

Quantitative Assessment of City's Smart Growth Level in China Using Fuzzy Comprehensive Evaluation

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Abstract. In this paper we develop an indicator system to evaluate the Smart Growth Level based on 3E's principles and calculate the Smart Growth Level of 70 mid-scale and large cities in China using fuzzy comprehensive evaluation model. We also divide these cities into four grades: outstanding, good, normal and terrible. The results are significant for governments to design a reasonable development plan.

1 Introduction

Urban Sprawl is low-density, non-continuous, automobile-dependent residential and non-residential development model, which needs to cost a remarkable amount of land and other natural resources. In china, this unsustainable development model has affected many cities recently, which brought several problems with environment, economy as well as society [1]. Smart growth is an urban planning theory that originated in 1990's as a means to curb continued urban sprawl and reduce the loss of farmland surrounding urban centres, which focuses on building cities that embrace the E's of sustainability—Economically prosperous, socially Equitable, and Environmentally Sustainable [2]. Therefore, the problem how to use the checking data to evaluate the Chinese cities' Smart Growth Level (SGL) has been the public concern.

Badill et al illustrated the work in the context of Sii-Mobility smart city project, which is to define a smart city architecture. A wide range of processes and data is presented [3]. Anna Luusua et al introduced a new way of designing called nonanthropocentric design to decenter the human as the focus of design while the smart city agenda is critique for its focus on technology and business led solutions [4]. Chang Saisai et al proposed a fuzzy comprehensive evaluation model based on Analytic Hierarchy Process(AHP) to judge whether a city's growth plan is reasonable [5].

In this paper, we studied the SGL of 70 large and mid-scale cities in China to find the one that the City Sprawl is the most serious, which can give some constructive suggestions when the government makes a new development plan.

2 Gathering SGL elements

2.1 Data Collection

Collecting sufficient data is the basis of developing a complete index system. We searched the China Economic and Social Development Statistics Database [6] and found 22 indicators of 70 mid-scale and large cities firstly based on 3E's principles.

2.2 Data filling

It is important to ensure the continuity and authenticity of research data. However, some data is missing because not all data is provided in the website. To address this problem, two methods are proposed to complete the data, which are as follow,

2.2.1 Average value

If we can found the data of an indicator for most of cities except few cities, the average value of other cities can be taken as the missing. For example, the number of public libraries in Dali is missing so we adopt the average value of other 69 cities to replace it. As these figures are really few, it affects little to the the evaluation result.

2.2.2 GM(1,1) model

As the frequently used grey model, GM(1,1) is particularly available to such random unconfirmed issue. If the data before can be obtained, GM(1,1) Model is adopted to predict the figures we need. For example, the data for Rural Subsistence Expenditure, Total Import and Export, Urban Social Security Engagement Rate, Expenditure on Education Expenditure, Number of Health Institutions in Hefei in 2015 is missing while the

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figures before are available, so GM(1,1) Model is used to forecast the figures[7].

Assume that

$$X^{(0)} = [x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)]$$

is a sequence of raw data, its 1-AGO sequence $x^{(1)}$ is

$$X^{(1)} = [x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)]$$

$$x^{(1)}(k) = \sum_{i=0}^k x^{(0)}(i), k = 1, 2, \dots, n$$

and the sequence mean generated of consecutive neighbors $x^{(1)}$ is

$$Z^{(1)} = [z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)]$$

Where

$$z^{(1)}(k) = 0.5x^{(1)}(k+1) + 0.5x^{(1)}(k), k = 2, 3, \dots, n$$

and the 1-IAOG sequence of $\alpha^{(1)} X^{(0)}$ of $X^{(0)}$ is

$$\alpha^{(1)} X^{(0)} = (\alpha^{(1)} x^{(0)}(1), \alpha^{(1)} x^{(0)}(2), \dots, \alpha^{(1)} x^{(0)}(n))$$

$$\alpha^{(1)}(k) + \alpha z^{(1)}(k) = b$$

is called a grey differential equation, and is also called the model GM(1,1).

The equation

$$\frac{dx^{(1)}}{dt} + \alpha x^{(0)} = b$$

is called a whitization equation of the grey differential Equation.

The result is shown in Figure.1 to Figure.5 and Table.1.

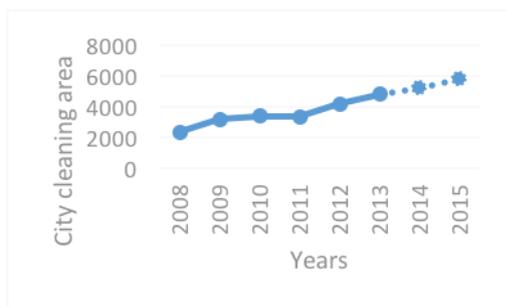


Figure. 1.The prediction of City cleaning area.

