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Research on Urban Green Transformation Based on Grey Theory and Fuzzy Clustering

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Abstract. In the exist study of urban green transformation, most of the city clustering algorithms calculate and cluster the evaluation targets at specific time points, but cities under evaluation are likely to have data mutation due to policies and other reasons, resulting in the distortion of the clustering result and losing the guiding significance of policy and urban development. In order to solve this problem, this paper improves the gray relational analysis by using the CRITIC method. Firstly, the multidimensional time series of some evaluation indexes in a city are dimensionally reduced. On this basis, the gray relational degree matrix is transformed into the equivalent matrix, and clustering the city according to fuzzy clustering analysis. Finally, the proposed algorithm is numerically tested.

Keywords: green transformation, grey relational analysis, fuzzy clustering analysis

1. Introduction

In recent years, the concept of green transformation and healthy living has gradually gained popular support and has become an important direction for the development of the country's macroeconomic policies. Cities are the basic unit in the national green transition. Therefore, urban clustering for green transformation has guiding significance for the national macroeconomic policies and urban development initiatives.

In the literature, Xin (2011) constructed a low carbon city evaluation index system including target layer, standard layer and index layer, and evaluated low-carbon city from six aspects of economy, infrastructure, lifestyle, low-carbon technology, low-carbon policy and ecological environment. Wang (2011) divided the criteria of the indicator system into six subsystems: low-carbon economy, low-carbon society, low-carbon energy, low-carbon life philosophy, low-carbon environment and low-carbon policy, and then selected 38 evaluation indicators with the reference of relevant national documents, and analyzed the low-carbon performance of Hangzhou in 2008 through the combination of analytic hierarchy process and comprehensive index method. Zhou (2015) discussed the implications of low-carbon cities and how they were evaluated based on worldwide prevalence, and developed tools based on Excel to package metrics and interpret data source directives. Tan (2011) divided the evaluation index system of low-carbon city into 13 indicators in three levels, giving a comprehensive evaluation from the generation and treatment of carbon emissions to the final result, and applied factor analysis method to Nanjing and Shanghai in

2000-2009 Year factor comparison analysis. Tan (2017) identified a new framework for low-carbon city indicators for comprehensive evaluation and analysis of low-carbon cities. The framework considers different development categories, including economic, social and environmental factors of different indicators and uses entropy weights. And a comprehensive assessment methodology is used to conduct a low-carbon development assessment of 10 selected cities in different regions of the world. Liu (2011) established a "decoupling" index system for low-carbon cities. The system is divided into three levels, with the decoupling mode as the evaluation target, economic development, carbon emission and pollutant emission as the criteria. Under the criterion, the specific indexes are subdivided, and finally this paper takes Shenyang as an example to judge whether the indicators are decoupled or not in each year. Yang (2013) described the specific requirements and importance of establishing a low-carbon life from the aspects of traffic, construction and daily life, and provided the basis for establishing a low carbon city evaluation index system. Taking Qingdao as an example, Tao (2011) described the direction and measures for low-carbon development in Qingdao from several aspects such as energy supply system, industrial development system, pollution control system, environmental protection and low carbon awareness, and provided a low-carbon city evaluation with a number of important sub-indicators. Fu (2010) used the main index method and composite index method to construct the evaluation index system of low carbon city from the economic, social and environmental aspects. Based on the green development support system, the green production vitality system and the green ecological environment system, Zhu (2013) built a comprehensive evaluation system of economic green transition containing 18 evaluation indexes, and determined the weight of each index by the information entropy method. Fujian Province, for example, uses regression analysis to verify the indicators at multiple isolated time points.

In summary, Xin (2011), Wang (2011), Zhou et al. (2015), Tan (2011), Tan et al. (2017) , Liu et al. (2011), Yang et al. (2013), Tao(2011) all have carried on the related research to the urban evaluation index system construction related to the green transformation. But in the analysis of green transition cities, some literatures analyze the urban green transition from some specific time points. Although some literatures have analyzed many variable indexes in many years, they have analyzed many isolated points and failed to integrate the results. In addition, in the context of Chinese city green transformation based on clustering, the whole process involves the value and analysis of multiple objects at different sampling points. Therefore, the amount of data is large, the time series dimension is more, and the direct processing of data is more complex.

