Inner Mongolia (NM)	0.5314	0.5787	0.5465	0.4647	0.4654
Liaoning (LN)	0.6008	0.5843	0.5501	0.5155	0.4963
Jilin (JL)	0.7081	0.5895	0.5294	0.539	0.5513
Heilongjiang (HLJ)	0.6349	0.5968	0.5191	0.4985	0.5157
Shanghai (SH)	0.8	0.4945	0.7895	0.6885	0.7013
Jiangsu (JS)	0.6973	0.4592	0.7595	0.6757	0.7414
Zhejiang (ZJ)	0.7919	0.488	0.8214	0.6576	0.671
Anhui (AH)	0.7739	0.5137	0.7145	0.7237	0.7625
Fujian (FJ)	0.7628	0.4945	0.6588	0.5953	0.6648
Jiangxi (JX)	0.5927	0.6151	0.6102	0.5163	0.5398
Shandong (SD)	0.812	0.5388	0.8259	0.6059	0.6153
Henan (HN)	0.7689	0.5611	0.7068	0.5956	0.6552
Hubei (HB)	0.6647	0.5317	0.6431	0.5663	0.6361
Hunan (HU)	0.5926	0.6034	0.5924	0.5771	0.6574
Guangdong (GD)	0.7577	0.5008	0.7369	0.6425	0.6825
Guangxi (GX)	0.6432	0.6016	0.6156	0.6059	0.5708
Hainan (HA)	0.6276	0.5776	0.5218	0.4869	0.4695
Chongqing (CQ)	0.7723	0.5043	0.8691	0.6989	0.602
Sichuan (SC)	0.5246	0.5399	0.5524	0.5712	0.5253
Guizhou (GZ)	0.6562	0.4917	0.6009	0.5115	0.5699
Yunnan (YN)	0.6318	0.6636	0.6355	0.5037	0.4914
Shanxi (SA)	0.6722	0.5918	0.6168	0.5644	0.5189
Gansu (GS)	0.6351	0.5939	0.5591	0.4737	0.4681
Qinghai (QH)	0.5811	0.6841	0.4945	0.465	0.4748
Ningxia (NX)	0.5554	0.5817	0.5425	0.4799	0.4633
Xinjiang (XJ)	0.6981	0.5154	0.5868	0.4648	0.4717

(3) The high-quality development level in efficiency dimension by year

By calculating the efficiency level of the manufacturing industry's high-quality development degrees during the period from 2013 to 2017, we can acquire the results shown in Table 5. The values are in the range of [0.53,0.74]. As can be seen from Figure 7, in terms of efficiency dimension, the overall levels in 2014, 2015 and 2016 are higher, and the regional difference is the most significant in 2013. The efficiency levels fluctuate violently without an obvious time-changing trend. To ensure the long-term development of regional efficiency, it's necessary to pay close attention to the international and domestic environment and pay attention to the improvement rate of economic and product competitiveness while increasing GDP. We will strengthen and give full play to the role of manufacturing in promoting economic development, promoting employment, and stabilizing the national economy and people's livelihood.

