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Grey comprehensive evaluation of development performance of provinces in China based on spatiotemporal probability function and variable weight strategy

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ABSTRACT

In the new stage of promoting high-quality economic development, the effect of the transformation of development momentum and the ability of sustainable development has become the key factors for the competitiveness of provinces in China. Especially in the context of the impact of COVID-19 and the obstacles of world trade protectionism, the sustainability of development performance is increasingly important. In the past, when evaluating the development performance of various provinces in China, a single index weight was usually used. In view of evaluation criteria, the lack of consideration of regional differentiation factors would result in the evaluation results deviating from reality. This paper introduces the entropy weight method to determine the weight of regional indicators of differentiated development. Based on the space-time probability function, a grey clustering evaluation model of regional development performance is constructed to conduct a comprehensive grey evaluation of the development performance of various provinces in China from 2009 to 2019. It is found that the new evaluation model can correct the deficiencies of similar probability functions and single index weight and obtain more accurate evaluation results. It's found that the development performance evaluation results of each province are always in a dynamic adjustment process, which needs to be verified with the help of subsequent expansion analysis.

1. Introduction

Unbalanced regional development is a prominent feature of China's economic and social operation. Influenced by multiple factors such as continuous technological innovation, the international division of labor adjustment, and industrial digital transformation, the development gap between China's provinces has further widened, and the imbalance of development has shown more complex changes. In fact, an imbalance is a normal state with a profound theoretical basis. For example, Peru put forward the growth pole theory, emphasizing that the main driving force of economic development is scientific and technological progress and innovation, which has led to a trend of successive diffusion of development (Miao, 2016). Lewis's dual economic structure theory (Sun, 2017), comparative advantage theory (Zheng, 2019), and sustainable development theory (Yang, 2021) also analyzed and proved the development imbalance from different aspects. Because of the unbalanced development, it is obviously unfair to measure the development performance of each province with a ruler. Especially when there are multiple evaluation objects and the evaluation objects are gradient differences, it is easy to produce deviation or illusion by adopting unified evaluation standards. This performance evaluation does not take into account the differences caused by history, time and space, geography, etc.

Many researchers have made beneficial attempts to carry out performance evaluation more scientifically and objectively under unbalanced conditions. Sun Zhiyan and others emphasized the polarization and spillover effects of economic growth in developed regions on backward regions and the balance formed on this basis (Sun & Hou, 2019). Zhao et al. (2021) tested the influence of geographical spatial factors on the convergence of the green development index in the face of the

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ladder evolution characteristics of economic development in the East, Middle, West, and Northeast regions of China. In terms of methods, Hong Mingyong and others studied the regional differences and spatial-temporal characteristics of agricultural ecological efficiency in China based on the panel data of 31 provinces from 1997 to 2016, using the SBM-Undesirable model and spatial data analysis method (Hong & Zheng, 2020). Yang Rong and others studied and analyzed the space-time evolution of economic differences in the Beijing-Tianjin-Hebei region by using the first-order decomposition of the Theil index and ESDA to explore spatial data analysis methods (Yang et al., 2019). Geng Rushai et al. took the macroeconomic situation of 10 cities in China for five years as the object and carried out a grey probability function clustering evaluation on the information aggregation value (Geng et al., 2020). In determining the weight, Ma Yong used the entropy weight TOPSIS method to evaluate the economic development level of urban agglomeration in the middle reaches of the Yangtze River and analyzed the impact factors that caused economic differences (Ma & Tong, 2016). Li (2022) introduced the entropy weight method to quantitatively evaluate the unbalanced development of e-commerce in rural areas of Northeast China. Based on OGM (1, N), BP neural network, and partial least squares regression prediction model, Lu et al. (2022) constructed a variable weight multiple combination model using the reciprocal method of variance to predict China's carbon dioxide emissions. In the above studies, the regional classification of unbalanced research is not accurate enough; In terms of research methods, most of them are traditional econometric methods, without considering the fuzzy situation. The determination of weight is often a single method without considering the influence of multiple factors.

Therefore, according to the national general classification method, this paper divides 31 provinces except for Hong Kong, Macao, and Taiwan into three regions, namely, the East, the Middle, and the West, constructs 16 performance evaluation indicators for development, moderate and restricted categories, introduces the space-time possibility function, constructs the grey cluster evaluation model, and evaluates the development performance of the indicator data from 2009 to 2019. In particular, the same standard will be adopted for cross-province regions under specific conditions rather than for the whole so that the evaluation results can better reflect the current situation and development trend of each province. At the same time, the information entropy weight is used to obtain the weights of performance evaluation indicators of different trans-provincial regions to reduce the artificial judgment error and meet the regional reality. Finally, according to the results of the grey clustering evaluation, the development performance of 31 provinces is ranked, and relevant opinions and suggestions are put forward. See Figure 1 for the research flow of the paper.

