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Cellular Automata for Urban Growth Modelling:

A Review on Factors Defining Transition Rules

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Abstract: Urban growth modelling has attracted considerable attention over the past two decades. This article reviews the driving factors that have been identified and studied in cellular automata (CA); one of the popular methods in urban growth modelling. Over a hundred articles published between 1993 and 2012 were selected and reviewed. We extracted the driving factors from CA transition rules and arranged them in a list. The list contributes to early spatial research for the selection of factors in CA models. Our analyses show that studies between 1993 and 2000 mainly focused on using earth's physical factors in predicting urban growths, while recent studies combined them with socio-economic factors, resulting with models with a greater number of inputs. Nevertheless, the human-behaviour factors impacting urban growth were 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 is needed to address issues in understanding and modelling rapid urban growth processes in developing countries.

1. INTRODUCTION

Studies on the selection of factors affecting urban growth – the transformation of a non-urban into an urban area – have existed for decades. The earliest concepts of urban growth proposed that urban growth is the consequence of two factors, the distance to the city centre and the transport cost (Alonso, 1960; Ullman, 1941). The selection of factors affecting urban growth and the concept of urban systems has evolved since then, largely because urban studies have attracted researchers from various disciplines other than the geographer (Ullman, 1941). Factors affecting urban growth, hereafter called urban driving factors or factors, have been implemented to explain the urban system, and for projecting possible urban growth by implementing these factors in a model to bring insight on the location, distribution, and size of a new urban area. Through urban modelling, urban researchers are able to simulate and visualize portions of an urban system and analyse it in order to improve the understanding of urban growth mechanisms.

The urban modelling approach that counts explicitly the urban driving factors and the influence of the surrounding area is the cellular automata (CA) approach. CA has become a dominant tool among urban modellers in the last three decades (Barredo et al., 2003; Batty, 1997; White and Engelen, 1993). The popularity of CA in urban studies can be attributed to its ability to represent complex urban morphology with simple rules and its intuitive appearance which provides a strong message to its users (Itami, 1994; Jantz et al., 2004).

In its generic form, CA consists of four basic elements (Batty, 1997); the cell, the state of cells, the transition rules, and the neighbourhood. The transition rules are an element that determines the changing state of a cell. For urban studies, the transition rule in CA models plays a key role in determining how the cell changes its land cover attribute, for example from non-urban into urban states (Lau and Kam, 2005; Silva and Clarke, 2005). The transition rules reflect the mechanism and the individual contribution of the driving factors to urban growth. The transition rules require urban driving factors as an input to govern the transition of a cell's state.

In the absence of consensus among urban modellers on how to derive the input for CA transition rules, a vast array of urban driving factors has appeared in the literature. Various approaches have been used in determining the driving factors. The selection of the driving factors in CA models can be derived based on the scale of analysis i.e. city-scale, regional-scale, or global; the geomorphology of the region being modelled i.e. slope, elevation, water body; or on the data availability(Hagoort et al., 2008; Irwin and Geoghegan, 2001; Wu and Webster, 2000). Within the same region, the input in the CA transition rules may exhibit a distinct selection of factors because the background knowledge of the researchers and the approaches they took were different (see Han et al., 2009; Zhang et al., 2011, for example). Faced with this wide array of factors, researchers in their early careers in urban modelling have difficulties in grounding the selection of factors for the CA models. Thus a systematic review on the selection of the driving factors on urban growth models from past studies is needed.

A number of review works on CA based urban studies have been reported in the literature. Haase and Schwarz (2009) reviewed 19 models of different approaches; the economy approach, 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 designed for urban shrinkage studies (a process that is marked by the decline of urban population and economic growth). The most recent review was by Silva and Wu (2012) who classified 64 CA urban models based on their level of analysis, the spatio-temporal scale, and tasks performed. These aforementioned reviews focus on the selection of CA models and gave less attention to the selection of factors based on the transition rules. Sante et al. (2010) provided a more thorough review of CA urban models including the selection of factors. They found that the transition rules of their 33 reviewed articles implement the repeated 19 factors in the models. While the review by Sante et al. (2010)provides an improved picture of the application of factors in the urban models, they left knowledge gaps on whether the selection of factors has changed over time, and on the location of CA that have been tested. Therefore, follow up work that reviews the two knowledge gaps could bring a more complete picture on the selection of urban driving factors and the spatial spread of CA models.

With the above reasons, this article focuses on the two aspects that were overlooked in previous review works; the time of study and the geographic location of CA urban models. Specifically, we hypothesise 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 and discussion sections, urban growth factors were recorded and presented according to time and implementation across different regions. The empirical results from this research serve as an entry point for subsequent studies in urban modelling practice and hopefully foster more young urban researchers to adopt CA in urban modelling in the future.