This paper draws on the index system of the city green transformation, and makes appropriate adjustments, finally gets the system of city green transformation index. This paper also uses the CRITIC method to weight tuning method of grey correlation analysis, grey correlation evaluation calculation by the city to achieve dimensionality reduction of multidimensional time series, combined with fuzzy clustering, is established evaluation of city green transformation model, then clustering analysis was carried out on the main city of our country, improvement cannot be combined in the traditional context of city green transformation index clustering years analysis and comprehensive analysis of the problem, the formation of new city cluster, in order to promote the development of the city at all levels of government planning and related policies. In addition, CRITIC method is used to optimize the weights of gray relational analysis method which is used to calculate the gray relational degree of the evaluated cities in order to reduce the dimension of multidimensional time series. Combining with fuzzy clustering, this paper establishes a green transition evaluation model of cities, conducts cluster analysis on major cities in China. This method improves the problem of multi-year analysis and comprehensive analysis of indicators in urban clustering which cannot be combined under the traditional green transition situation and forms a new urban cluster to promote the planning of specific cities and the formulation of relevant policies at all levels of government.

2. Urban Clustering Based On Gray Theory And Fuzzy Clustering For Urban Green Transformation

Determination of urban green transformation evaluation index system

The construction of urban green transformation evaluation index system must conform to the relevant policy of green transition in China. Only by complying with the characteristics of ecology and economy, can we make a more accurate clustering of cities, so that the clustering results can be targeted to the designation of policies and the implementation of specific measures, thus promoting the green transformation and development of cities.

The establishment of the evaluation index system of urban green transition extensively draws on the experience of predecessors. Xin (2011), Wang (2011), Tan (2011), Tan et al. (2017), Liu et al. (2011), Tao(2011) Indicator systems are all related to economic, industrial emissions and the environment, which would be adopted by the establishment of the index system in this paper. Some of the literature in the index system involves a low-carbon awareness, green management, and so on. Because many experts and scholars in the green transition evaluation index system didn't consider these factors, they will not be included in the index system. In the selection of specific sub-indicators, GDP is selected as the sub-indicator of economic development. In the field of industrial waste, most of the literature used industrial solid waste emissions, industrial waste water emissions or industrial waste gas emissions as measurements. Because industrial waste water and industrial waste gas have a greater impact on the social environment, and the overlap with social environmental indicators will make the indicator system redundant. In the social environment, green coverage area, public transport volume, air quality and good rate and other indicators are very common. Considered with the index selection principle, this paper selected the air quality indicator, the number of public transport operations, green coverage. In summary, this paper establishes the following urban green transformation evaluation index system:

Table 1. Urban Green Transformation Evaluation Index System

Urban Green Transformation Evaluation Index System		
Economic Development	Industrial Waste	Social Environment

GDP	industrial solid waste emissions	the air quality indicator	the number of public transport operations	green coverage area

The value of a certain evaluation index of a city $x_i(i = 1,2, \dots, d)$ at multiple points in time constitutes a time series of the indicator $x(t)$. Therefore, based on d evaluation index,

d time series of length n are made up, or $d \times n$-dimensional time series, which could be represented by a matrix:

$$[x_{i,t}]^{d\times n} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \cdots & & \cdots \\ x_{d,1} & \cdots & x_{d,n} \end{bmatrix}$$

$x_{i,t}$ represents the sampled value of the i-th dimension variable at the time point t.

algorithm ideas

In the urban cluster oriented to green transformation, because it involves the evaluation of multiple evaluation indexes at different time sampling points in multiple cities, several multidimensional time series databases will be formed. In this paper, the data analysis is done by first processing the multi-dimensional time series database separately and then integrating all the data. When dealing with multidimensional time series database, gray relational analysis can not only reduce the dimension of time series, but also take the urban index into consideration. Therefore, this paper selects the gray correlation analysis method to analyze the relevant data of urban evaluation index Pre-treatment.

From a theoretical point of view, there is no clear research shows that the comprehensive calculation of urban green transition indicators is more scientific with some methods so far. But from the historical point of view, Wang (2011), Tan et al. (2017), Chen et al. (2012), Hua et al. (2011) all use the weighted method to calculate the index. Therefore, this article also uses this method.

In the urban clustering of urban green transformation, there is no clear distinction between classes and classes in city, and their boundaries are ambiguous. Therefore, the fuzzy clustering method is used to cluster the cities.

