Cellular Automata for Urban Growth Modeling: a Chronological Review on Factors in Transition Rules

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Abstract

Urban growth studies have attracted considerable attention over the past two decades. This article reviews the driving factors been identified and studied in cellular automata (CA) urban growth modeling. Over a hundred articles published between 1993 and 2012 were selected and reviewed. The driving factors were extracted from the transition rules and classified according to their similarity and mechanism in influencing urban growth. Our analysis shows that researches between 1993 and 2000 mainly focus on using geomorphological factors while recent studies tend to also include socio-economic factors, resulting in more sophisticated urban CA models. Nevertheless, the human-behavior factors impacting urban growth are generally under-represented. Geographically, more applications of the CA urban growth models have been seen in the developed countries compared with those in the developing countries, suggesting substantial work needed to address issues in understanding and modeling rapid urban growth in the developing countries.

1. Introduction

Urban growth portrays a spatial representation of community perspectives of their environment and future expectations (Barredo et al., 2004; UN-HABITAT, 2010). With its inherent complexity, urban growth has been the center of questions which has attracted considerable attention among geographers and urban planners.

One of the well-known modeling tools to study urban growth is cellular automata (CA). CA consists of four basic elements (Batty et al. 1997): (i) cell, (ii) state, (iii) transition rules, (iv) neighborhood, with additional (v) temporal dimension (Liu, 2008). Amongst them, the transition rules, which determine the change of a cell in reaction to the driving factors, are considered as the most important element in CA modeling (Lau and Kam, 2005; Silva and Clarke, 2005). Transition rules represent the mechanism behind the dynamics of urban systems.

Several reviewing works have been reported in the literature concerning CA urban growth studies; for instance, Haase and Schwarz (2009) reviewed 19 different models with different approaches including economy, system dynamic, agent-based, and CA models. Schwarz et al. (2010) provided a general review of 21 urban models where they found no models were specifically designated for urban shrinkage study (a process that is marked by the decline of urban population and economic growth). Sante et al. (2010) provided a more systematic and rigorous review by selecting 33 articles. They classified the models based on the transition rules and extracted the factors used in each model. The most recent review was by Silva and Wu (2012) who classified 64 CA urban models based on the level of analysis, the spatio-temporal scale, and tasks performed. All these reviews, except Sante et al. (2010), focus on the selection of the CA models (or the combination of models) but not in particular investigating *the factors* employed in the models. Thorough review on the selection of the driving factors on urban growth is thus needed.

For CA-based urban models, the selection of the driving factors for urban growth is not a trivial task. The selection can be based on; 1) the unique characteristics of the area, such as its functions, geomorphology, or regulated bodies; 2) the perspectives that urban modelers convey, for instance, socio-economic or sustainability approach; 3) the way in which these factors were derived, for instance, through literature review, expert knowledge, or model-driven; 4) the scenarios proposed upon various agents; and 5) the scale of analysis i.e. macro, meso, micro factors (Hagoort et al., 2008; Irwin and Geoghegan, 2001; Wu and Webster, 2000). In addition, the selection of factors might also be attributed to data availability which might be the case in particular in developing countries (Burgi et al., 2004; Thapa and Murayama, 2012).

With the vast possible factors to be selected, modelers might get difficulty in grounding their selection criteria. Hence, a survey of factors used in currently developed CA urban models is of prime importance. This article reports our survey of the CA models published between 1993 and 2012. Our analysis focuses on two crucial aspects, that is, time and geography. Our hypotheses are that the selection of factors driving urban growth is not independent, has changed over time, and varies in different geographical areas. Thus, in the analysis section, factors were recorded and presented according to its implementation across different regions and its time frame. The empirical results from this research can serve as an entry point for subsequent studies in urban modeling practice.

2. Methods and materials

2.1. Selection procedure

The selection of articles comprises of three stages (fig.1). In the first stage, the keywords "cellular automata AND urban*" were used to search the Web of Knowledge (WoK) database. The wildcard "*" was used to include various terms such as *urban*, *urbanization*, or *urbanism*. By 25th October 2012, the WoK returned 470 articles.

