Comprehensive Modelling and Planning of Urban Smart Growth

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***Abstract*—Implementation of smart growth theories into city planning has become increasingly important and necessary. In this paper, a metric to measure the success of urban smart growth was defined as Success Index and the relationship between Success Index and the three E's components was established based on principal component analysis (PCA). Cellular automata (CA) method was applied to simulate the dynamic growth processes of Pittsburgh and Zurich. Some planning regulations were made based on economic, environment and geography. The developed model can be used to evaluate the success of smart growth and to make smart urban planning with high degree of adaptability and predictability.**

Keywords-smart growth; success index; principle component analysis; cellular automata; insert

I. Introduction

Smart growth is an urban planning theory originated in 1990's that concentrates growth in compact walkable urban centers to avoid sprawl [1-4]. Many communities are implementing smart growth initiatives in an effort to consider long range, sustainable planning goals [5-7]. Smart growth focuses on building cities that embrace the E's of sustainability–economically prosperous, socially equitable, and environmentally sustainable, and this task becomes more important than ever as the world is rapidly urbanizing. In the past, many studies have been done to propose the ways to curb continued urban sprawl and to reduce the loss of farmland surrounding urban centers [8-10], and some models have also been developed to simulate the development and land-utilization of a city [11-14]. However, there was little study on the model based on a metric to measure the success of smart growth by considering the three E's and 10 principles of smart growth simultaneously. Moreover, in view of the fact that a city has the characteristics of high complexity and dissipative structure, a spatio-temporal discrete dynamics method is considered to be proper to study the complicated city system with the spatio-temporal dynamic variety.

In the present work, a comprehensive model has been developed to design the smart growth of a city, and the following specific contributions have been included in the model: (1) three principal components (Economic prosperity, social Equity and Environment sustainability) are extracted from ten factors based on principal components analysis (PCA), (2) a metric (Success Index) to measure the success of smart growth of a city is defined, and (3) cellular automata (CA) is applied to simulate the dynamic process of city transformation and the practical measures for urban smart growth are proposed.

II. Proposed Methodology

A. *Metric for Smart Growth Success Based on PCA*

In order to establish a model to assess the development of a specific city, it is need to explore several factors which can describe the smart growth of a city completely. According to the three E's sustainability and ten principles for smart growth [15], ten critical factors from different aspects should be considered to represent the smart growth of a city.

1) Selection of critical factors: Ten representative factors, including land-use diversity, residential density, population density, housing units, soft mobility, museums and theaters, cultivated acreage proportion, household maintenance, public transportation, and poor population are selected by considering the three aspects of economy, equality and environment, as shown in Table I.

2) A metric for smart growth success based on PCA: Considering the fact that the ten representative factors could be dependent on each other and some correlations may exist among the ten factors, it is need to extract the linearly-independent variables. Thus, a bilayer structure is designed to contain the representations of economy, society and environment, as shown in Figure I.

TABLE I. REPRESENTATIVE FACTORS SELECTED FOR SMART GROWTH

Symbol	Factor
x_1	Land-use diversity
x_2	Residential density
x_3	Population density
x_4	Housing units
x_5	Soft mobility
x_6	Museums and theaters
x_7	Cultivated acreage proportion
x_8	Household maintenance
x_9	Public transportation
x_{10}	Poor population

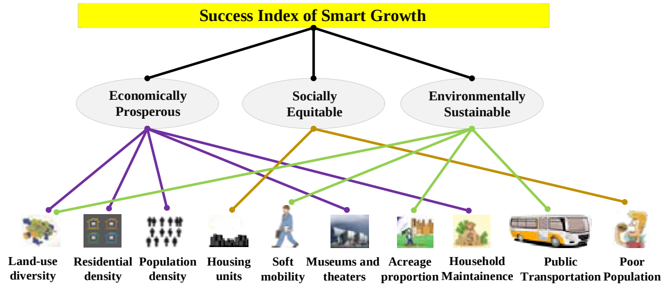

FIGURE I. MAPPING RELATION BETWEEN TEN FACTORS AND THE THREE E'S.

The method of principal components analysis (PCA) is applied to combine the ten factors together to make an evaluation on the success of smart growth. As shown in Figure I, the expression of smart growth success has been established by using the PCA method twice. The first step is to establish the mapping relationship between three E's and the ten representative factors, while the second step is to establish the relationship between the success index and three E's.