To sum up, this paper proposes the following algorithmic framework for urban clustering research, which is as follows:

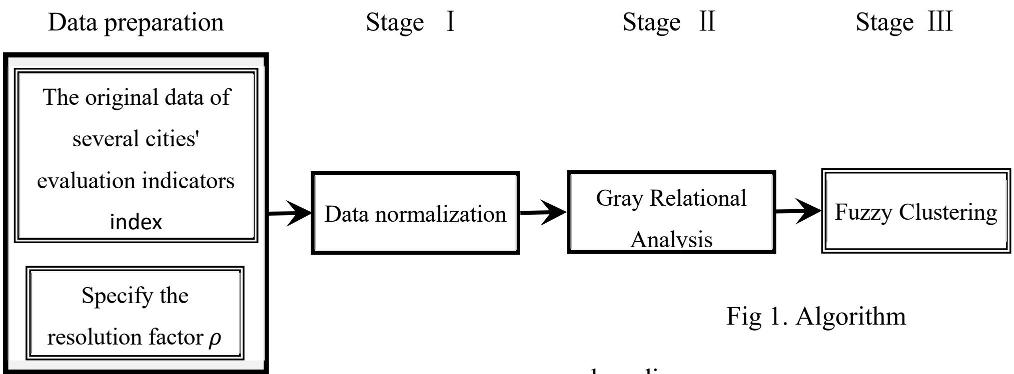

Fig 1. Algorithm procedure diagram

Algorithm description

In this paper, we use the gray correlation analysis and the fuzzy clustering method in the urban clustering algorithm. For the sake of convenience of expression, we first give the relevant discussion.

The measure of the correlation between the two systems as the changes in time or subjects is called the degree of association. Gray relational analysis method is based on the similarity or dissimilarity of the development trend between factors, namely "gray relational degree", as a measure of the correlation between factors.

In the process of system development, if the trend of the two factors is consistent, that is, the degree of synchronization changes is high, the correlation between the two is high; on the contrary, the degree is lower. The steps for evaluation using gray relational analysis are as follows:

1) Identify reference sequences and compare sequences

The data sequence reflecting the characteristics of the system's behavior is called the reference sequence x_0. The sequence of data that affects the behavior of the system is called the comparison number, denoted as x_i :

$$x_i = \{x_i(k) | k = 1,2 \dots, n\}$$

$$= \left(x_i(1), x_i(2), \dots, x_i(n)\right)$$

$$(i = 1,2, \dots, d)$$

2) Non-dimensional treatment of reference sequence and comparison sequence

Presumably, there is a series:

$$x = (x(1), x(2), \dots, x(n))$$

So, a mapping:

$$f: x \rightarrow y$$

$$f\left(x(k)\right) = y(k), \quad k = 1,2 \dots, n$$

Is the mapping from sequence x to sequencey.

Mapping function the z-score method and the $\mathrm{Min} - \mathrm{max}$ method are the common data normalization methods:

$$x'_{ij} = \frac{x_{ij} - \bar{x}_i}{s_i}$$

$$\mathrm{x}_{\mathrm{ij}}'' = \frac{\mathrm{x}_{\mathrm{ij}}' - \mathrm{x}_{\mathrm{k_{min}}}'}{\mathrm{x}_{\mathrm{k_{max}}}' - \mathrm{x}_{\mathrm{k_{min}}}'}$$

Z-score method normalize the data from the horizontal and vertical, while the $\mathrm{Min} - \mathrm{max}$ method ensures that $\mathrm{x}_{\mathrm{ij}}''$ is mapped to $[0,1]$. In this equation:

a) $\bar{x}_i$ represents the mean of x_{ij}, $\bar{x}_i = \frac{1}{n}\sum_{j=1}^{n} x_{ij}$.

b) s_i represents the standard deviation of x_{ij}, $s_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(x_{ij} - \bar{x}_i)^2}$;

c) $x'_{k_{max}}$, $x'_{k_{min}}$ are the maximum and minimum values of x'_{ij} $(i = 1,2,\dots,d)$.

3) Gray correlation coefficient between reference sequence and comparison sequence

The reference sequence x_0 is selected:

$$\mathrm{x}_0 = \{\mathrm{x}_0(\mathrm{k}) | \mathrm{k} = 1,2 \dots, \mathrm{n}\}$$
$$= (\mathrm{x}_0(1), \mathrm{x}_0(2), \dots, \mathrm{x}_0(\mathrm{n}))$$

k represents the point in time, $\mathrm{x}_0(\mathrm{k})$ is usually a single target optimal value.