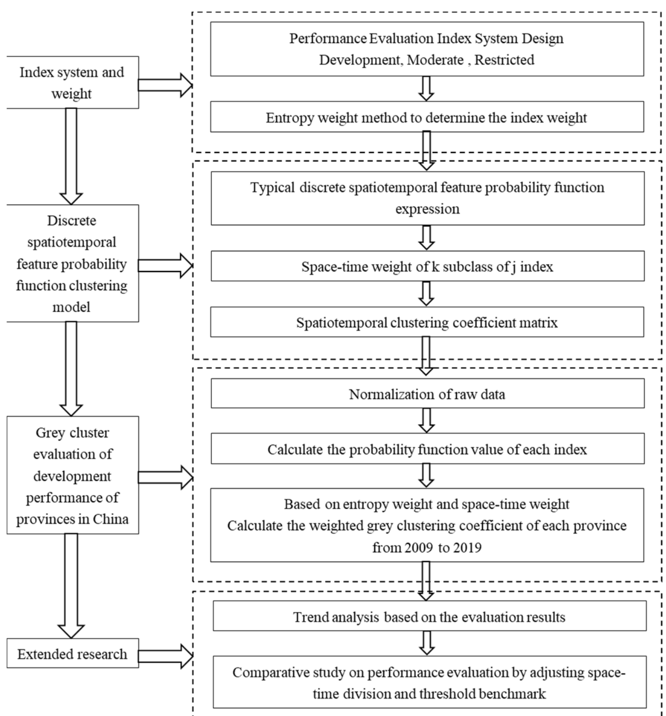

Fig. 1. Research Framework

2. Thinking of grey performance evaluation of provincial development performance under space-time characteristics

2.1 Index design and data acquisition

The indicator system design is divided into two stages, namely, the initial determination and screening of indicators. The initial timing of indicators needs to overcome the problems and deficiencies in previous studies. For example, not all indicators selected by Xie (2008) can obtain reliable data. Wu Qingtian and others analyzed the correlation between financial support for agriculture input and rural macro and micro output and revealed the influencing factors but did not consider regional differences and classified research (Wu & Fang, 2012). Wu Yanxia and other comprehensive evaluations of the level of urban development tend to be social indicators and more comprehensive evaluations of the impact of urban development than output and effect (Wu & Zhang, 2005). In this paper, considering the sufficiency, feasibility, stability, necessity, and other factors of indicators, the following design principles of the indicator system are determined: (1) Most indicators have strict exogenous assumptions; (2) Combined application of positive and negative indicators; (3) It is necessary to define the nature of various indicators reasonably. The larger the data of development indicators is, the better. The more moderate the index data is, the better. The smaller the data of restrictive indicators is, the better. After investigation, screening, and testing, 16 indicators of development, moderate and restricted categories were initially determined, including GDP, per capita GDP, general budget income, the proportion of the added value of the tertiary industry, total labor productivity, turnover of the technology market, disposable income of residents and urbanization rate. Moderate indicators include the proportion of general budget revenue to GDP, the proportion of R&D expenditure to GDP, and the proportion of science and technology expenditure to general budget expenditure. Its significance is that the index value is not the greater, the better, or the smaller, the better. It is the best choice to be at a moderate value according to the development level and stage of each province. The restricted indicators include the dependence on fixed assets investment of the whole society, the ratio of urban and rural income, power consumption per unit GDP, sulfur dioxide emissions per unit GDP, and chemical oxygen demand emissions per unit GDP. The sample data are from China Statistical Yearbook 2009-2019 and other public databases.

2.2 Determination of index weight by entropy weight method

The basic idea of the entropy weight method is to determine the objective weight according to the size of index variability. This method conforms to the fact that different regions determine the development weight of their own indicators. This method is called the variable weight strategy. For example, in economically developed regions, the combination of science and technology, industrial economy, and information technology is considered the main driving force for development, while in economically underdeveloped regions, industrialization and agricultural modernization are often regarded as the driving factors for development. Generally, the smaller the information entropy of the indicator, the greater the degree of variation of the indicator value, the more information provided, the greater the role it can play in the comprehensive evaluation, and the greater its weight. On the contrary, the greater the information entropy of an indicator, the smaller the degree of variation of the indicator value, the less information provided, the smaller the role it plays in the comprehensive evaluation, and the smaller its weight. The specific steps of applying the entropy weight method are as follows:

Step1: standardize the indicator data

(1) Construct a calculation data matrix

Set the value of the j-th$(j = 1,2,\cdots,m)$index of the i-th$(i = 1,2,\cdots,n)$scheme be a_{ij}(generally, the index value $a_{ij} \geq 0$), then all a_{ij}forms the attribute matrix.

(2) Calculate normalized data matrix

The higher the value of the development category indicator is the better, its effect measurement $r_{ij} = \frac{a_{ij}}{max\{a_{ij}\}}$,$\{a_{ij}\}$ can be an indicator data set of all schemes, or an indicator data set of all schemes in different years.

The index value of the moderate category tends to be the best, its effect measurement $r_{ij} = \frac{a_{ijo}}{a_{ijo}+|a_{ij}-a_{ijo}|}$,and a_{ijo} is the moderate value of index j.

The smaller the restricted index value is the better, its effect measurement $r_{ij} = \frac{min\{a_{ij}\}}{a_{ij}}$

There are many methods to normalize the indicator data. The above normalization methods can avoid some indicators becoming zero after processing and prevent the difference from being artificially amplified after normalizing the indicator data.

Step2: calculate the proportion of the index value of item j in scheme i

$$Y_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}}$$

Step3: calculate the information entropy of the j-th index

$$e_j = -k \sum_{i=1}^{n} (Y_{ij} \times ln\, Y_{ij})$$

among them, $k = 1/\, ln\, n$.

Step4: Calculate the average value of information entropy weight in different years e_j'

Step 5: calculate the information entropy redundancy

$$d_j = 1 - e_j'$$

Step 6: Calculate the index weight

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

According to the variable weight strategy, the eastern, central, and western provinces of China are respectively taken as the calculation objects of the entropy weight method. The eastern part contains 11 provinces, the central part contains 8, and the western part contains 12. After processing the original data of each index, the weight of each index in each region is calculated according to the steps of the entropy weight method. The calculation results show that the technical market turnover index variation is too large. The weights of the eastern, central, and western provinces are 0.359, 0.520, and 0.169, respectively. The proportion of this index in the central provinces is about 10 times that of other indicators. The index's weight is too large, which can easily cause the index to determine the evaluation results to a large extent. Therefore, removing this index will not affect the objectivity of the evaluation system. After recalculating the weight, the same consideration is basically given, and the sulfur dioxide emission index per unit of GDP is removed. After applying the entropy weight method to calculate again, the final performance evaluation index system and the index weight of each region and province will be formed (as is shown in Fig. 2). It can be seen from the indicator weight bubble chart of each region that the central region has the largest difference in indicator weight, and there is an obvious imbalance. The western region has the smallest difference in indicator weight and has a trend of homogenization. The eastern region has a moderate difference in indicator weight, and it is in a good state of development only from this point of view.