PCA is a statistical procedure concerned with transforming the correlated variations into several linearly-independent ones. Each independent variation is called principal component which involves every input factor. The advantage of PCA is not only to reduce the dimension of primary data, but also to determine the coefficient for every primary factor. The process of PCA method executes as the followings.

a) Step 1: Suppose that the variables of x_{ki} represent the factors and then the covariance matrix of S_{ij} is computed for the primary data. In order to eliminate the inconsistency, the primary data should be standardized according to (1).

$$S_{ij} = 1/(n-1)\sum_{k=1}^{n}(x_{ki}-\bar{x}_i)(x_{kj}-\bar{x}_j) \tag{1}$$

b) Step 2: Calculate the eigenvalues of matrix $\sum$ and the corresponding eigenvectors. Then, each group composed of the eigenvectors is used as the coefficients for the primary factors.

c) Step 3: Every eigenvalue can be deduced to calculate the contribution of each component by (2) and those components with larger contribution should be selected.

$$\alpha_k = (\sum_{k=1}^{q}\lambda_k)/(\sum_{k=1}^{n}\lambda_k) \tag{2}$$

where α is the contribution of a component, and λ is the eigenvalue.

d) Step 4: Sort the eigenvalues in a descending order and determine the component number by calculating the cumulative contribution until the value is over 99%.

e) Step 5: Choose n principal components and use (3) to express the relationship between the principal components and the ten factors. The synthesized variable can also be calculated from the components of $c_1, \ldots, c_n$.

$$\begin{cases} c_1 = u_{11}\tilde{x}_1 + u_{12}\tilde{x}_2 + \cdots + u_{110}\tilde{x}_{10} \\ c_2 = u_{21}\tilde{x}_1 + u_{22}\tilde{x}_2 + \cdots + u_{210}\tilde{x}_{10} \\ \vdots \\ c_n = u_{n1}\tilde{x}_1 + u_{n2}\tilde{x}_2 + \cdots + u_{n10}\tilde{x}_{10} \end{cases} \tag{3}$$

where c_i is the principal component and the coefficients of u_{ki} are required to meet the relationship expressed by (4).

$$u_{k1}^2 + u_{k2}^2 + \cdots u_{k10}^2 = 1\,(1 \le i \le 10) \tag{4}$$

Finally, the method of PCA is used again to determine the mapping relationship from the three E's to the final comprehensive score, i.e., Success Index (I).

B. Urban Planning Based On Cellular Automata

As we know, development of a city would be affected by the neighboring regions from many different aspects, such as geographical location, economic condition and other social factors. Therefore, as long as the interaction between the regions is figured out, the transformation can be predicted in general. Then, the pertinent regulations can be designed by the government to guide the transformation towards a positive direction.

One of the best methods to visualize the dynamic transformation of such a discrete system is the cellular automata. The cellular automaton consists of cells which locates in several finite grids. Each cell also has the finite statuses. The simulation process is to calculate the new status of each cell on the basis of fixed rules by considering the relationship between the neighboring cells at a specific moment. This method has been widely applied to many fields such as the sociology economics and military, etc.

Chen et al [16] proposed several equations to consider the three constraints of a city development, i.e., city form, agricultural land and distribution of urban and countryside, and whether a region is urbanized or non-urbanized is based on the piecewise function, as shown in (5).

$$S_{t+1}(ij) = \begin{cases} Developed,\ p_{ij} > p_{\text{threshold}} \\ Undeveloped,\ p_{ij} < p_{\text{threshold}} \end{cases} \tag{5}$$

where p can be regarded as the urbanization possibility of a specific region, which is calculated by (6).

$$P = (\text{Dis.}) \times (\text{Agri.}) \times (\text{Loc.}) \times (\text{Con.}) \times (\text{Dens.}) \times (\text{Ra.}) \tag{6}$$

where *Dis.*, *Agri.*, *Loc.*, *Con.*, *Dens.* and *Ra.* respectively represent the distance from the city center, agricultural characteristics, weight value of economic and sustainability, condition function, density of land development, and randomness of development. Therefore, the cells of cellular automata in the present work are defined with two states, i.e., developed and undeveloped ones. By the prediction for 10 years and 20 years, the distribution for both urbanized and non-urbanized lands can be visualized, and thus the proportion for urbanized and non-urbanized land in each region can be obtained.

III. EXPERIMENT

A. *Coefficients of Smart Growth Success*

In order to establish the model, the factors from eight cities have been collected and then the coefficients are determined by using PCA to form the expression of smart growth success. The bottom level of PCA is determined by (7).

$$\begin{cases} E_1 = 0.2234x_1 - 0.3789x_2 + 0.4067x_3 + 0.4255x_6 + 0.3123x_8 \\ E_2 = 0.2135x_4 + 0.7070x_{10} \\ E_3 = 0.4540x_1 - 0.3080x_5 + 0.3205x_7 + 0.2969x_9 \end{cases} \tag{7}$$

where x_1~x_{10} are the selected ten factors, E_1 denotes the economic prosperity, E_2 denotes the social equity and E_3 denotes the environment sustainability.

As mentioned above, E_1, E_2 and E_3 must be combined to form the success index of smart growth. Thus PCA is employed once again and the expression for success index (I) is obtained, as shown in (8).

$$I = 43.905E_1 + 53.944E_2 + 22.503E_3 \tag{8}$$

B. *Application of Cellular Automata in Proposing Practices*

In this section, the two cities, Pittsburgh and Zurich, are chosen as the investigating objectives. According to the criteria for distinguishing urbanized and non-urbanized cell, the modelling process based on cellular automata is implemented with Matlab. It is worthwhile to note that the geographical distance is scaled by the real distance. Through iterating for 100 times and 200 times which stand for 10 years and 20 years respectively, the distribution graph of urbanized and non-urbanized are obtained for both Pittsburgh and Zurich, as shown in Figure II. In Figure II, the cells colored green represent the non-urban districts while those colored blue denote the urban districts. It can be noted that after a decade (from tenth year to the twentieth year), the urban expansion extents of Pittsburgh and Zurich are greatly restricted under the smart growth plan.