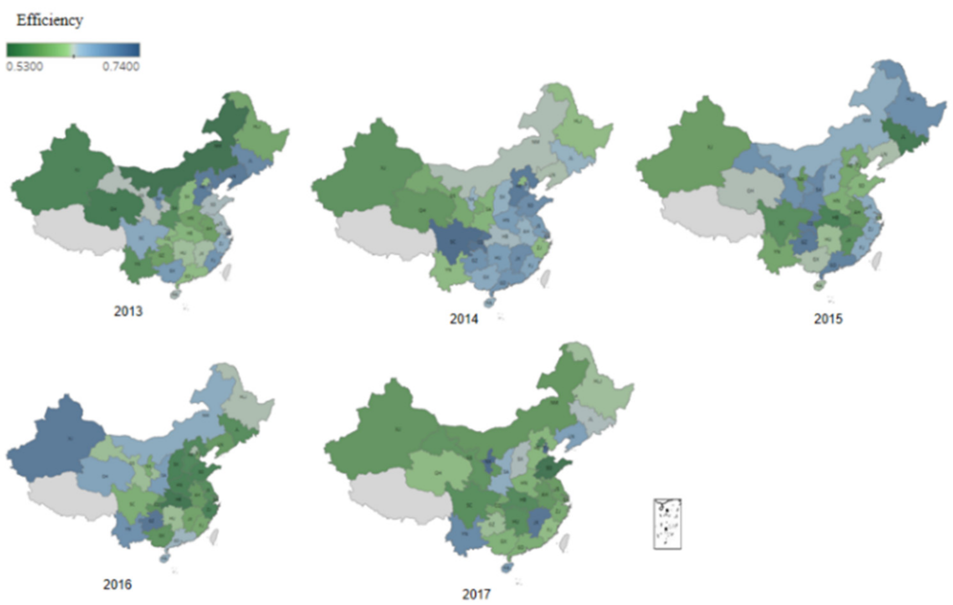

Figure 7. The changing trend in efficiency dimension from 2013 to 2017.

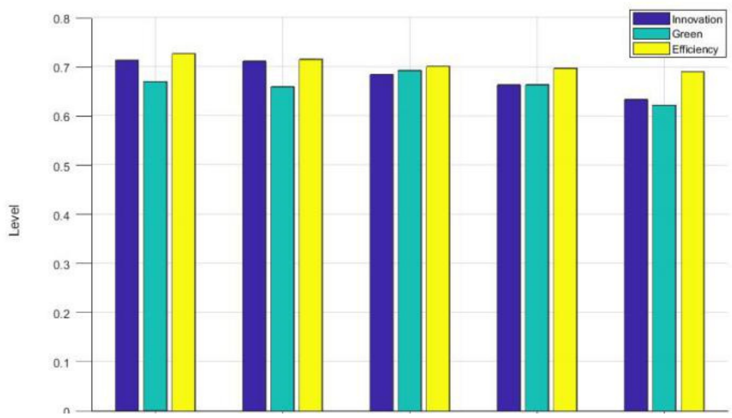

Figure 8. High-quality development levels from innovation, green and efficiency in different areas.

Table 5. Efficiency levels of high-quality manufacturing development in various regions from 2013 to 2017.

Area	High-quality development level of manufacturing industry in efficiency				
	2013	2014	2015	2016	2017
Entire Country	0.6174	0.7063	0.5873	0.5645	0.586
East Area	0.6653	0.6613	0.6605	0.57	0.6102
Central Area	0.648	0.6471	0.6359	0.6225	0.669
West Area	0.6446	0.6582	0.6071	0.6208	0.6809
North-East Area	0.681	0.6262	0.6027	0.5889	0.6365
Beijing (BJ)	0.6241	0.6217	0.641	0.632	0.5537
Tianjin (TJ)	0.6796	0.6607	0.6025	0.5939	0.7278
Hebei (HE)	0.7111	0.7129	0.5969	0.5577	0.616
Shanxi (SX)	0.6176	0.6484	0.6584	0.5484	0.6372
Inner Mongolia (NM)	0.5316	0.6339	0.6505	0.653	0.5771
Liaoning (LN)	0.714	0.6327	0.6323	0.5794	0.6659
Jilin (JL)	0.6946	0.6448	0.5416	0.5642	0.637
Heilongjiang (HLJ)	0.5945	0.6232	0.6874	0.6334	0.6293
Shanghai (SH)	0.6921	0.6606	0.6257	0.5649	0.5948
Jiangsu (JS)	0.6392	0.6709	0.6533	0.5642	0.5833
Zhejiang (ZJ)	0.6501	0.6209	0.6564	0.5503	0.6
Anhui (AH)	0.5871	0.6451	0.5775	0.5804	0.5766
Fujian (FJ)	0.6809	0.6607	0.6552	0.5973	0.6243
Jiangxi (JX)	0.6312	0.6907	0.5669	0.5914	0.7172
Shandong (SD)	0.6384	0.6891	0.6136	0.5501	0.5347
Henan (HN)	0.5891	0.6699	0.6051	0.5496	0.6086
Hubei (HB)	0.6138	0.6401	0.5501	0.5349	0.5603
Hunan (HU)	0.6293	0.6696	0.6282	0.628	0.5638
Guangdong (GD)	0.6226	0.6788	0.7026	0.6418	0.6058
Guangxi (GX)	0.6727	0.6546	0.6321	0.5721	0.61
Hainan (HA)	0.6365	0.6451	0.6299	0.6463	0.6665
Chongqing (CQ)	0.6202	0.7203	0.7127	0.5703	0.5949
Sichuan (SC)	0.6566	0.7288	0.5655	0.6053	0.5656
Guizhou (GZ)	0.5888	0.6824	0.7138	0.718	0.6284
Yunnan (YN)	0.5676	0.6215	0.5947	0.6844	0.6924
Shanxi (SA)	0.5634	0.6131	0.6958	0.6694	0.6514
Gansu (GS)	0.6354	0.5978	0.685	0.6284	0.5738
Qinghai (QH)	0.5419	0.5762	0.6344	0.6614	0.6215
Ningxia (NX)	0.6838	0.6444	0.5787	0.6031	0.7315
Xinjiang (XJ)	0.553	0.5719	0.5846	0.7125	0.5761