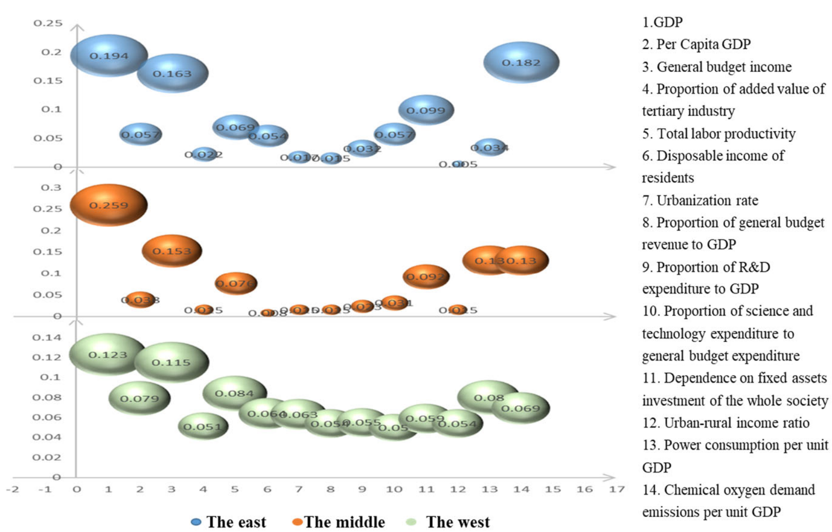

Fig. 2. Grey comprehensive evaluation index system and weight bubble chart of development performance of provinces in different regions in China

2.3 Discrete spatiotemporal feature probability function clustering model

For the comprehensive grey evaluation of the development performance of provinces in China, the turning point of the probability function exists in the form of discrete observation points. Time has a fixed interval, and data at different time points have obvious differences. For this reason, the probability function of the discrete type is given.

Definition 2.3.1 The value of n objects with respect to index j can be divided into s grey classes, the spatial feature of object $i(i = 1,2,\cdots,n)$ is p_i ,Object $i(i = 1,2,\cdots,n)$'s observation value $x_{ij}(t)(i = 1,2,\cdots,n; j = 1,2,\cdots,m)$ of index $j(j = 1,2,\cdots,m)$ at time $t(t = 1,2,\cdots,T)$, The typical spatiotemporal feature possibility function of subclass k of index j is

$f_j^k[x_j^k(p_i,t,1), x_j^k(p_i,t,2), x_j^k(p_i,t,3), x_j^k(p_i,t,4)], t = 1,2,\cdots,T$

among them,$x_j^k(p_i,t,l) = h_j^k(p_i,t,l)$,$h_j^k(p_i,t,l)$ is a function of p_i and *t*.

If the possibility degree function has no first and second turning points, then $f_j^k(\bullet)$ is the spatiotemporal feature possibility function of the lower limit measure, marked as $f_j^k[-,-,x_j^k(p_i,t,3), x_j^k(p_i,t,4)]$.

If the second and third turning points of the possible degree functions coincide, then $f_j^k(\bullet)$ is the spatiotemporal feature possibility function of the moderate measure, marked as $f_j^k[x_j^k(p_i,t,1), x_j^k(p_i,t,2), -, x_j^k(p_i,t,4)]$.

If the probability function has no third or fourth turning point, then $f_j^k(\bullet)$ is the spatiotemporal feature possibility function of the upper limit measure, marked as $f_j^k[x_j^k(p_i,t,1), x_j^k(p_i,t,2), -, -]$.

Proposition 2.3.1 The typical expression of the probability function of discrete spatiotemporal characteristics is:

$$f_j^k(x_i(t)) = \begin{cases} 0 & x_i(t) \notin [x_j^k(p_i,t,1), x_j^k(p_i,t,4)] \\ \dfrac{x_i(t) - x_j^k(p_i,t,1)}{x_j^k(p_i,t,2) - x_j^k(p_i,t,1)} & x_i(t) \in [x_j^k(p_i,t,1), x_j^k(p_i,t,2)] \\ 1 & x_i(t) \in [x_j^k(p_i,t,2), x_j^k(p_i,t,3)] \\ \dfrac{x_j^k(p_i,t,4) - x_i(t)}{x_j^k(p_i,t,4) - x_j^k(p_i,t,3)} & x_i(t) \in [x_j^k(p_i,t,3), x_j^k(p_i,t,4)] \end{cases}, \quad t = 1,2,\cdots,T$$

1) The expression of the spatiotemporal feature probability function of the lower limit measure is:

$$f_j^k(x_i(t)) = \begin{cases} 0 & x_i(t) \notin [0, x_j^k(p_i,t,4)] \\ 1 & x_i(t) \in [0, x_j^k(p_i,t,3)] \\ \dfrac{x_j^k(p_i,t,4) - x_i(t)}{x_j^k(p_i,t,4) - x_j^k(p_i,t,3)} & x_i(t) \in [x_j^k(p_i,t,3), x_j^k(p_i,t,4)] \end{cases}, \quad t = 1,2,\cdots,T$$

2) The possible degree function expression of spatiotemporal characteristics of the moderate measure is:

$$f_j^k(x_i(t)) = \begin{cases} 0 & x_i(t) \notin [x_j^k(p_i,t,1), x_j^k(p_i,t,4)] \\ \dfrac{x_i(t) - x_j^k(p_i,t,1)}{x_j^k(p_i,t,2) - x_j^k(p_i,t,1)} & x_i(t) \in [x_j^k(p_i,t,1), x_j^k(p_i,t,2)] \\ \dfrac{x_j^k(p_i,t,4) - x_i(t)}{x_j^k(p_i,t,4) - x_j^k(p_i,t,3)} & x_i(t) \in [x_j^k(p_i,t,2), x_j^k(p_i,t,4)] \end{cases}, \quad t = 1,2,\cdots,T$$

3) The expression of the spatiotemporal feature probability function of the upper limit measure is:

$$f_j^k(x_i(t)) = \begin{cases} 0 & x_i(t) < x_j^k(p_i,t,1) \\ \dfrac{x_i(t) - x_j^k(p_i,t,1)}{x_j^k(p_i,t,2) - x_j^k(p_i,t,1)} & x_i(t) \in [x_j^k(p_i,t,1), x_j^k(p_i,t,2)] \\ 1 & x_i(t) \geq x_j^k(p_i,t,2) \end{cases}, \quad t = 1,2,\cdots,T$$