$\xi_{\mathrm{i}}(\mathrm{k})$ is the correlation coefficient of the comparison sequence x_{i} to the reference sequence x_0 at time k :

$$\xi_{\mathrm{i}}(\mathrm{k}) = \frac{\Delta(\min) + \rho\Delta(\max)}{\Delta_{0\mathrm{i}}(\mathrm{k}) + \rho\Delta(\max)}$$

a) $\Delta(\min)$, $\Delta(\max)$ is the comparison environment of x_{i} and x_0. They respectively represent the two-stage minimum difference and the two-stage maximum difference.

b) $\rho \in [0,1]$ is the distinguishing coefficient, shows how the environment changes. This article uses a common value, calculated according to $\rho = 0.5$.

Correlation coefficient is to describe the reference sequence and compare sequence correlation degree index, which have a correlation coefficient in every moment. Therefore, information dispersion is not conducive to subsequent calculation, and the correlation coefficient is centralized in the form of grey relational degree.

4) The Calculation of Gray Relational Degree

Because the correlation coefficient is the correlation degree between the comparison sequence and the reference sequence at each moment, the correlation coefficient is actually a time series, and the information is too scattered to compare with the whole set. Therefore, it is necessary to centralize the correlation coefficients of each moment as a value, which is defined as the number of the correlation degree between the comparison sequence and the reference sequence, defined as, which is the correlation degree of the series x_i of the comparison to the reference sequence x_0:

$$p_{oi} = \sum_{i=1}^{d} W_i \times \xi_i(k)$$

p_{oi} is a comparison of the correlation degrees of x_i to the reference sequence x_0, which is the comprehensive measure of each time point for the W_i and the correlation coefficient, $\xi_i(k)$. The correlation degree $P = (p_{o1}, p_{o2}, \dots, p_{od})^T$ is a comprehensive evaluation of each index. The gray relational grade matrix G can be formed by the correlation degree series of each sample C_q $(q = 1,2, \dots, n)$:

$$G = [P_1, P_2, \dots, P_n]$$

Generally speaking, the average value method is used to calculate the correlation degree in the grey relational analysis. While in the context of green transition, the importance of each index is not the same. And it’s too subjective to determining the index weight by human. In addition, the conflicts between indicators also need to be considered. Therefore, this paper makes an improvement on the average value method by a more objective way, which could consider both the degree of index variation and the index conflict. Finally, the CRITIC method is used to improve the weight of the grey relational analysis. This paper defines the weights of index $\mathrm{W_i}$:

$$\mathrm{W_i} = \frac{\mathrm{I_i}}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{I_i}} \ (\mathrm{i} = 1,2, \dots, \mathrm{d})$$

In this equation:

a) I_i represents the amount of information contained in the index, $I_i = \sigma_i \sum_{j=1}^{n}(1 - l_{ij})$;

b) σ_i is the standard deviation of the i-th indicator;

c) l_{ij}) represents a quantitative measure of conflict between the i-th index and other indicators. l_{ij} refers to the correlation coefficient between the i-th index and the j-th index. The larger it is, the greater the amount of information contained in the i-th index, the more important the i-th index is.

At this time the weight W_i is satisfied $\sum_{i=1}^{d} W_i = 1$ and $W_i \in [0,1]$ $(i = 1,2, \dots, d)$.

Fuzzy clustering is realized by squaring the self-composition operation of the fuzzy similarity matrix and intercepting the appropriate level value.

After the gray relational analysis of the selected city's several dimensional databases, we can get several gray correlation degree series $P_n = (p_{n1}, p_{n2}, \dots, p_{nd})^T$. The correlation degree series of each sample can constitute the gray incidence matrix G:

$$G = \begin{bmatrix} g_{1,1} & \cdots & g_{1,n} \\ \cdots & & \cdots \\ g & \cdots & g_{d,n} \end{bmatrix} = [P_1, P_2, \dots, P_n]$$

For fuzzy clustering, its raw data is required that the domain $X = \{x_1, x_2, \dots, x_n\}$ is the state of n evaluation objects represented by d evaluation indexes:

$$x_i = \{x_{i1}, x_{i2}, \dots, x_{id}\} \ (i = 1,2, \dots n)$$

The domain X is the original data matrix of fuzzy clustering $A = (x_{ij})_{n\times d}$. The fuzzy matrices can be obtained by normalizing the original data matrix $A = (x_{ij})_{n\times d}$.