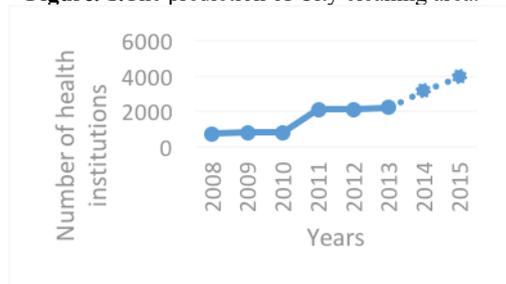


Figure. 2.The prediction of Number of health institutions.

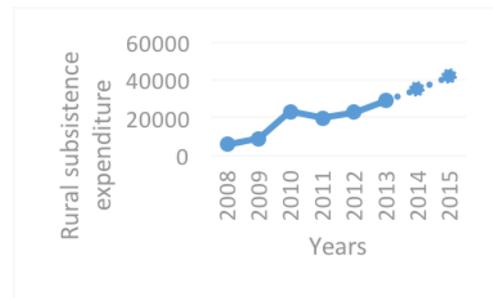


Figure. 3.The prediction of Rural subsistence expenditure.

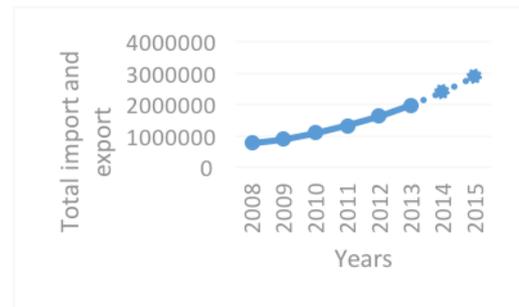


Figure. 4.The prediction of Total import and export

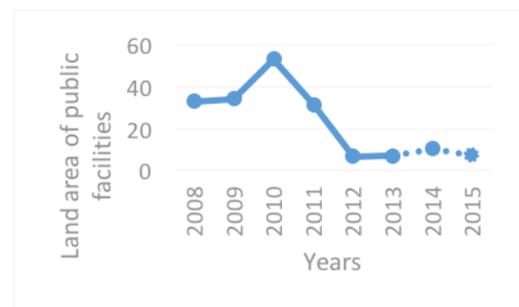


Figure. 5. The prediction of Land area of public facilities.

Indicators	Absolute error
Rural Subsistence Expenditure (10,000yuan)	0.00579%
Total Import and Export (ten thousand US dollars)	0.09882%
Urban Social Security Engagement Rate. (%)	0.09658%
Expenditure on Education Expenditure (10,000 yuan)	0.41376%
Number of Health Institutions (unit)	0.04802%

The results show that using the GM(1,1) model to forecast the missing data involves a smaller sample and less information. It's easier to build the model and the prediction precision is better.

3 Primary indicator system

3.1 Select indicators

22 initial indicators are selected to evaluate the SGL of cities based on 3 E's principles refers to Economically prosperous, socially Equitable, and Environmentally Sustainable [8]-[11]. The indicator system is shown in Table.2.

Table. 1.Indicator system of SGL.

First layer	Second lever	Third layer
Smart Growth Level	Economic prosperity	Per Capita GDP (100 million yuan)
		Tertiary Industry GDP ratio (%)
		Total Import And Export (ten thousand US dollars)
		Total Retail Sales of Social Consumer Goods (10,000 yuan)
		Average Salary of Employees (yuan)
		Real Estate Development Investment (10,000 yuan)
	Social justice	Urban Social Security Engagement Rate. (%)
		Number of Urban Employees (10,000)
		Number of Public Libraries (unit)
		Average Number of Secondary Schools (unit)
		Unemployed Population (10,000)
		Number of Health Institutions (unit)
		Expenditure on Education Expenditure (10,000 yuan)
		City Cleaning Area (10,000 square meters)
		Land Area of Public Facilities (square kilometers)
		Funding Number of Participants (person)
		Rural Subsistence Expenditure (10,000yuan)
	Environmentally sustainable	Urban Green Coverage (%)
		Industrial Waste Water Discharge (tons)
		Eco-environment Industry Social Groups (unit)
		Garbage Disposal (%)
		Per Capita Green Area (square meters)

3.2 Quantitative assessment of SGL

We apply the Minimum Relative Deviation Distance method in comprehensive evaluation model as this way does not require data pre-processing.