Proposition 2.3.2 For typical spatiotemporal features possible degree functions, set $\lambda_j^k(p_i,t) = \frac{1}{2}(x_j^k(p_i,t,2) + x_j^k(p_i,t,3))$,$t = 1,2,\cdots,T$;for the spatiotemporal feature possibility function of the lower limit measure, set $\lambda_j^k(p_i,t) = x_j^k(p_i,t,3)$,$t = 1,2,\cdots,T$; for the spatiotemporal feature possibility function of the moderate limit measure, set $\lambda_j^k(p_i,t) = x_j^k(p_i,t,2)$,$t = 1,2,\cdots,T$, then $\lambda_j^k(p_i,t)$ is the spatiotemporal critical value of *k* subclass of *j*-index. Marked as:

$$\eta_j^k(p_i,t) = \frac{\lambda_j^k(p_i,t)}{\sum_{j=1}^m \lambda_j^k(p_i,t)}, t = 1,2,\cdots,T$$

then $\eta_j^k(p_i,t)$ is the space-time weight of the subclass of j index k.

Proposition 2.3.3 Set $x_{ij}(t)$ is the observed value of index *j* at time *t*, $f_j^k(\bullet)$is the spatiotemporal feature possibility function of the *j*-index *k* subclass, $\eta_j^k(p_i,t)$ is the space-time weight of sub-class *k* of *j*-index. Marked as:

$$\sigma_i^k(t) = \sum_{j=1}^m f_j^k(x_{ij}(t)) \cdot \eta_j^k(p_i,t), t = 1,2,\cdots,T$$

Then $\sigma_i^k(t)$ is the spatiotemporal clustering coefficient of the object *i* belongs to *k* grey class at time *t*. Marked as:

$$\sigma_i^k = \frac{\sum_{t=1}^T \sigma_i^k(t)}{T}$$

Then σ_i^k is the spatiotemporal clustering coefficient of the object *i* belongs to *k* grey class. Marked as:

$$\sigma_i = (\sigma_i^1, \sigma_i^2, \cdots, \sigma_i^s,)$$

Then σ_i is the spatiotemporal clustering coefficient vector of object *i*.

$$\sigma = \begin{pmatrix} \sigma_1^1 & \sigma_1^2 & \cdots & \sigma_1^S \\ \sigma_2^1 & \sigma_2^2 & \cdots & \sigma_2^S \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_n^1 & \sigma_n^2 & \cdots & \sigma_n^s \end{pmatrix}$$

is the spatiotemporal clustering coefficient matrix.

Proposition Set $\max_{1\le k\le s}\{\sigma_i^k\} = \sigma_i^{k*}$, then object *i* belongs to grey class $k*$.

3. Grey cluster evaluation of development performance of provinces in China based on spatiotemporal possibility function

According to the evaluation idea, based on the consideration of regional development imbalance, applying the grey evaluation model of development performance based on the space-time possibility function is necessary to correct the deviation of the traditional evaluation model. Based on the data of 14 performance evaluation indicators in each region from 2009 to 2019, different probability functions are set for each region, and the probability function value is calculated by combining the weight calculated by the entropy weight method. The calculation results of each indicator are divided into three categories: excellent, good, and medium. The steps of grey cluster evaluation of the development performance of provinces in China based on spatiotemporal possibility function are as follows:

(1) Normalization of raw data

Based on the maximum data of 31 provinces in the current year, the data of the current year is normalized. For example, the GDP normalization matrix of eastern provinces is shown in Table 1, and the normalization of other indicators in each region is similar.

Table 1
Standardized data on GDP indicators of provinces in the eastern part of the array from 2009 to 2019

Province	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.308	0.307	0.305	0.313	0.314	0.315	0.316	0.317	0.312	0.312	0.329
Tianjin	0.191	0.200	0.213	0.226	0.231	0.232	0.227	0.221	0.207	0.193	0.131
Hebei	0.437	0.443	0.461	0.466	0.455	0.434	0.409	0.397	0.379	0.370	0.326
Shanghai	0.381	0.373	0.361	0.354	0.348	0.348	0.345	0.349	0.341	0.336	0.354
Jiangsu	0.873	0.900	0.923	0.947	0.952	0.960	0.963	0.957	0.957	0.952	0.925
Zhejiang	0.582	0.602	0.607	0.607	0.604	0.592	0.589	0.584	0.577	0.578	0.579
Shandong	0.859	0.851	0.853	0.876	0.880	0.876	0.865	0.841	0.810	0.786	0.660
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hainan	0.042	0.045	0.047	0.050	0.051	0.052	0.051	0.050	0.050	0.050	0.049
Liaoning	0.385	0.401	0.418	0.435	0.436	0.422	0.394	0.275	0.261	0.260	0.231
Fujian	0.310	0.320	0.330	0.345	0.350	0.355	0.357	0.356	0.359	0.368	0.394

(2) Build possibility function expression according to the definition

In the selected data material, there are 11 provinces in total, and each province is represented as p_i(i=1,2…,11). The time from 2009 to 2019 is expressed as t(t=1,2,…,11).