While the gray correlation degree is calculated by (4), p_{oi} contains two variables W_i, $\xi_i(k)$. W_i is determined by the CRITIC method, $W_i \in [0,1]$. $\xi_i(k)$ is the gray correlation coefficient. In (3):

$$\min_d \min_n |x_0(t) - x_d(t)| \geq |x_0(k) - x_d(k)|$$

So, $\xi_i(k) \in [0,1]$, $p_{oi} \in [0,1]$.

In summary, the gray relational degree matrix G satisfies the requirements of fuzzy matrices in fuzzy clustering. There is no need to convert the G, and the G can be used to calculate the fuzzy similar matrix directly.

1) Calculation of fuzzy similarity matrix

The domain $X = \{x_1, x_2, \dots, x_n\}$, $x_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}$ $(i = 1,2, \dots n)$ is fuzzy matrix $A = (x_{ij})_{n\times d}$. The degree of similarity between x_i and x_j is called the similarity coefficient $r_{ij} = R(x_i, x_j)$. Quantitative product method is a way to determine the similarity coefficient r_{ij}:

$$r_{ij} = \begin{cases} 1, & i = j \\ \frac{1}{M}\sum_{k=1}^{d} x_{ik} \cdot x_{jk}, & i \neq j \end{cases}$$

In this equation, $M = \max_{i \neq j}(\sum_{k=1}^{d} x_{ik} \cdot x_{ik})$.

2) Fuzzy clustering

According to the obtained fuzzy similar matrix R, R 's transitive closure R^* can be calculated by the square method

$$R^* = R \circ R \circ R \circ \ldots \circ R$$

The intercept λ can be determined from large to small to take a group of $\lambda \in [0,1]$. The elements of fuzzy equivalence matrix R^* are defined as:

$$\overline{r_{ij}{}^*} = \begin{cases} 1, & r_{ij}{}^* \geq \lambda \\ 0, & r_{ij}{}^* < \lambda \end{cases}$$

The classification of the samples could be determined by the value of $\overline{r_{ij}{}^*}$.

Based on the above idea, the urban clustering based on the gray theory and fuzzy clustering for urban green transformation is as follows:

Original Data: Several cities' evaluation indicators and specify the resolution factor ρ.

Step 1 The multidimensional time series formed by the evaluation index of urban green transformation is standardized, and the weight of each evaluation index is calculated by CRITIC method.

Step 2 Construct a reference sequence x_i. Calculate the gray correlation coefficient p_{oi} based on the resolution coefficient ρ and the reference sequence

x_i. 2009-2013 urban low-carbon green transition evaluation trends could be obtained by the gray relational matrix G.

Step 3 Transform the city gray relation matrix G into fuzzy similarity matrix R with the method of quantity product

Step 4 The equivalence matrix R^* is calculated from the fuzzy similarity matrix R, and the samples could be clustered.

3. Experiment and result analysis

Experimental data

Based on the related research work, this paper selects 13 cities including Beijing, Tianjin, Shijiazhuang, Taiyuan, Shanghai, Nanjing, Hangzhou, Jinan, Nanning, Haikou, Chengdu, Lanzhou and Urumqi as the sample. Indicator variables are GDP, industrial solid waste emissions, air quality indicators, the number of public transport operations, green coverage area. A multi-dimensional time series database with time $t = 5$, sample $n = 13$ and variable length $i = 5$ was constructed with 2009-2013 as the time sampling point. The data of this paper are derived from China Statistical Yearbook and China Energy Statistical Yearbook and so on.

Nanning City, for example, the original data in 2009-2013 is in Table 2:

Table 2. 2009-2013 experimental data of Nanning City

	GDP	industrial solid waste emissions	air quality indicators	the number of public transport operations	green coverage area
2009	7759.16	410.00	352.00	22.22	32.70

2010	9569.85	380.00	362.00	27.16	33.70
2011	11720.87	407.70	349.00	30.91	35.00
2012	13035.10	348.75	351.00	34.98	37.40
2013	14378.00	356.49	352.00	38.57	37.50

There are indicators of negative data in the indicator system, such as industrial solid waste emissions. Considering the rationality and directness of the subsequent calculation, this paper takes this kind of data as the inverse number, and then makes no differentiation calculation.

Experimental results analysis

According to the principle and procedure of the algorithm, the experimental results are obtained.