In the second stage, articles having titles or abstracts in which they contain terms such as "traffic", "ecology or ecological", "remote sensing" and "land use" were excluded. By excluding these articles, we intended to focus on recording factors directly implemented in modeling urban land use changes rather than general and indirect factors commonly appear in articles with "land use" terms (see Lambin et al. (2001) for various causes of land use and land cover change). We also wanted to avoid technical and more detailed factors generally found in remote sensing's articles.

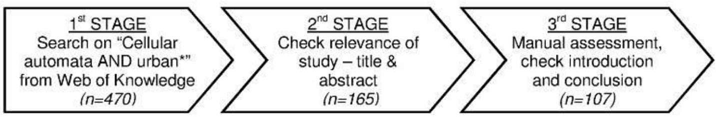

Fig. 1. The selection procedure of articles

In the third stage, manual classification was performed to select articles which focused on urban growth studies. As one of the objectives is to analyze the factors reported in the literature geographically, articles using simulated data were excluded from the selection list at this stage. Due to space constraint, we report our analysis and results in section 3 while the full list of the articles selected and the driving factors modeled in the articles are available upon request to the corresponding author.

2.2. Analysis procedures

Three components were extracted from the selected articles (fig.2); (i) the land change driving factors, (ii) study areas, and (iii) the years being modeled.

Factors from CA transition rules were extracted and recorded in a table where each column represents one factor (table 1). A new factor was recorded if it was found in three or more articles. This was necessary in order to avoid redundancy of the factors (i.e., factors possibly referred to similar definition) and assert consistency in terminology. In addition, factors with comparable meanings were grouped together. For instance, a factor concerning *household size* has similar meaning as a *population density* factor; therefore, these two factors were grouped together in one column in Table 1. Similarly, factors concerning *aspect, angle, northing,* and *hillshade* all refer to the physical setting of the environment, which were also grouped as one factor for analysis.

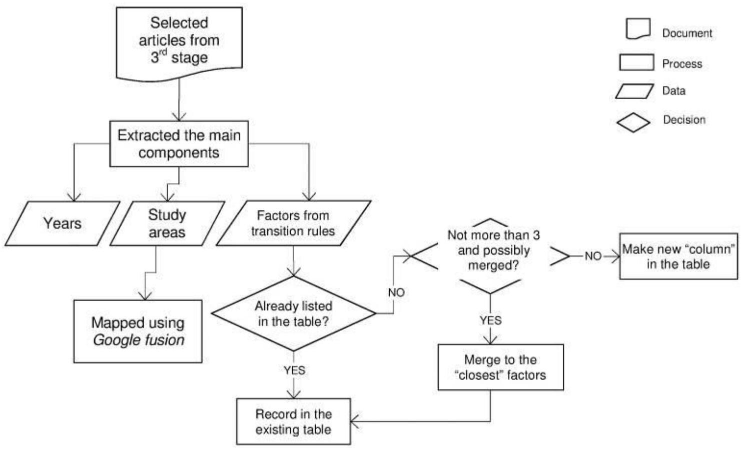

Fig. 2. Review procedure of CA urban growth modeling

The study areas were geo-mapped using *Google fusion* with the following consensus: 1) if an article applied a model in one area, then a pin point to the area was added on the map; 2) if an article applied a model in more than one cities, for example, Reginster and Rounsevell (2006), Clarke and Gaydos (1998), then the city with the most intensive discussion in the paper was chosen to display on the map. The year of publication of the articles was also recorded which enables chronological analysis to identify possible temporal trend and emerging factors used in CA urban models.

2.3. Definition and classification of the factors

Table 1 lists all factors extracted according to the procedures outlined in section 2.2. We classified the factors into nine broad categories, including *geomorphology, connectivity, facilities, government, demography, economy, constraint, economy,* and *land*. While *geomorphology* groups the physical setting of urban environment, the decision to separate them with *land* is based on how they were derived. The *geomorphology* factors were derived from Digital Elevation Model (DEM) from contour lines, while *land* factors were derived largely from land uses or land covers maps. *Constraints* factors were grouped separately because they impose strict limitation on the development of urban areas that is a binary (allowed or not allowed) cells for urban developments. The *demography* signifies factors that represent the demands of new urban and residential areas.

While most of the terminologies we use to define the factors are self-explanatory, the meanings of some factors were hidden or overlapping. This is inevitable given that some of the factors referring to similar meaning were merged into single factors for example *expressway*, *provincial road*, and *toll road* were merged into *highway*. This step was taken in order to reduce redundancy and ensure consistent terms for the factors. The following clarifies briefly the other overlapping factors.