1) The probability function expression of the upper measure is:

$$f_j^1(x_i(t))=\begin{cases}0 & x_i(t)<x_j^1(p_i,t,1)\\ \dfrac{x_i(t)-x_j^1(p_i,t,1)}{x_j^1(p_i,t,2)-x_j^1(p_i,t,1)} & x_i(t)\in[x_j^1(p_i,t,1),x_j^1(p_i,t,2)]\\ 1 & x_i(t)\geq x_j^1(p_i,t,2)\end{cases},\quad i=1,2,3,\ldots,11$$

2) The possible degree function expression of the moderate measure is:

$$f_j^2(x_i(t))=\begin{cases}0 & x_i(t)\notin[x_j^2(p_i,t,1),x_j^2(p_i,t,3)]\\ \dfrac{x_i(t)-x_j^2(p_i,t,1)}{x_j^2(p_i,t,2)-x_j^2(p_i,t,1)} & x_i(t)\in[x_j^2(p_i,t,1),x_j^2(p_i,t,2)]\\ \dfrac{x_j^2(p_i,t,4)-x_i(t)}{x_j^2(p_i,t,4)-x_j^2(p_i,t,3)} & x_i(t)\in[x_j^2(p_i,t,2),x_j^2(p_i,t,)]\end{cases},\quad i=1,2,3,\ldots,11$$

3) The probability function expression of the lower limit measure is:

$$f_j^k(x_i(t))=\begin{cases}0 & x_i(t)\notin[0,x_j^3(p_i,t,4)]\\ 1 & x_i(t)\in[0,x_j^3(p_i,t,3)]\\ \dfrac{x_j^3(p_i,t,4)-x_i(t)}{x_j^3(p_i,t,4)-x_j^3(p_i,t,3)} & x_i(t)\in[x_j^3(p_i,t,3),x_j^3(p_i,t,4)]\end{cases},\quad i=1,2,3,\ldots,11$$

(3) Determine the possibility function expression of each index as:

$f_j^1[x_j^1(p_i,t,1),x_j^1(p_i,t,2),-,-]$, $f_j^2[x_j^2(p_i,t,1),x_j^2(p_i,t,2),-,x_j^2(p_i,t,4)]$, $f_j^3[-,-,x_j^3(p_i,t,3),x_j^3(p_i,t,4)]$

The probability function of each index in the eastern region is:

$f_1^1(0.41,0.78,-,-)$ $f_2^1(0.62,0.77,-,-)$ $f_3^1(0.44,0.68,-,-)$
$f_1^2(0.25,0.41,-,0.69)$ $f_2^2(0.45,0.62,-,0.73)$ $f_3^2(0.27,0.44,-,0.62)$
$f_1^3(-,-,0.25,0.41,)$ $f_2^3(-,-,0.45,0.62,)$ $f_3^3(-,-,0.27,0.44,)$

$f_4^1(0.61,0.72,-,-)$ $f_5^1(0.57,0.73,-,-)$ $f_6^1(0.56,0.70,-,-)$
$f_4^2(0.50,0.61,-,0.71)$ $f_5^2(0.33,0.57,-,0.71)$ $f_6^2(0.39,0.56,-,0.63)$
$f_4^3(-,-,0.50,0.61)$ $f_5^3(-,-,0.33,0.57)$ $f_6^3(-,-,0.39,0.56)$

$f_7^1(0.75,0.85,-,-)$ $f_8^1(0.77,0.92,-,-)$ $f_9^1(0.58,0.77,-,-)$
$f_7^2(0.53,0.75,-,0.8)$ $f_8^2(0.65,0.77,-,0.88)$ $f_9^2(0.48,0.58,-,0.75)$
$f_7^3(-,-,0.53,0.85)$ $f_8^3(-,-,0.65,0.77)$ $f_9^3(-,-,0.48,0.58)$

$f_{10}^1(0.59,0.79,-,-)$ $f_{11}^1(0.39,0.59,-,-)$ $f_{12}^1(0.75,0.85,-,-)$
$f_{10}^2(0.35,0.59,-,0.69)$ $f_{11}^2(0.31,0.39,-,0.57)$ $f_{12}^2(0.53,0.75,-,0.80)$
$f_{10}^3(-,-,0.35,0.59)$ $f_{11}^3(-,-,0.31,0.39)$ $f_{12}^3(-,-,0.53,0.75)$

$f_{13}^{1}(0.54{,}0.78,-,-)$ $f_{14}^{1}(0.38{,}0.50,-,-)$
$f_{13}^{2}(0.38{,}0.54,-{,}0.76)$ $f_{14}^{2}(0.2{,}0.38,-{,}0.47)$
$f_{13}^{3}(-,-{,}0.38{,}0.54)$ $f_{14}^{3}(-,-{,}0.20{,}0.38)$

(4) Calculate the probability function value of each index

According to the above possibility function expression, the possible function of the development level of Category $k(k=1,2,3)$ under each indicator $j(1,2,\cdots,14)$ of the 11 eastern provinces with space-time characteristics can be obtained. As shown in Table 2, the probability function value of the development level of Class k under the GDP indicators of Eastern Province $p_i(i=1,2,\cdots,11)$ in 2009-2019 is similar to that of other regions.

Table 2
The probability function value of the development level of the eastern provinces under the GDP indicators in 2009-2019

Province	Level	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	Upper limit,	0	0	0	0	0	0	0	0	0	0	0
	Moderate	0.361	0.355	0.346	0.396	0.398	0.404	0.413	0.422	0.389	0.386	0.491
	Lower limit	0.639	0.645	0.654	0.604	0.602	0.596	0.587	0.578	0.611	0.614	0.509
Tianjin	Upper limit,	0	0	0	0	0	0	0	0	0	0	0
	Moderate	0	0	0	0	0	0	0	0	0	0	0
	Lower limit	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	Upper limit,	0.072	0.090	0.137	0.150	0.122	0.065	0	0	0	0	0
	Moderate	0.905	0.881	0.819	0.801	0.838	0.915	0.996	0.917	0.808	0.751	0.475
	Lower limit	0	0	0	0	0	0	0.004	0.083	0.192	0.249	0.525
Shanghai	Upper limit,	0	0	0	0	0	0	0	0	0	0	0
	Moderate	0.819	0.769	0.692	0.648	0.609	0.610	0.594	0.616	0.572	0.537	0.652
	Lower limit	0.181	0.231	0.308	0.352	0.391	0.390	0.406	0.384	0.428	0.463	0.348
Jiangsu	Upper limit,	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Moderate	0	0	0	0	0	0	0	0	0	0	0
	Lower limit	0	0	0	0	0	0	0	0	0	0	0
Zhejiang	Upper limit,	0.466	0.520	0.533	0.534	0.525	0.493	0.484	0.471	0.452	0.453	0.457
	Moderate	0.385	0.313	0.295	0.295	0.306	0.348	0.361	0.377	0.403	0.401	0.396
	Lower limit	0	0	0	0	0	0	0	0	0	0	0
Shandong	Upper limit,	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.676
	Moderate	0	0	0	0	0	0	0	0	0	0	0.107
	Lower limit	0	0	0	0	0	0	0	0	0	0	0
Guangdong	Upper limit,	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Moderate	0	0	0	0	0	0	0	0	0	0	0
	Lower limit	0	0	0	0	0	0	0	0	0	0	0
Hainan	Upper limit,	0	0	0	0	0	0	0	0	0	0	0
	Moderate	0	0	0	0	0	0	0	0	0	0	0
	Lower limit	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Liaoning	Upper limit,	0	0	0.021	0.069	0.069	0.033	0	0	0	0	0
	Moderate	0.846	0.945	0.972	0.909	0.909	0.957	0.898	0.157	0.068	0.064	0
	Lower limit	0.154	0.055	0	0	0	0	0.102	0.843	0.932	0.936	1.000
Fujian	Upper limit,	0	0	0	0	0	0	0	0	0	0	0
	Moderate	0.375	0.439	0.500	0.595	0.625	0.655	0.668	0.665	0.68	0.738	0.898
	Lower limit	0.625	0.561	0.500	0.405	0.375	0.345	0.332	0.335	0.320	0.262	0.102