3.1.1 Set up the relative deviation fuzzy matrix

The ideal alternative is

$$c = (c_1^0, c_2^0, c_3^0, c_4^0, \dots, c_m^0)$$

where

$$c_i^0 = \begin{cases} \max\{a_{ij}\} & a_{ij} \text{ is an efficiency indicator} \\ \min\{a_{ij}\} & a_{ij} \text{ is a cost indicator} \end{cases}$$

Set up the relative deviation fuzzy matrix with

$$R = (r_{ij})_{m \times n}, \text{ where } m \text{ is the number of}$$

Cities, n is the number of indicators.

$$r_{ij} = \frac{|a_{ij} - u_i^0|}{\max\{a_{ij}\} - \min\{a_{ij}\}}$$

3.1.2 Evaluation Model Based on Variation coefficient method

In this paper, variation coefficient method is adopted to calculate the weight vector in this section.

The coefficient of variation of each index is

$$v_i = \frac{s_i}{\bar{x}_i}$$

Where

$$\bar{x}_i = \frac{1}{n} \sum_{j=1}^n a_{ij}$$

is the average of the i th index,

$$s_i = \sqrt{\frac{1}{n-1} \cdot \sum_{j=1}^n (a_{ij} - \bar{x}_i)^2}$$

is the variance of the i th index

After the normalization of v_i , we can obtain the weight of each index:

$$w_i = \frac{v_i}{\sum_{i=1}^m v_i}$$

After the determination of weight of the indicators by variation coefficient method, the evaluation model of SGL is established.

$$SGL = 1 - \sum_{i=1}^{22} w_i r_{ij} \quad (j = 1, 2, 3, \dots, 70)$$

The result is shown in Figure.6. and Figure.7.

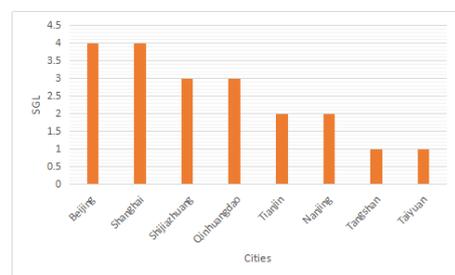


Figure.6. The SGL of some cities.

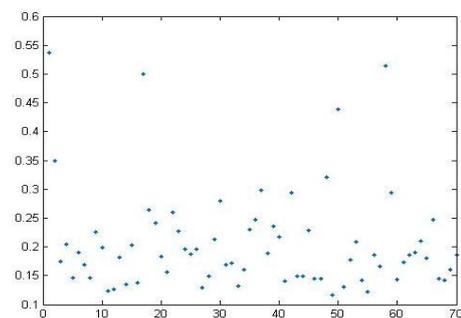


Figure. 7. The SGL of 70 mid-scale and large cities in China.

The larger SGL is, the development model of given city meets the requirements of Smart Growth better.

4 The Standard of Smart Growth

According to the SGL evaluation model aforementioned, we can get the standard of smart growth using K-means clustering method. Then the mean of the indicator centres is used as the standard boundary.

In this way, 70 cities are divided into for kinds: outstanding, good, normal and terrible. Terrible means that the development model has limited and threated the further development of given city. Normal means that the city has not realized smart growth in this area. And good means that the city has some success of smart growth in this area. Outstanding is used to describe when city has great success of smart growth. The standard of SGL and the classification of 70 mid-scale and large cities in China is shown in Table.3. and Table.4.[12][13]

Table. 3. The standard of SGL

Grade	SGL
terrible	0~0.175
normal	0.175~0.252
good	0.252~0.435
outstanding	0.435~1

Table. 4. The classification of 70 mid-scale and large cities in China

Grade	City
Outstand	Beijing, Shanghai, Shenzhen Chongqing
Good	Tianjin, Nanjing, Hangzhou, Xiamen, Yantai, Wuhan Guangzhou, Chengdu
Normal	Tangshan, Taiyuan, Shenyang, Dalian, Changchun, Harbin, Wuxi, Xuzhou, Ningbo Wenzhou, Jinhua, Hefei, Fuzhou Jinan, Qingdao, Jinan, Zhengzhou, Luoyang, Changsha Huzhou, Nanning, Haikou Guizhou, Zunyi, Kunming, Dali Xian, Urumchi
Terrible	Shijiazhuang, Hohhot, Municipality, Baotou, Dandong, Jinzhou, Jilin, Mudanjiang Yangzhou, Bengbu, Anqing Quanzhou, Nanchang, Jiuzhou Ganzhou, Pingdingshan Yichang, Xiangyang, Yueyang Changde, Shaoguan, Zhanjiang Guilin, Beihai, Sanya, Luzhou Nanchong, Lanzhou, Xining Yinchuan

4 Conclusion

There exists a great difference in the model and level of cities' development in China. Specifically speaking,

some cities like Beijing and Shanghai have achieved great success of smart growth while some of others like Yueyang and Lanzhou are suffering from a bottleneck period in pursuing development. Positive measures and smart growth plan should be adopted to help these cities to achieve smart growth.

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