Road includes intra-urban roads; secondary, tertiary and local roads while higher road hierarchy such as regional roads and any high-speed roads were merged into *highway*. In most of the articles, *road* signifies the distance of a cell from its nearest road, but others such as Tang (2011) or Park et al. (2011) used *road ratio* that is the ratio of an area with the dimension of road. In the table, however, we did not distinguish them. *Thematic* includes various factors signifying unique characteristics of a city but used in less than three articles. This includes proximity to electricity lines, religious facilities, or community centers. *Greenery* includes distance to gardens or croplands, or grade of environment assessments while *environment other* includes factors concerning air quality, noise disturbance, or water availability. *Institutional factor* includes consideration of the master planning; government allocated lands, prioritized or planned areas. *Land genetic* in essence is the conversion probability of other lands to urban areas. It includes Markov chain to produce urban conversion probability, urban propensity, repulsion-attraction, and historical calibration.

3. Results

3.1. Trend of CA urban modeling articles from 1993 to 2012

In order to examine the change of selection of various factors along the publication years, we divided the timeframe into four periods with five year ranges. This enables us to evaluate the temporal progression of CA based urban modeling practice. It is worth noting that, while the earliest article found from WoK was in 1993, articles concerning CA urban modeling do exist prior to 1993 (for example Batty (1991b); Batty (1991a), the WoK database however returned no result. As our review limits the selection of articles from WoK and no cross-referenced articles were considered, these articles were not included in the review process.

The number of articles concerning CA based urban modeling for the four periods since 1993 and the average number of articles per year show steady increase (fig.3). Starting with a modest 5 articles in 1993-1997, it rose considerably to 35 articles in 2003-2007. This increasing number of publications could be attributed to a well preferred CA model than other spatial analytical tools in the spatial research (Liu, 2012). Indeed, it is the simplicity of CA with appealing simulation results that was easily grasped by modelers with non-spatial background, resulting in wide spread applications of this modeling approach (Jantz et al., 2004). The easy coupling of CA with GIS to enable flexible spatial analysis to be performed based on CA principles in a raster GIS was also much acknowledged as a key factor in developing CA models by the GIS communities (Clarke and Gaydos, 1998; Wu, 1998).

Table 1. Key driving factors to urban growth extracted from existing CA models

Geo-morpho-logy	Connectivity	Facilities	Environment	Govern-ment	Constraints	Demography	Eco-nomy	Land
Elevation Slope Hill-shade	Highway Tollgate/ramp Road Waterways Railways Intersection	Station Airport Major towns Shopping center Business centre Industrial Existing developed areas School Health facilities Thematic Recreational	Greenery Other	Zoning Institutional factor	Water bodies National parks, forest Wetlands Protected areas	population size Annual growth rate Population density Migration	Gross domestic products (GDP) Land value Economic trends	Land suitability Land availability Land genetic

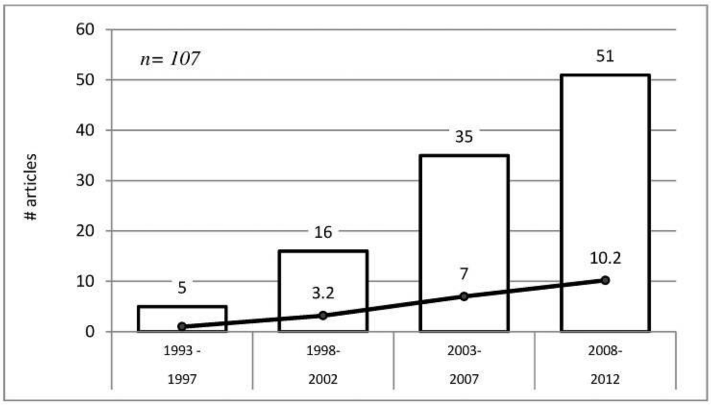

Fig. 3. Increase in the number of articles concerning CA urban modeling from 1993 to 2012. The total number of articles for the four periods identified is shown by the bar graph, and the average number of articles per year is represented by the line graph.