(5) Compute the spatiotemporal weights of the *j* index *k* subclasses

The spatiotemporal critical value of each indicator in the eastern province $p_i(i=1,2,\cdots,11)$ is

$\lambda_1^1=0.78$ $\lambda_1^2=0.41$ $\lambda_1^3=0.25$ $\lambda_8^1=0.92$ $\lambda_8^2=0.77$ $\lambda_8^3=0.65$
$\lambda_2^1=0.77$ $\lambda_2^2=0.62$ $\lambda_2^3=0.45$ $\lambda_9^1=0.77$ $\lambda_9^2=0.58$ $\lambda_9^3=0.48$
$\lambda_3^1=0.68$ $\lambda_3^2=0.44$ $\lambda_3^3=0.27$ $\lambda_{10}^1=0.79$ $\lambda_{10}^2=0.59$ $\lambda_{10}^3=0.35$
$\lambda_4^1=0.72$ $\lambda_4^2=0.61$ $\lambda_4^3=0.50$ $\lambda_{11}^1=0.59$ $\lambda_{11}^2=0.39$ $\lambda_{11}^3=0.31$
$\lambda_5^1=0.73$ $\lambda_5^2=0.57$ $\lambda_5^3=0.33$ $\lambda_{12}^1=0.85$ $\lambda_{12}^2=0.75$ $\lambda_{12}^3=0.53$
$\lambda_6^1=0.70$ $\lambda_6^2=0.56$ $\lambda_6^3=0.39$ $\lambda_{13}^1=0.78$ $\lambda_{13}^2=0.54$ $\lambda_{13}^3=0.38$
$\lambda_7^1=0.85$ $\lambda_7^2=0.75$ $\lambda_7^3=0.53$ $\lambda_{14}^1=0.50$ $\lambda_{14}^2=0.38$ $\lambda_{14}^3=0.20$

By $\eta_j^k=\frac{\lambda_j^k}{\sum_{j=1}^{14}\lambda_j^k}$, the spatiotemporal weight of each index in each province in the eastern region is obtained.

$\eta_1^1 = 0.0746$ $\eta_{j_1}^2 = 0.0513$ $\eta_{j_1}^3 = 0.0430$ $\lambda_8^1 = 0.0880$ $\lambda_8^2 = 0.0964$ $\lambda_8^3 = 0.1119$
$\eta_2^1 = 0.0736$ $\eta_2^2 = 0.0776$ $\eta_2^3 = 0.0775$ $\lambda_9^1 = 0.0736$ $\lambda_9^2 = 0.0726$ $\lambda_9^3 = 0.0826$
$\eta_3^1 = 0.0650$ $\eta_3^2 = 0.0551$ $\eta_3^3 = 0.0465$ $\lambda_{10}^1 = 0.0755$ $\lambda_{10}^2 = 0.0738$ $\lambda_{10}^3 = 0.0602$
$\eta_4^1 = 0.0688$ $\eta_4^2 = 0.0763$ $\eta_4^3 = 0.0861$ $\lambda_{11}^1 = 0.0564$ $\lambda_{11}^2 = 0.0488$ $\lambda_{11}^3 = 0.0534$
$\eta_5^1 = 0.0698$ $\eta_5^2 = 0.0713$ $\eta_5^3 = 0.0568$ $\lambda_{12}^1 = 0.0813$ $\lambda_{12}^2 = 0.0939$ $\lambda_{12}^3 = 0.0912$
$\eta_6^1 = 0.0669$ $\eta_6^2 = 0.0701$ $\eta_6^3 = 0.0671$ $\lambda_{13}^1 = 0.0746$ $\lambda_{13}^2 = 0.0676$ $\lambda_{13}^3 = 0.0654$
$\eta_7^1 = 0.0841$ $\eta_7^2 = 0.0976$ $\eta_7^3 = 0.1239$ $\lambda_{14}^1 = 0.0478$ $\lambda_{14}^2 = 0.0476$ $\lambda_{14}^3 = 0.0344$

(6) Calculate the weighted grey clustering coefficient of each province from 2009 to 2019

According to the grey class, each area index k the basic values of λ_j^k, get the weight of ash class $\boldsymbol{k}$. In this paper, in the second part has the entropy weight method is adopted to calculate the index information of entropy in different areas, set the weight of index j be $\delta_j(p,t)$, through the synthesis of information entropy weight and spatiotemporal weight, the comprehensive weight is obtained.

$$w_j^k(p_i,t) = \frac{\delta_j^k(p_i,t) \times \eta_j(p,t)}{\sum_{j=1}^{14} \delta_j^k(p_i,t) \times \eta_j(p,t)}$$

Then the weighted grey clustering coefficient of each province can be obtained from the following formula.

$$\sigma_i^k = \sum_{j=1}^{14} f_j^k(x_{ij}) \times w_j(p_i,t)\,, \sigma_i^1 = \sum_{j=1}^{14} f_j^1(x_{ij}) \times w_j(p_i,t)\,, \sigma_i^2 = \sum_{j=1}^{14} f_j^2(x_{ij}) \times w_j(p_i,t)\,, \sigma_i^3 = \sum_{j=1}^{14} f_j^3(x_{ij}) \times w_j(p_i,t)$$

Table 3 shows the clustering coefficient of each ash category in the eastern provinces from 2009 to 2019, similar to other regions.