For the results based on cellular automata, the urbanization and non-urbanization proportions of each region are mainly focused on. According to the cellular density in each unit, 80% of high density urban land is used as commercial land while 20% of low density is used as residential land in Pittsburgh. On the other hand, 50% of medium density urban land is used as commercial land while 20% is also used for commerce and the rest for resident in Zurich. Finally, the land use distributions for Pittsburgh and Zurich are shown in Table II.

After the planning process and data manipulation, the values of ten representative factors for Pittsburgh and Zurich are adjusted according to the results from cellular automata, as shown in Table III. And with the smart growth metric, the predicted Success Indexs (I) are compared between the current and after-planning ones for both cities, which can be used to testify that the plan is positive for the city development, as shown in Figure III.

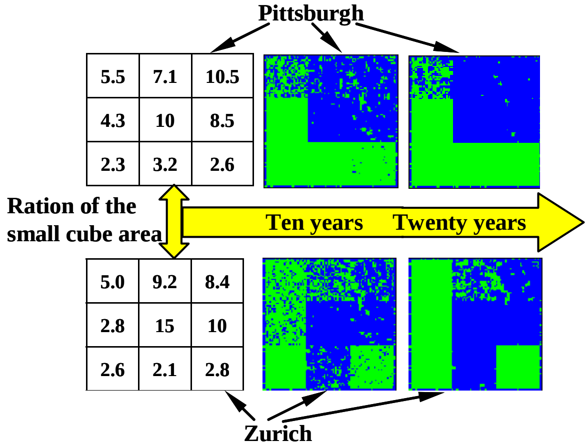

FIGURE II. CELLULAR DISTRIBUTION OF PITTSBURGH AND ZURICH

TABLE II. PLANNING OF URBAN LAND IN PITTSBURGH AND ZURICH

City	Commercial land	Residential land	Non-urban land
Pittsburgh	17.0%	63.7%	19.3%
Zurich	16.7%	60.6%	22.7%

TABLE III. EVALUATION RESULT

Factor	Pittsburgh		Zurich	
	Current	*After-plan*	*Current*	*After-plan*
Land use diversity	0.962	0.984	0.906	0.939
Residential density	2820.5	2452.9	2972.5	2667.0
Population density	5521.4	4450.8	5576.9	5039.5
Housing units	156165	215608	164581	234433
Soft mobility	5.4	8.3	5.5	8.33
Museums and theaters	57	63	57	63
Acreage proportion	0.169	0.018	0.170	0.167
Household maintenance	2.54×10^9	2.73×10^8	2.62×10^9	3.03×10^8
Public transport	0.256	0.254	0.258	0.252
Poor population	0.229	0.146	0.234	0.160

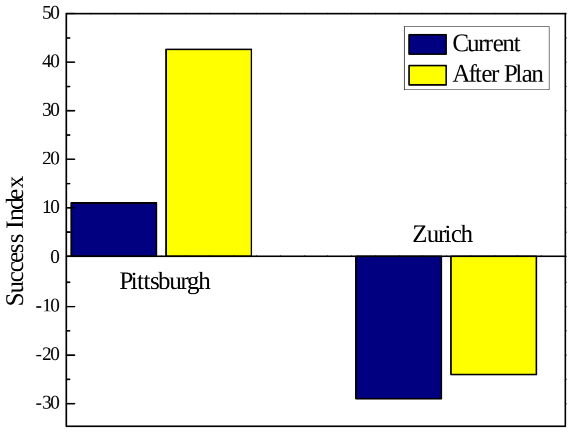

FIGURE III. SUCCESS INDEX (I) FOR PITTSBURGH AND ZURICH.

It can be found in Figure III, that the redesigned growth plan works well in both cities but the effect in Zurich is not as good as that does in Pittsburgh. By comparing the backgrounds of the two cities, the speculation can be made that because Pittsburgh has been an industrial city for a very long time, smart growth plan can do much better under such circumstance. On the other hand, Zurich is the biggest city in Switzerland, which is one of the most harmonious countries in the world, the smart growth plan may has been carried out in some ways for a while, namely the smart growth plan has nearly reach its limitation.

IV. CONCLUSIONS

A comprehensive model was established based on principal component analysis to evaluate the success of urban smart growth. Meanwhile, cellular automaton was applied to predict the city transformation in the future. Several developing plans were proposed which can be testified to be beneficial for improving the extent of smart growth under the present model.

The established model is a complex iterative network of the relationships among a variety of factors, and the metric defined in the model can be used to measure the success of the smart growth of a city.

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