3.2. Application coverage of urban CA models

According to the study areas in which CA models have been implemented, USA, China, and Europe are the dominant regions (Table. 2). Some notable applications of early urban CA models were in Amherst and San Francisco Bay regions USA and in Guangzhou, China (Batty and Xie, 1994; Clarke et al., 1997; Wu and Webster, 1998). The study areas, however, reflect more of research clusters, as suggested by Hengl et al. (2009), rather than the actual urban problems largely faced by the developing countries (UN-HABITAT, 2010).

Table. 2 Number of CA urban modeling articles amongst different regions

Year	USA		China		Europe+		Other Asia--		Others**	
	articles	%	articles	%	articles	%	articles	%	articles	%
1993-1997	5	100	0	0	0	0	0	0	0	0
1998-2002	3	19	13	81	0	0	0	0	0	0
2003-2007	12	34	7	20	7	20	4	11	5	14
2008-2012	6*	12	12	24	13	25	13	25	4	8

*including Canada
+including United Kingdom and Ireland
--including Australia
** including South America and Africa

USA and China altogether dominated the CA urban modeling applications in the early period of CA urban research in 1993-2002. In 2003-2007, CA models were equally applied in regions outside USA, China, and Europe; notably in Australia, Asia and South America (Leao et al., 2004; Loibl and Toetzer, 2003; Samat, 2006; Ward et al., 2003). Applications in the most recent period in 2008-2012 show an increasing interest in CA applications in Asia (Guan et al., 2011; Kim, 2009; Maithani, 2009; Naimah et al., 2011; Samat, 2006; Thapa and Murayama, 2011). Fig. 2 shows geo-referenced locations where CA urban models have been implemented over the four periods from 1993 to 2012. This highlights potential regions to be explored which include Africa, Russia, and South America.

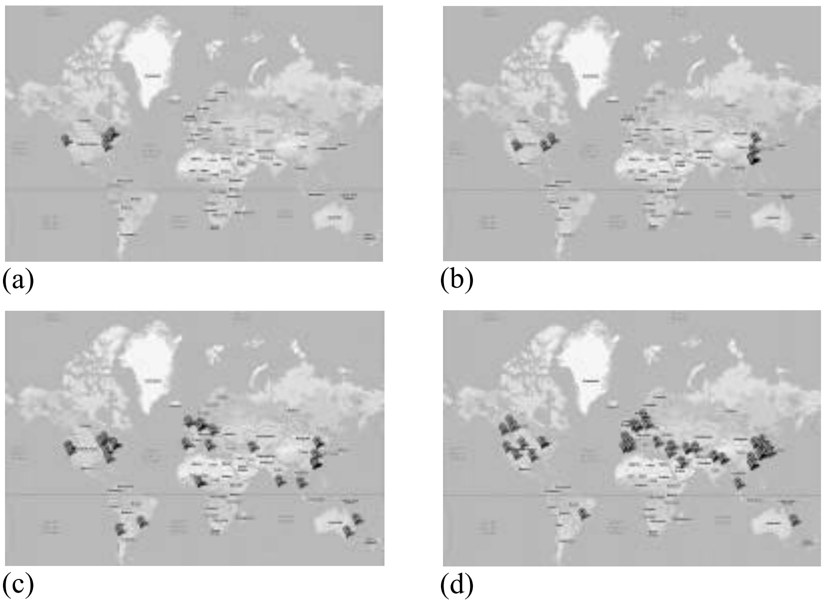

Fig. 4. Geo-referenced locations where CA models were implemented for urban growth modeling. (a) 1993-1997; (b) 1998-2002; (c) 2003-2007; (d) 2008-2012. Interactive high resolution color figures are available online; link to the website can be requested from the corresponding author

3.3. Increasing number of factors in CA models

The average number of factors identified and modeled in urban CA models increased in general (fig.5). In 1993-1997, there was an average of 3.4 factors used in the articles while in 1998-2002 the number increased to 6.6. This number slightly decreased in 2003-2007 but climbed up to 7.8 in 2008-2012.

In the early period in1993-1997, CA urban models were simple and used in a prototype fashion with limited number of factors being modeled (Batty and Xie, 1994; Clarke et al., 1997). The key intention was to introduce the early concept of CA method rather than to model urban dynamics (Batty and Xie, 1994).