Table 3
Clustering coefficient of the "excellent" grey category in eastern provinces from 2009 to 2019

Province	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Beijing	0.677	0.676	0.693	0.691	0.565	0.561	0.562	0.575	0.557	0.556	0.552	0.606
Tianjin	0.511	0.486	0.535	0.546	0.516	0.517	0.533	0.561	0.561	0.497	0.243	0.501
Hebei	0.102	0.087	0.092	0.109	0.062	0.051	0.029	0.042	0.049	0.064	0.081	0.070
Shanghai	0.671	0.661	0.661	0.661	0.567	0.567	0.588	0.608	0.615	0.622	0.640	0.624
Jiangsu	0.503	0.545	0.645	0.650	0.612	0.628	0.627	0.521	0.545	0.559	0.530	0.579
Zhejiang	0.421	0.484	0.581	0.515	0.516	0.483	0.518	0.428	0.456	0.462	0.393	0.478
Shandong	0.400	0.355	0.307	0.303	0.296	0.291	0.285	0.353	0.276	0.277	0.232	0.307
Guangdong	0.384	0.382	0.375	0.380	0.355	0.374	0.370	0.355	0.377	0.372	0.352	0.371
Hainan	0.108	0.070	0.043	0.054	0.060	0.053	0.046	0.075	0.050	0.055	0.079	0.063
Liaoning	0.163	0.150	0.150	0.168	0.102	0.091	0.066	0.125	0.136	0.146	0.133	0.130
Fujian	0.129	0.108	0.085	0.068	0.070	0.069	0.078	0.072	0.089	0.105	0.116	0.090

The calculation results show that the average value of the clustering coefficient of the "excellent" grey category in the eastern provinces from 2009 to 2019 is 0.347, which is normal, ranking in the order of Shanghai, Beijing, Jiangsu, Tianjin, Zhejiang, Guangdong, Shandong, Liaoning, Fujian, Hebei, and Hainan. However, the clustering coefficients of the provinces are extremely unbalanced. The highest clustering coefficient of Shanghai is 10 times that of the lowest Hainan, indicating that the eastern, central division of western provinces can be further optimized. The result in Table 3 is changed to a legend, which can more intuitively reflect the status of the clustering coefficient of the "excellent" grey category in the eastern provinces from 2009 to 2019 (as is shown in Fig. 3).

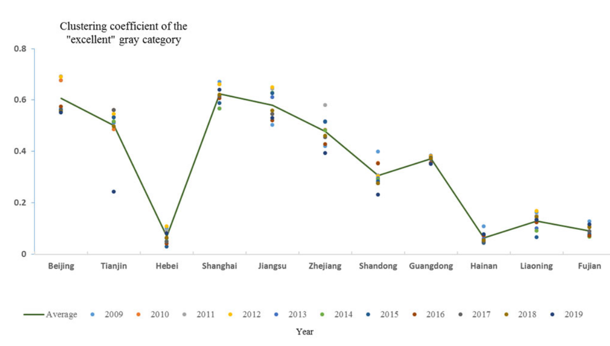

Fig. 3. The expression of the clustering coefficient of the "excellent" grey category in the eastern provinces from 2009 to 2019

In particular, in terms of stability, the values in Guangdong each year are relatively concentrated and stable, while the values in Tianjin, Zhejiang, Shandong, and other provinces are scattered and have poor stability. The results can also be obtained from the clustering coefficients of other grey categories in the eastern provinces and the clustering coefficients of the central and western provinces.

(6) Determine the grey cluster evaluation results of each province from 2009 to 2019

The clustering values of each year belonging to the *k* development grade of each province and county are taken to mean the clustering result σ_i^k of the province belonging to a certain development grade; based on $\max\limits_{1\le k\le 3}\left\{\sigma_i^k\right\} = \sigma_i^{k^*}$, it can be concluded that the *i*-th province belongs to the development level of class k^* (as is shown in Fig. 4), different colors represent different development levels, and the value under the province name is the clustering result of the province under the specific development level.

Fig. 4. Grey cluster evaluation results of development performance of provinces in China based on space-time possibility function and variable weight strategy

3. Conclusions and Suggestions

The grey cluster evaluation of the development performance of 31 provinces in China based on the spatiotemporal possibility function and variable weight strategy can change the single evaluation criteria and achieve the effect of correction. According to the data, based on the grey evaluation of the spatial-temporal possibility function, 14 of China's 31 provinces are in the stage of development excellence, namely, Shanghai, Beijing, Chongqing, Hubei, Jiangsu, Tianjin, Zhejiang, Jilin, Inner Mongolia, Shaanxi, Sichuan, Hunan, Henan, and Heilongjiang, with a distribution of 5 in the east, 4 in the middle and 5 in the west. Eight provinces are in the excellent stage of development, and 12 provinces are in the middle stage of development. The results are in line with reality. The study found that neighboring provinces are often at the same level of development due to similar resources and environment, competition, and comparison. The evaluation results also show that in the eastern region with rapid development and at a similar stage of development, if the development momentum is insufficient, the grey evaluation results of development performance may fall behind the central and western provinces. Under this evaluation system, the provinces with rapid development in the west and central regions can also be rated as excellent development, and the evaluation results are more scientific and reasonable. In order to better apply the grey clustering evaluation model constructed in this paper, some necessary conditions should also be considered, and relevant expansion research should be carried out.