(4) The high-quality development level in different regions

To further observe and analyze the relationship between the high-quality development of manufacturing industry and regional conditions, we further analyze the high-quality development of manufacturing industry in China from the perspective of regional differences among the entire country, eastern, central, western and northeast regions.

As shown in Figure 8, the entire country and the eastern region have a significant development shortcoming in the green dimension. The central region is weak in the development of the innovation dimension. The strength of the western region is efficiency, while the level of innovation and green development is similar. The situation of green development in northeast China is the most severe, and its innovative development also has a certain gap compared with other regions. On the whole, the high-quality development level of the manufacturing industry in the eastern region is consistent with the national level. But the other regions are left behind. Especially the western region and the northeast region have a large gap with the national level.

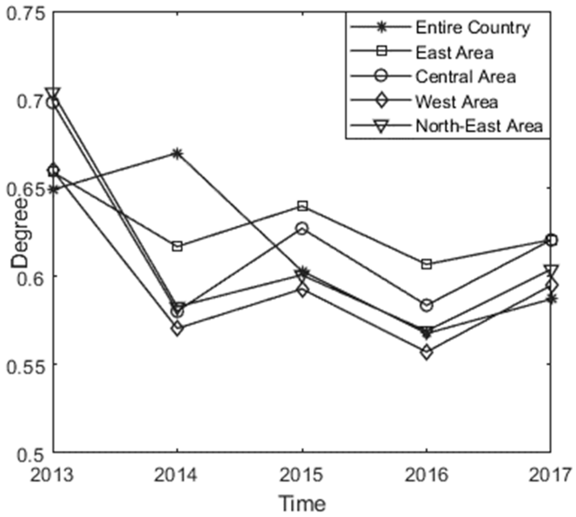

Figure 9. The trend of the high-quality development level for manufacturing industry in different areas.

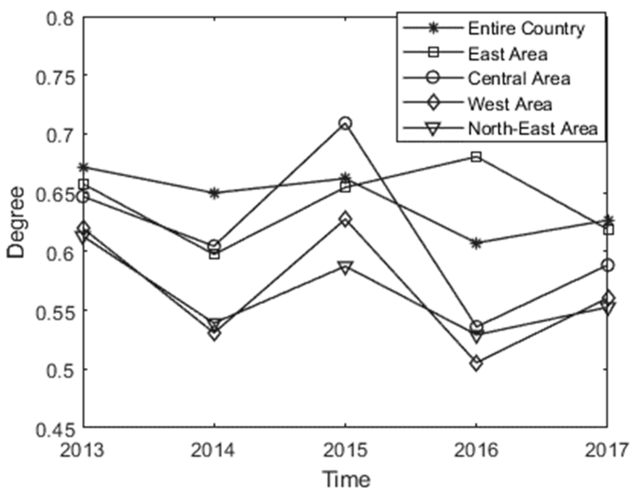

Figure 10. The trend in innovation dimension in different areas.