The increasing number of factors used in CA models since 1998 can be attributed to two reasons, including the variation of transition rules and the combination of other models in CA. While the SLEUTH model (Dietzel and Clarke, 2004; Jantz et al., 2004) retains fixed input for its model, thus its transition rules, other models such as MOLAND and Metronamica allow more factors to be included in the transition rules (see Petrov et al. (2009) for examples). The combination of CA with others modeling techniques such as logistic (or multiple) regression analysis, System Dynamic (SD), multi-criteria evaluation (MCE), Artificial Neural Network (ANN) and so on allowed one to consider a large range of factor including indirect and external factors in the models (Lagarias, 2012; Lauf et al., 2012).

The question whether the number of factors to be included in CA urban model will continue to raise in the future remains open. We tend to agree with Park et al. (2011) that the number of factors in CA model will reach a "saturated level" where adding additional factors in CA model will give diminutive contribution in predicting urban growth . Indeed, the non-deterministic nature of urban dynamic means putting more factors in the model may not necessarily produce better prediction in urban growth (Itami, 1994; Syphard et al., 2005).

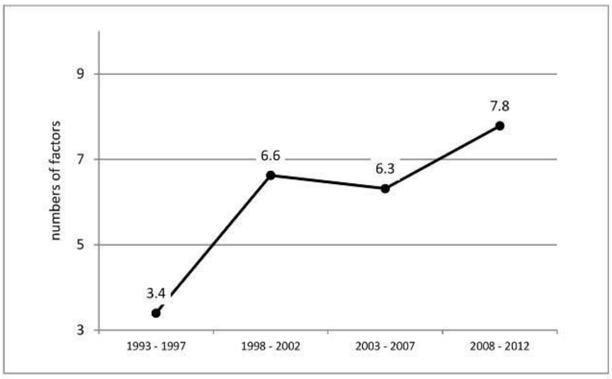

Fig. 5. Average number of factors used in urban CA models

3.4. Variation of factors over regions

Fig.6 presents the frequency of factors been modeled across different regions. A common factor used in all regions is *road*, with a high peak in fig.6. Models applied in the USA tend to use fewer factors (shown with fewer peaks in fig.6) than in other regions, where the dominant factors being modeled include *slope*, *road*, *water bodies* (as constraints) and *land genetic*. This is arguably due to the influence of the early CA model such as SLEUTH which has been adopted as one of the standard model for urban growth in USA (US-EPA, 2000).

In China, CA urban models included more factors (that is, more peaks shown in fig. 6) than other regions. The most commonly used factors include *highways*, *railways*, and *major towns,* indicating the polycentric urban areas. On the other hand, *population size* and *GDP* factors were also frequently used, indicating the influence of foreign investment in shaping the urban growth patterns (Han et al., 2009).

In Europe, *land suitability* and *zoning* amongst other factors were most frequently modeled. This is largely due to the limited land available for development, creating highly competitive land markets. For instance, (Ligtenberg et al., 2004) showed that the urban areas compete highly with agriculture land. Subsequently, strict regulations were imposed by authorities to maintain balanced land distribution and ensuring the best suitable lands for supporting urban activities (Hansen, 2010).

In the rest of Asia, *existing developed areas* hold a key factor in the CA models. Developing settlement areas near work places and existing infrastructures are the two advantages for continuous outward expansion of urban areas in Asia (Maithani, 2010; Thapa and Murayama, 2011).

3.5. Change of factors over time

Fig.7 presents a frequency distribution of the factors used in CA urban growth models over time. The most frequently used factors in the CA urban models are *road*, *land slope* and *land genetics*. The fact that over time *road* is a common factor constantly used in CA models corroborates with what Sante et al. (2010) found where *road* is indeed the main driving factors in many urban studies and that modern urban systems consistently rely upon (Iacono et al., 2008).

The distribution of the factors over the four time periods also indicates a changing pattern of selection of factors in CA urban models. The 2008-2012 period exhibits more peaks than previous periods. Specifically, compared to the 1993-1997 period (see dotted line in fig. 7) where the majority of factors (highest peaks) represent *geomorphology* and *accessibility*, models developed since 1998 include both *constraints* and proximity to *facilities*, and factors such as *environment, demography,* and *economy* also appear in more recent articles (see chart for the 2003-2012 period). This indicates that more factors were used in the later period (e.g., 2008-2012) than in the previous period. The addition of factors in recent CA models could be attributed to a number of reasons, but the availability of data in particular *the demography and economy factors,* could be the most significant reason for incorporating such factors in the model (Irwin et al., 2009; Lauf et al., 2012). However, in the less developed countries, the difficulty in data acquisition, especially concerning *demography* and *economy* factors, is still hindering many urban studies (Barredo et al., 2004; Thapa and Murayama, 2012).