2. METHODS AND MATERIALS

2.1 The procedure for selecting the articles

The selection of articles consists of three stages (*Figure 1*). On the first stage, the initial search was done using the Web of Knowledge (WoK) database by inserting the keywords ‘cellular automata’ and ‘urban*’. The wildcard ‘*’ aimed to expand the search coverage by including any articles containing the multiple ‘urban’ terms such in *urban*, *urbanization* or *urbanism*. By October 2012, the first stage returned 470 articles. These articles contain a mixture of themes not necessarily related to urban growth models such as traffic flow modelling, ecological sustainability, and disaster management. Clearly, these articles need to be screened further to be in line with the focus of this study on modelling urban growth. In the second stage, articles were filtered-out based on their aim and objectives that are relevant to the CA urban modelling themes. This was done by reading through the title and abstract of each article.

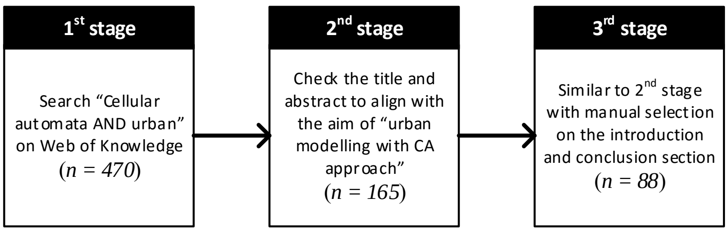

Figure 1. The selection procedure of articles

There were articles that contained the word ‘urban’ both in the title and its abstract but that were reporting non-urban land changes, such as modelling agricultural fields, or modelling the shrinking of forest regions. As the driving factors for modelling non-urban land covers differed from the ones of urban areas (Lambin et al., 2001), the last screening stage aimed to further refine the selected articles based on the following two points. First, by reading through entire articles, it could be decided whether the focus of the selected articles is on the urban growth or shrink modelling, thus in line with the aim of this study. Secondly, it could be checked whether the models were using real case studies. The latter aimed to record the geographical location of the model which is impossible if the study uses simulation data. The complete list of the 88 selected articles that were reviewed in this paper can be obtained from the correspondent author.

2.2 The extraction of the driving factors from transition rules

We extracted three components from the selected articles (*Figure 2*): (i) the driving factors that were implemented as inputs in the urban growth model, (ii) the study area where the model was applied, and (iii) the year of the study, approximately represented by the publication year of an article.

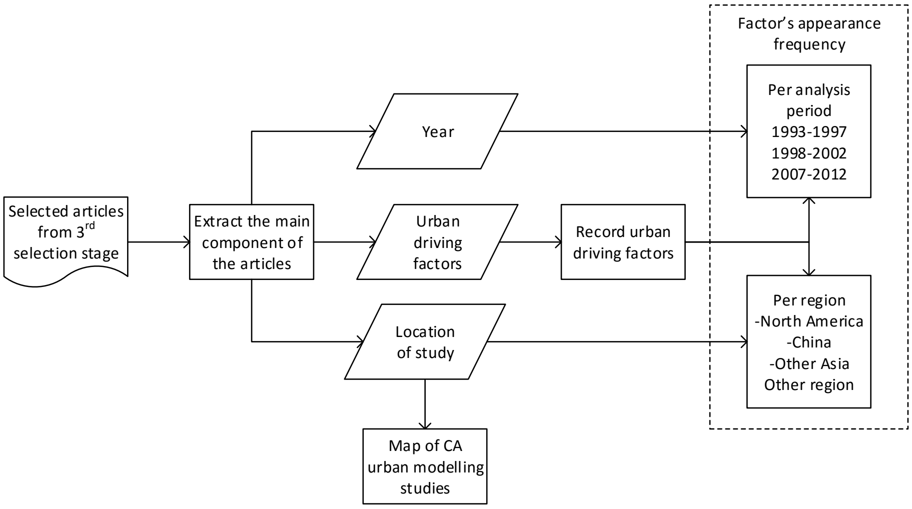

Figure 2. Reviewing procedure of CA urban growth modelling

Table 1 records the driving factors of urban models with the following procedure: each column in *Table 1* represents a single factor referring to a distinct urban driving factor. The terms used in the selected article to refer to the factor in the CA model might vary from one article to another. An example using earth's physical factors is that authors mentioned *aspect, angle,* and *hillshade* to refer to the same physical attribute of the sloping face of land. To avoid redundancy on the naming of factors, factors referring to similar urban factors were grouped together in one column on *Table 1*. The new factors previously unregistered in the current columns will be placed in the new column, thus expanding the column in *Table 1* with the rule that it appears at least in three articles, otherwise, the factor will be merged with the existing factor with the closest meaning. The factors in *Table 1* were named using the terms mostly appearing in CA literature and with less ambiguous meanings.

Despite efforts to reduce redundancies and ambiguous terms of factors in *Table 1*, a few driving factors need to be clarified further to align with the context of urban studies. The following describes the factors that have ambiguous meaning,

- *Thematic* refers to the local characteristic of a city that drives the urban growth in the area. These local characteristics could be the existence of a community centre, the religious facilities, or facilities such as power lines.
- *Greenery* refers to factors that trigger urban growth in an area due to its proximity to vegetated areas such as a city garden, croplands, or agricultural fields.
- *Environment other* factor includes any environmental considerations such as air quality, noise disturbance, or water availability.
- *Institutional factors* include government intervention in urban growth, other than zoning regulations, such as appointed urban development on government allocated lands or area prioritisation for urban development.
- *Land genetic* is defined as the conversion probability of non-urban to urban areas, for example, the Markov transition

probability, urban propensity, the repulsion-attraction due to neighbouring cells, or land change calibration factors (Guan et al., 2011; Zhang et al., 2011).