Table 3. Determination of index weights by the CRITIC method

GDP	industrial solid waste emissions	air quality indicators	the number of public transport operations	green coverage area
0.3963	0.1619	0.1129	0.1231	0.2059

The results of grey relational matrix G are as follows:

$$G = \begin{pmatrix} 0.4021 & 0.4671 & 0.594 & 0.6987 & 0.9313 \\ 0.4177 & 0.4518 & 0.5515 & 0.6576 & 0.7664 \\ 0.4022 & 0.4404 & 0.6955 & 0.8267 & 0.9101 \\ 0.4097 & 0.5463 & 0.7883 & 0.9237 & 0.8901 \\ 0.4022 & 0.4759 & 0.6075 & 0.7344 & 0.9312 \\ 0.4058 & 0.4861 & 0.7073 & 0.7617 & 0.9275 \\ 0.4058 & 0.4419 & 0.6968 & 0.7084 & 0.9276 \\ 0.4028 & 0.4823 & 0.6109 & 0.7661 & 0.9306 \\ 0.4086 & 0.4659 & 0.6538 & 0.7821 & 0.9248 \\ 0.4028 & 0.4823 & 0.6109 & 0.7661 & 0.9306 \\ 0.4071 & 0.4706 & 0.6003 & 0.6922 & 0.9262 \\ 0.4044 & 0.548 & 0.883 & 0.8831 & 0.8704 \\ 0.4063 & 0.5059 & 0.6844 & 0.8241 & 0.927 \end{pmatrix}$$

According to the grey relational degree matrix G from 2009 to 2013, we can obtain the closure of green transformation transmission in different cities:

Table 4. The transitive closure of urban fuzzy clustering

BJ	TJ	SJZ	TY	SH	NJ	HZ	JN	NN	HK	CD	LZ	WLMQ
1	0.95	0.98	0.95	0.98	0.98	0.97	0.98	0.98	0.87	0.98	0.95	0.98
0.95	1	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.87	0.95	0.95	0.95
0.98	0.95	1	0.95	0.98	0.98	0.97	0.98	0.98	0.87	0.98	0.95	0.98
0.95	0.95	0.95	1	0.95	0.95	0.95	0.95	0.95	0.87	0.95	0.97	0.95
0.98	0.95	0.98	0.95	1	0.98	0.97	0.99	0.98	0.87	0.98	0.95	0.98
0.98	0.95	0.98	0.95	0.98	1	0.97	0.98	0.98	0.87	0.98	0.95	0.98
0.97	0.95	0.97	0.95	0.97	0.97	1	0.97	0.97	0.87	0.97	0.95	0.97
0.98	0.95	0.98	0.95	0.99	0.98	0.97	1	0.98	0.87	0.98	0.95	0.98
0.98	0.95	0.98	0.95	0.98	0.98	0.97	0.98	1	0.87	0.98	0.95	0.98
0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	1	0.87	0.87	0.87
0.98	0.95	0.98	0.95	0.98	0.98	0.97	0.98	0.98	0.87	1	0.95	0.98
0.95	0.95	0.95	0.97	0.95	0.95	0.95	0.95	0.95	0.87	0.95	1	0.95
0.98	0.95	0.98	0.95	0.98	0.98	0.97	0.98	0.98	0.87	0.98	0.95	1

(BJ stands for Beijing, TJ stands for Tianjin, SJZ stands for Shijiazhuang, TY stands for Taiyuan, SH stands for Shanghai, NJ stands for Nanjing, HZ stands for

Hangzhou, JN stands for Jinan, NN stands for Nanning, HK stands for Haikou, CD stands for Chengdu, LZ stands for Lanzhou, WLMQ stands for Urumqi.)

For the fuzzy clustering of 13 cities appraised, when $\lambda = 0.97$, transitive closure can be obtained: Haikou is a class; Beijing, Shijiazhuang, Shanghai, Nanjing, Jinan, Nanning, Chengdu, Urumqi, Hangzhou; Tianjin is a category; Taiyuan, Lanzhou is a category. City fuzzy cluster transfer closure as shown in Table 5:

Table 5. Urban Fuzzy Clustering Transitive Closure

Beijing	1	0	1	0	1	1	1	1	1	0	1	0	1
Tianjin	0	1	0	0	0	0	0	0	0	0	0	0	0
Shijiazhuang	1	0	1	0	1	1	1	1	1	0	1	0	1
Taiyuan	0	0	0	1	0	0	0	0	0	0	0	1	0
Shanghai	1	0	1	0	1	1	1	1	1	0	1	0	1
Nanjing	1	0	1	0	1	1	1	1	1	0	1	0	1
Hangzhou	1	0	1	0	1	1	1	1	1	0	1	0	1
Jinan	1	0	1	0	1	1	1	1	1	0	1	0	1
Nanning	1	0	1	0	1	1	1	1	1	0	1	0	1
Haikou	0	0	0	0	0	0	0	0	0	1	0	0	0
Chengdu	1	0	1	0	1	1	1	1	1	0	1	0	1
Lanzhou	0	0	0	1	0	0	0	0	0	0	0	1	0
Urumqi	1	0	1	0	1	1	1	1	1	0	1	0	1

According to the gray relational degree matrix G of each city in 2009-2013, we can draw the green transition trend of each city:

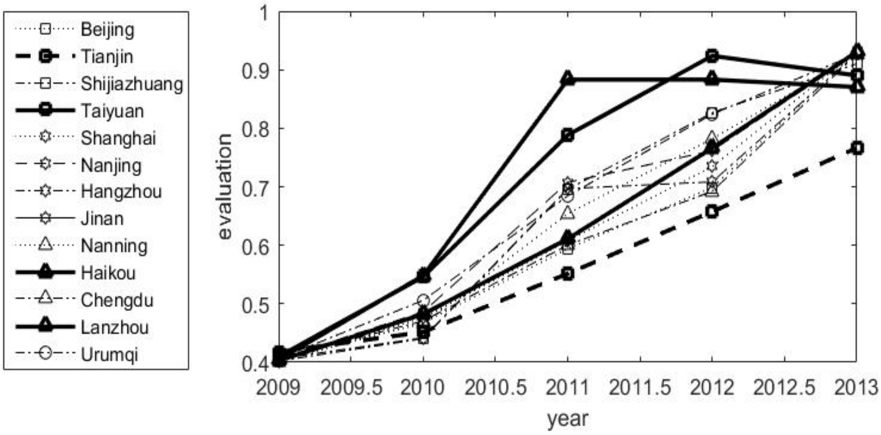

Fig 2. 2009-2013 urban green transition evaluation trends

As can be seen from the figure, although Haikou is located in a densely populated area, its overall long-term linearity shows that its green transformation has been developing steadily and well. Taiyuan City and Lanzhou City in 2011 there was a clear downward trend. Tianjin was at a low level throughout the evaluation period, with a certain gap from other cities. The levels of green transformation in other cities fluctuated slightly, but basically steadily increased. In addition, the evaluation of green transition in all cities under evaluation has been on an upward trend, which is also inseparable from the attention paid by the government and governments at all levels to green transformation.

Combined with the transitive closure of fuzzy clustering and the trend analysis of green transition in cities, we can see that the clustering results are reasonable from two aspects of reality and data experiment. Haikou has achieved a very high score in all the evaluation indicators. In this sense, Haikou City has been based on tourism for economic development and attached great importance to sustainable development. The 9 cities of Beijing, Shijiazhuang, Shanghai, Nanjing, Jinan, Nanning, Chengdu, Urumqi and Hangzhou basically belong to cities that have steadily risen in terms of sustainable development. The long-term trends are generally the same, but there all have obvious fluctuations. Tianjin's rise in the previous two years is the same as that of the 9 cities mentioned before, but the upward trend has slowed significantly in the next few years. Therefore, Tianjin is a self-contained one. Taiyuan is a heavily industrialized city with heavy consumption of resources. Lanzhou has many problems such as its geographical location, backward technology, and poor sustainability. Therefore, the backgrounds of green transition in the two cities are very similar. As can be seen from the images, Taiyuan and Lanzhou are basically in the upward trend from 2009 to 2011, while there both have a clear downward trend in 2012, so Taiyuan and Lanzhou are in a class.

Comparison of traditional algorithm and the algorithm in this paper

The clustering method used in this paper with the method of CRITIC to improve indicators' weights. This method not only considers the importance of different indicators, but also assigns the weights of indicators to improve the indicators conflict issue in the green transformation evaluation indicators. This is better than traditional clustering.