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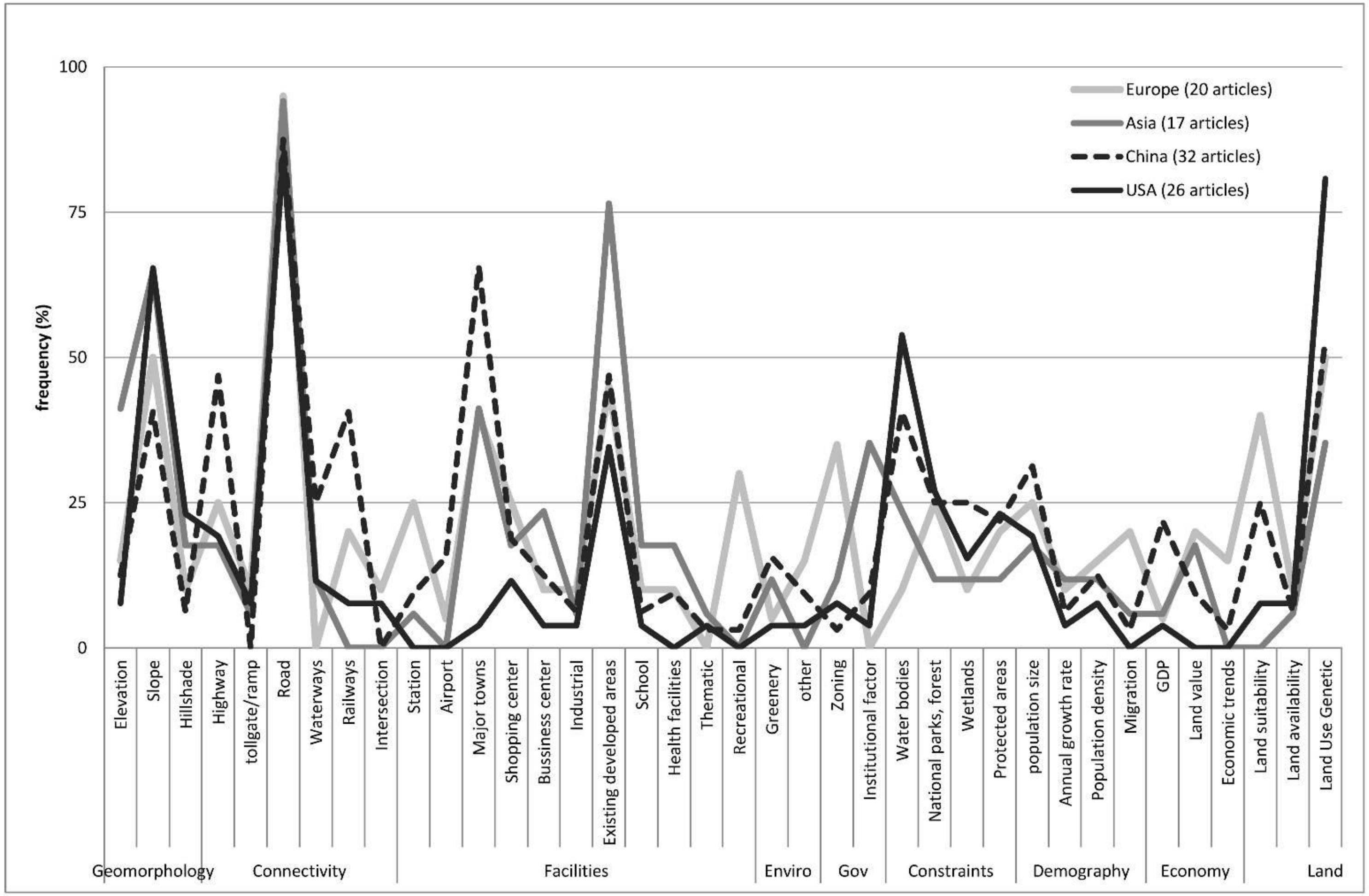