As shown in Figure 9, from 2013 to 2017, the high-quality development of the manufacturing industry in western China is always at the lowest level in all regions. The development trend of the high-quality manufacturing industry is not optimistic. The level decreases slightly in the fluctuation. From 2016 to 2017, the development degree of the high-quality manufacturing industry has been improved. Corresponding measures should be taken to maintain good development momentum. The growth rate of the manufacturing industry slows down in the eastern region. But it develops rapidly in the other three regions. This phenomenon is related to the original scale and structure of manufacturing industry in different regions.

As shown in Figure 10, from 2013 to 2017, the manufacturing industry in the eastern and central regions shows outstanding performance in the innovation dimension. The degree of the eastern region is stable with a small fluctuation range and has maintained continuous growth from 2014 to 2016. The central region's performance in the innovation dimension is fluctuant. In 2014 and 2015, it is at the nationally leading level, but it drops significantly in 2016. The western region and the northeast region lag in innovation development. However, the western region has the fastest growth in innovation from 2016 to 2017, while the northeast region doesn't have an ideal growth rate.

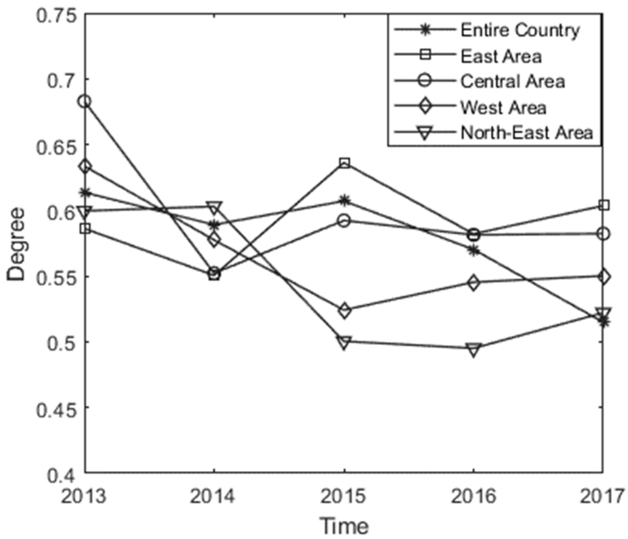

Figure 11. The trend in green dimension in different areas.

According to Figure 11, the green development ranking changes greatly. The eastern region is at the bottom in 2013, and by 2015, it becomes the top and stabilized its dominant position from 2015 to 2017. The manufacturing industry in the central region has the most stable development in the green dimension since 2015. The advantage of green development in the west is declining. From 2014 to 2016, the green development level of the manufacturing industry is always lower than the national level. The foundation of the northeast region's manufacturing industry in green development is weak. It fails to effectively solve the dilemma in green development and the developing situation is still worrying. The local government needs to promote green manufacturing policies and optimize the industrial structure.

From Figure 12, the development trend of manufacturing industry is good in the dimension of efficiency development. The western region has the most rapid improvement in efficiency development, rising from the lowest in 2013 to the top in 2017. The eastern region has encountered the bottleneck period of efficiency development since 2015. Although the efficiency development degree has rebounded from 2016 to 2017, it still lags in the ranking among all regions. The development degree of the central region in the efficiency dimension is stable, with a small fluctuation range and a slight improvement in five years. The development degree of the northeast region in the efficiency dimension experiences the biggest drop, and it continues to decline from 2013 to 2016.