(1) The introduction and proper application of the spatiotemporal possibility function requires the scientific and reasonable judgment of spatiotemporal division and critical value. From the perspective of spatial dimension, according to the degree of development, China's traditional regional division is adopted, that is, the country is divided into three types of regions, namely, the east, the middle, and the west. In fact, other division criteria can also be used, such as development similarity, resource endowment similarity, etc. The regional division depends on the purpose and nature of the evaluation. Regional division can also be greater than three categories, in which case the number of provinces with excellent development will increase. From the perspective of the time dimension, this chapter selects a total of 11 years from 2009 to 2019 for

evaluation. The time span is adjusted according to the needs of the evaluation. Different probability functions can be used for different periods. The focus is on the degree of data fluctuation so as to prevent the weighted average of individual data from seriously affecting the evaluation results.

(2) The cluster evaluation of development performance based on spatiotemporal possibility function and variable weight strategy can be supplemented by trend analysis for in-depth research. A trend chart can be drawn by arranging the grey clustering coefficients of each province from 2009 to 2019. Through the trend analysis of the top 15 provinces in the development of the excellent grey category (as is shown in Figure 5), it is found that the development performance of Hubei, Sichuan, Chongqing, and Hunan is on the rise, while that of Tianjin, Jilin, Heilongjiang, Guangdong, Zhejiang, and Jilin is on the decline, while that of Shanghai, Beijing, Henan, Jiangsu, and Shaanxi is relatively stable. It can also be seen from the trend chart that the development direction of Tianjin, Jilin, Hunan, Shaanxi, Heilongjiang, and other provinces has been reversed from 2016 to 2019, which indicates that in the context of promoting high-quality development, the transformation of development mode is facing challenges, and more powerful measures need to be taken to promote high-quality development.

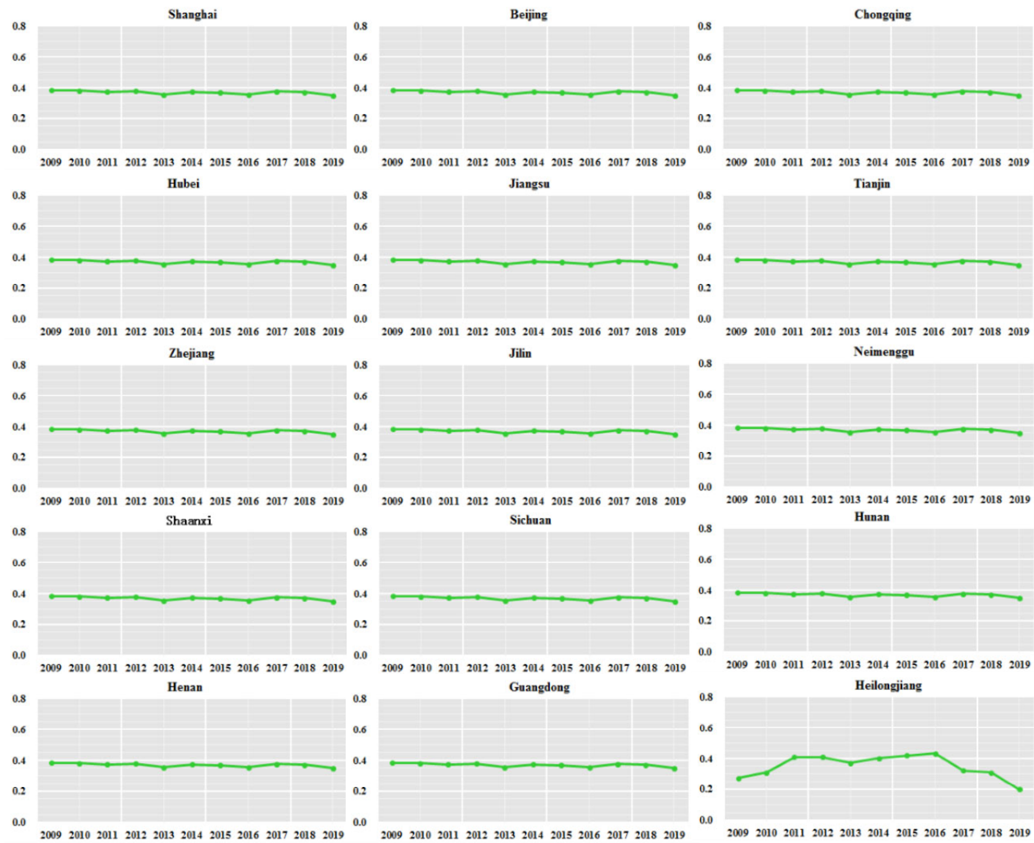

Fig. 5. Trend chart of clustering coefficient of grey "excellent" in 15 provinces from 2009 to 2019

(3) The comprehensive evaluation under the goal of rectification cannot replace the special evaluation, and the comprehensive application of various evaluation methods can achieve better results. For the performance evaluation of a single indicator, the eastern provinces are often in the category of superior development. Under the grey cluster evaluation based on the spatial-temporal possibility function, while taking into account the regional GDP, investment, consumption, science and technology, environment, and other indicators, some eastern provinces will be excluded from the category of superior development, which is in line with the characteristics and actual situation of the comprehensive evaluation. However, in some emerging industries and scientific and technological innovation projects, it is still necessary to adopt special performance evaluation and take the performance evaluation results as the basis for budget allocation to achieve the purpose of key breakthroughs and general drive.

(4) The grey evaluation of county-level financial project performance under the space-time possibility function needs to be carried out around the regional characteristics and the application of results. Generally speaking, in the face of common external situations, policy, and environment, if there is an external regional influence in the development performance evaluation, it is necessary to consider this influence when constructing the space-time possibility function. In the case of the construction of main functional areas, the policy may have a significant impact in a certain period of time. Similarly, based on the spatial-temporal possibility function, the development performance evaluation results of various provinces in

China can be obtained. The evaluation results can be analyzed in depth to find out the common laws and characteristics so as to propose regional policies and measures for regional economic and social development.

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