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3 **Fig. 6.** Summary of factors used in CA urban growth models with application in different regions

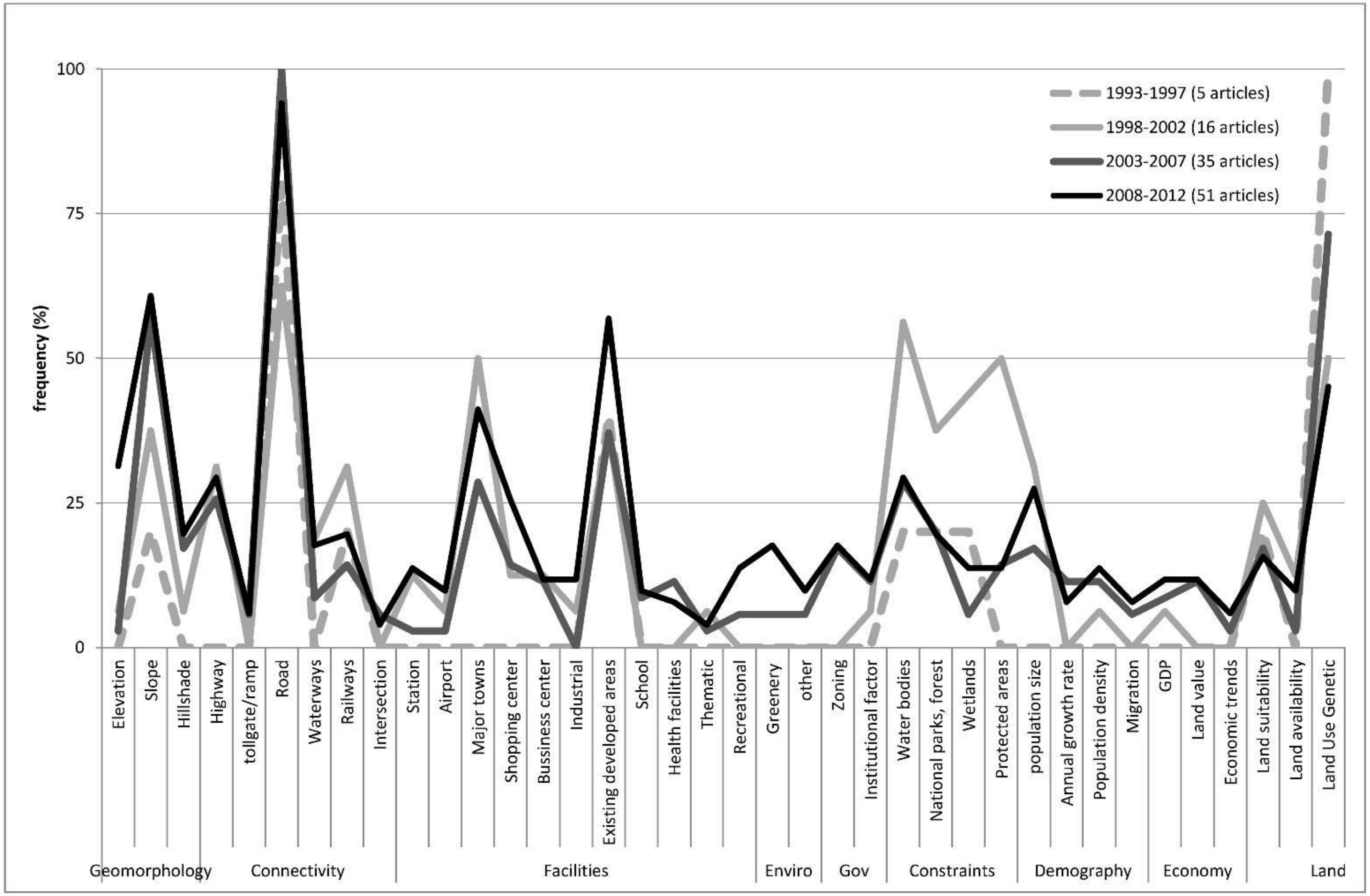

Fig. 7. Summary of urban growth factors commonly used in CA models extracted from articles in 1993 to 2012