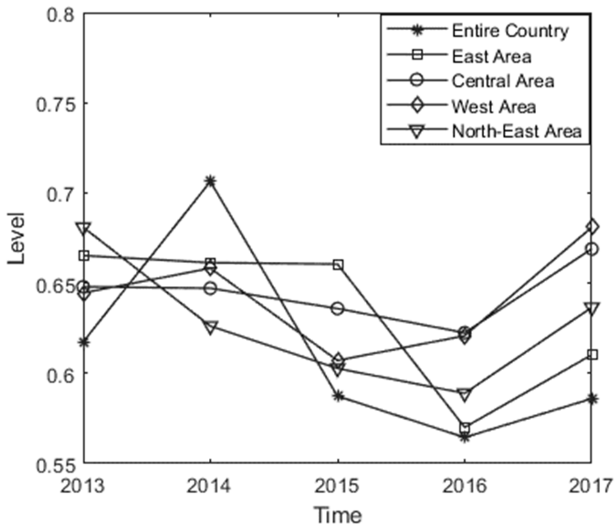

Figure 12. The trend in efficiency dimension in different areas.

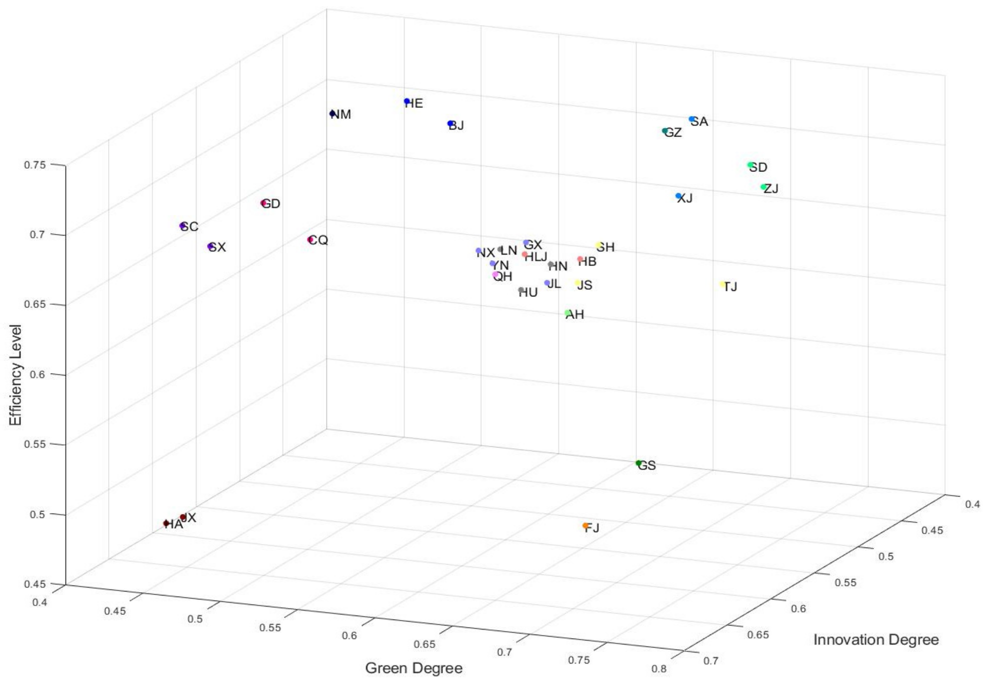

Figure 13. Three dimensions' high-quality development degrees in different regions.

The combinations of three-dimensional cluster results of different regions are shown in Figure 13.

Areas in the same color mean they have the most similar development structure. Fourteen provinces are qualified or excellent in the three dimensions, ten provinces that are qualified or excellent in any two dimensions, and the remaining 6 cities that are qualified or excellent in at least one dimension. The 30 provinces can be classified and summarized into 16 combinations according to the clustering results.