The clustering results of traditional methods and the CRITIC method are compared as follows:

Table 5. Comparison of clustering results of different weight determination method

CRITIC method ($\lambda = 0.97$)	Traditional method ($\lambda = 0.95$)
$x_1 = \{$ Beijing, Shijiazhuang, Shanghai, Nanjing, Jinan, Nanning, Chengdu, Urumqi, Hangzhou$\}$	$x_1 = \{$ Beijing, Shijiazhuang, Shanghai, Nanjing, Jinan, Nanning, Haikou Chengdu, Urumqi, Hangzhou$\}$
$x_2 = \{$Tianjin$\}$	$x_2 = \{$Tianjin$\}$
$x_3 = \{$Taiyuan, Lanzhou$\}$	$x_3 = \{$Taiyuan$\}$
$x_4 = \{$Haikou$\}$	$x_4 = \{$Lanzhou$\}$

The main differences between the clustering results are whether the Haikou alone as a class, and whether Taiyuan, Lanzhou can be classified as a class. As can be seen in Figure 2, both Taiyuan and Lanzhou show a trend of first rising and then falling in long-term trends. Therefore, it is reasonable to classify Taiyuan and Lanzhou as one. However, Lanzhou made a turning point in 2011 and a turning point of Taiyuan was 2012, so it is acceptable to classify Taiyuan and Lanzhou into two different categories.

But for Haikou, Haikou and other cities are obviously different in two points. First, Haikou rose in line with linear growth in 2009-2013, and the whole process was almost undulating. Second, the original data of Haikou City, compared with other cities, has obvious superiority. Moreover, starting from the actual situation, Haikou takes tourism as the main pillar of economic development and as a national low-carbon pilot, Haikou has been actively and rapidly developing a green transformation. Therefore, the green transformations of Haikou and other cities are obviously different from the theoretical and practical angles, and cannot be classified into one category.

In summary, the green transition city clustering algorithm in this paper has some advantages and rationality compared with the traditional clustering algorithm.

4. Conclusion

The urban clustering method based on gray theory and fuzzy clustering for urban green transformation proposed in this paper overcomes the problem that the time and comprehensive evaluation of traditional green transitional cities cannot be balanced, and achieves the purpose of comprehensive analysis of the city according to multiple indicators at multiple time points. Among them, the gray relevancy analysis after CRITIC method optimization makes the weights of evaluation indicators not only meet the requirement of differences in the importance of indicators, but also consider the problem of indicators' conflicts, which can make the clustering result better reflect the development characteristics of the evaluated city in the green transformation and provide a more complete reference for the formulation and implementation of policies and measures. However, in the part of clustering, this paper only complies with the city's own comparison and urban clustering in the long-term development and does not realize the horizontal comparison among cities, so it needs to be supplemented.

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References

Chen Jing, Chen Ning, et al., Evaluation of Urban Green Transition Based on Gray Relational Analysis and Entropy, Urban Studies, 2012(19): p. 96-102.

Fu Yun, Liu Yijun and Wang Yunlin, Evaluation Method and Supporting System of Low Carbon Cities, CHINA POPULATION, RESOURCES AND ENVIRONMENT, 2010(20): p. 44-47.

Hua Jian, Ren Jun, Research on Low-Carbon City Evaluation with ANP, Science&Technology and Economy, 2011(24): p. 101-105.

Liu Zhu, et al., Lowcarbon City's Quantitative Assessment Indicator Framework based on Decoupling model, CHINA POPULATION, RESOURCES AND ENVIRONMEN, 2011(04): p.19-24.

Tan Qi, The Evaluating Indicator System and Empirical Analysis of Low-Carbon Cities Taking Nanjing and Shanghai Dynamic Contrast as an Example, Ecological Economy, 2011(12): p. 81-84+96.

Tan, S., et al., A holistic low carbon city indicator framework for sustainable development. Applied Energy, 2017(185): p. 1919-1930.

Tao, Z., Strategy of City Development in Low-Carbon Economic Mode-A Case Study on Qingdao. Energy Procedia, 2011(5): p. 926-932. [2]. Wang Yingzheng, Construction of Low Carbon City Evaluation Index System and Empirical Analysis, Statistical Theory and Practice, 2011(01): p. 48-50.

Xin Ling, Construction of Evaluation Index System of Low Carbon City, Statistics & Decision, 2011(07): p. 78-80.

Yang, L. and Y. Li, Low-carbon City in China. Sustainable Cities and Society, 2013. (09): p. 62-66.

Zhou, N., et al., ELITE cities: A low-carbon eco-city evaluation tool for China. Ecological Indicators, 2015(48): p. 448-456.

Zhu Bin, Shi Xuanya, The Comprehensive Evaluation and Strategies Analyses of Regional Industry Green Transformation: Based on Fujian Province's Data, Ecological Economy, 2013(11): p. 100-105.