4. Discussion and conclusion

Unlike previous works which used the *models* as the focus for review, this study takes the *factors* in CA urban growth models as its main review objective. Two important aspects were observed; the geographical regions where CA urban growth models were applied for and the timeline of these factors. The result shows that over the period from 1993 to 2012, there has been a change in the selection of factors in CA urban models. In general, an increasing number of factors were observed. In particular, factors commonly used in early CA urban modeling such as *road, slope*, and *land genetic* have been included together with new factors concerning socio-economic status such as *population size*, *migration* and *GDP* in more recent studies. Nevertheless, the question on whether the effort to include more factors in the modeling practice is worthwhile remains unclear, or doubtful (Clarke, 2004). With simple models using simple factors, urban growth models could explain the majority of processes in urban dynamics without the need to add other factors. This argument could hold true and should be regarded as warning in selection of factors for the models. The intention of urban modeling should be carefully planned to select the most influential factors in modeling the urban systems. With the improvement of computing power in urban modeling, more rigorous sensitivity analysis can be conducted to calibrate a model with the most sensitive driving factors to urban growth being selected and modeled.

Geographically, CA models have been widely developed and applied in the US, China, and Europe which reflected leading research clusters rather than the real problems faced by major cities in the world. Different regions have different combination of factors in their urban CA models, indicating that the selection of factors is dependent on the regions where the models were implemented.

In certain regions such as Africa, the lack of and limited access to data are hindering the implementation of some factors –notably socio-economy data– in the CA urban models (Barredo and Demicheli, 2003). Potentially, however, applying CA in less developed countries like in Asia and Africa, offers new perspective in perceiving urban mechanism. These cities are known as less regulated with large population growth driving the growth of the urban areas. Cities with more than 10 million population like Delhi, Mumbai, Kolkata (India), Jakarta (Indonesia), or in West Africa will grow tremendously fast and potentially pose threat to a sound and sustainable urban future if they are not well understood and anticipated (Bhatta, 2009;

UN-HABITAT, 2010). Thus, it would be more prominent and challenging to see applications of the CA models in simulating and predicting urban growth in these mega cities.

This review contributes to understanding the *factors* commonly used in CA urban growth modeling and provide a guideline for quick reference on what others have been taken as *factors* in their models. The factors listed in table 1 serves as a benchmark for the selection of factors for subsequent CA urban growth studies. Early urban modelers could base their decision on the selection of factors according to the region where the CA models have been implemented (in fig.6) and adapting or calibrating the *factors* based on their needs.

While this review considers two important aspects of the literature in CA modeling, including the timeline and the geographic location of the study areas, it is worth noting that the selection of *factors* also varies depending on how the models were derived, the type of CA models being employed, the scope of the study (multi scale or local scale), and so on. These considerations were not recorded and analyzed exclusively in the current research, a task to be explored in future studies.

It is also worth noting that table 1 is not an exhaustive list of all driving factors to urban growth in the CA literature. Though considered important and should be included in the CA models, *human behavior factors* were not appears in many articles thus not presented in our table (Thapa and Murayama, 2011). The absent of *human behavior factors* in many CA models possibly due to large data requirement where every human agent needs to be represented and every behavior needs to be simulated which at the end requires large computation powers (Batty et al., 2012). Another reason could be the mainstream in CA urban models paradigm where pattern-based models - represented with suitability type of factors which try to mirror the spatial configuration of cities- dominate the process-based models represented with *human behavior factors* (Cheng and Masser, 2004; Irwin and Geoghegan, 2001). Indeed, one of the critics in CA model where the exact process in urban growth –the transformation of non-urban into urban land use– happens based not only on the urban suitability type of factors but also on the behavior of different stakeholders in selecting the lands for development. These stakeholders include urban planners, land developers as well as local residents. In many CA urban growth models, however, such *human behavior* factors were not well represented (Benenson, 1999; Li and Liu, 2008).

This review also highlights the possibility and importance in using *crowd-sourced* data for urban growth modeling (Batty, 2012). Information for CA urban growth model may be gathered as an aggregated data from individual opinions. These *factors* may influence selection of factors for instance when people decide which factors they think important, or to urban growth model itself for example people demand new residential lands. Such crowd-sourced data will enable modelers to simulate the *human behavior* factors and how such behavior factors interact with other physical, socio-economic and institutional factors in driving the process of land use change and urban growth processes. A new school of urban modeling based on cellular automata and human agents will emerge in future urban modeling practice.

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