Combination 1 includes Beijing and Hebei. They should keep the advantage in innovation and green development, pay attention to development results and development trends a the same time. Combination 2 includes Tianjin, Shanghai and Jiangsu. The manufacturing industry in these three provinces has a high level of high-quality development. On the one hand, they need to maintain the advantages of innovation and green development, on the other hand, they need to put efforts to further break the bottleneck of efficiency development. Combination 3 includes Shanxi and Sichuan. They have outstanding achievements in efficiency dimension. Green development is the biggest weakness restricting further development. Innovation development also needs to be strengthened. Combination 4 only includes Inner Mongolia, where the high-quality development of manufacturing industry is weak. Inner Mongolia should take the advantage of efficiency development and break through the two development dilemmas in innovation and green development simultaneously. Combination 5 includes two provinces, Liaoning and Henan. The high-quality development of the manufacturing industry is at a medium level in the country. It must identify its regional advantages to have a better development. Combination 6 includes Jilin and Guangxi. The development level of the manufacturing industry is high, and efficiency development is their advantage. They need more investment in innovation and green development. Combination 7 includes Heilongjiang and Hubei. The development level of manufacturing industry is above medium. Innovation is the strength of regional development. We should strengthen the scientific and technological innovation and promote green and efficient development. Combination 8 includes Zhejiang and Shandong. They are in the leading position in green development is in China. But the efficiency and innovation development need to be strengthened.In particular, they should pay more attention to innovation, which is a key factor restricting the development of manufacturing. Combination 9 only includes Anhui. It has a stable development trend and green development is its advantage. By increasing investment in innovation and efficient development, it can further narrow the gap with developed regions. Combination 10 only includes Fujian. Innovation is the strength of its development, but its biggest weakness is in the efficiency development. Innovation must play a leading role in Fujian. Combination 11 includes Jiangxi and Hainan. Their development level is low. We should keep their advantages in innovation development, and put more effort to improve green and efficient development. Combination 12 includes Guangdong and Chongqing. Their innovation development is in the leading position, but the trend of its green development is not optimistic, which needs to improve. Combination 13 only includes Guizhou. Innovation is the main factor restricting the high-quality development of its manufacturing industry. It should increase R&D investment and promote the transformation of R&D achievements in the next period. Combination 14 includes Shanxi and Xinjiang. They should keep the advantages in efficiency development, attract talented people and increase R&D investment. Combination 15 only includes Gansu, which performs well in green development and needs improvement in innovation and efficiency development. Combination 16 only includes Qinghai. The development trend of Qinghai is optimistic, but it still needs to improve green development while maintaining the development speed.

6. Conclusions

To study the level of high-quality development and regional differences in manufacturing, we design the evaluation index system from the dimensions of innovation, green and efficiency, and construct a grey incidence approach based on panel data. Our research mainly draws the following conclusions. (1) The high-quality development level for manufacturing industry in China is generally high, but there exists much uneven development in different regions. The eastern, central, western and northeast regions have great regional differences in innovation, green and efficiency dimensions. In terms of innovation and efficiency dimensions, the eastern region has the highest development level. In the green dimension, the central region has the highest development level. The development level of the western and northeastern regions are lower than the national average on all three dimensions. These two regions where manufacturing industry development lag behind, face different developing problems. In the western region, the development speed of innovation and efficiency is fast and the development situation is great, but the neglect of green development may cause problems in the future. However, the development situation of northeast China is not optimistic. Innovation, green and efficiency development are all in a serious development bottleneck period, and the development structure needs to be transformed urgently. (2) In terms of innovation dimension, there are 26 regions at excellent and qualified levels. The other 4 provinces at poor level fall far behind them. In the green dimension, there are 21 regions at excellent and qualified levels, the gap between different levels is small, and the southeast coastal areas have large advantages in green development. In terms of efficiency, we have 26 regions at an excellent or qualified level. There are large gaps between different levels. We can classify 30 provinces into 16 combinations, and give bits of advice according to their development levels and advantages. In terms of years, the innovation development performs best in 2015, but the subsequent efforts are insufficient. Green development in the north and northwest is regressing and needs improvement. Inefficiency dimension, regional differences appear significantly in 2013, and it performs well from 2014 to 2016. Overall, the high-quality development of China's manufacturing industry is characterized by obvious regional differences, different development stages and different constraints.

The model we proposed in this paper is based on static data. However, the current external environment changes rapidly. We will consider incremental learning algorithms in future research to achieve a real-time evaluation of high-quality development and facilitate decision-making. At the same time, this paper mainly analyzes from the perspective of the whole country's manufacturing industry. Future research can further conduct more detailed analysis and research on a single provinceand gain an in-depth understanding of the development characteristics of different provinces.

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Conflict of interest

This work does not involve any conflict of interest.

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