The broader groups in the driving factors classification help urban modellers when collecting data in the field. There are different classification systems for grouping urban driving factors in the literature. The classification of urban driving factors can be based on the geographical unit of analysis such as macro-meso-micro scale factors, for example the national economic policy that plays a part in a macro level of analysis (Engelen et al., 1995). The macro-meso-micro has an affinity with the local-regional-state scale classification that sees the influence of factors on the spatial-scale context (Stanilov and Batty, 2011; Zhang et al., 2010). A classification based on field of study was proposed by Burgi et al. (2004). They classified the urban driving factors as a groups of socioeconomic, political, technological, natural, and cultural factors which this study adopted. An addition of group factors was necessary to accommodate the urban driving factors which are not covered in Burgi's list.

Despite that the concept of cellular automata has existed since the 1980s (Tobler, 1979), the analysis period was set between 1993 and 2012. The starting period of 1993 was selected as this was the year when the earliest article of CA – based on the selection criteria in this paper – was found. Four periods each with five year ranges 1993-1997, 1998-2002, 2003-2007, and 2008-2012, were set to determine the timeframe for the subsequent analysis. The timeframe allows the chronological observation of urban growth factors in CA models.

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

Group	Driving factor
Earth physical	Elevation
	Slope
	Hill-shade
Connectivity	Highway
	Tollgate/ramp
	Road
	Waterways
	Railways
	Road intersection
Facilities	Station
	Airport
	Major towns
	Shopping centre
	Business centre
	Industrial area
	Existing developed areas
	School
	Health facilities
	Thematic
	Recreational
Environment	Greenery
	Environment-other
Government	Zoning regulation
	Institutional factor
Constraints	Water bodies
	National parks, forest

	Wetlands
	Protected areas
Demography	Population size
	Annual growth rate
	Population density
	Migration
Economy	Gross domestic products (GDP)
	Land value
	Economic trends
Land suitability	Land suitability
	Land availability
	Land genetic

3. RESULTS

3.1 The general trend of CA urban articles from 1993 to 2012

Between the periods of 1993 and 2012, there has been a steady increase in CA urban studies (*Figure 3*). Starting with a modest five articles in the periods of 1993 to 1997, the number raised seven-fold to 35 articles in the 2003-2007 period. On average, there was an increasing trend from five articles annually in 1993 to 1997 to seven articles annually in the 2008 to 2012 period.

The increasing number of publications in CA urban modelling suggests an increasing popularity of CA within spatial research (Liu, 2012). A reason for an increasing number of published CA urban studies could be linked to the ability of CA in capturing the complex shape of urban changes. The possibility of an urban areas ability to grow or shrink (urban changes) relates to a number of urban driving factors acting together, and using a deterministic approach with a linear regression equation, it is impractical to find the optimum solution for such complex urban changes. Instead, with CA, the solution for estimating urban changes comes from observing the area in the surrounding and their previous land statuses. Moreover, the natural solution in CA exhibits an uncertainty which is more intuitive where, for instance, the conversion rate from a non-urban to an urban area increases as the surrounding becomes urban area.

Another reason for CA popularity relates to its spatial shape akin with raster-based layers in GIS. With CA resemblance to the raster data type, the coupling of CA with spatial analysis (i.e. buffering, zonal analysis) within GIS becomes straightforward. The dynamic properties of each cell in CA can be transferred immediately into the attributes in a GIS raster layer. This seamless coupling of CA in GIS is a key advantage in developing urban CA models, which was much preferred by urban modellers (Clarke and Gaydos, 1998; Wu, 1998).

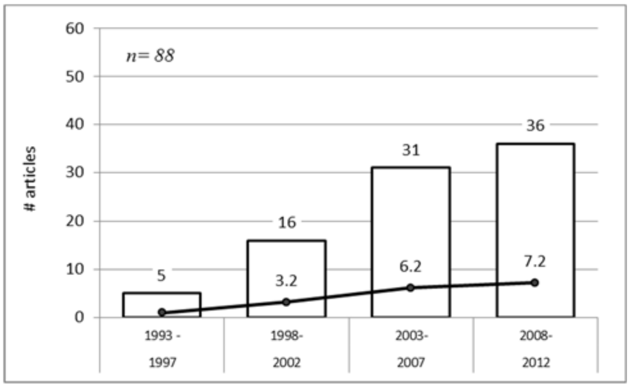

Figure 3. The increasing number of articles in CA urban modelling from 1993 to 2012. The number of articles for each of the five-year periods is shown by the bar graph, and the annual average number of articles is represented by the line graph

3.2 The spatial coverage of CA urban model applications

While CA has been implemented in cities across the globe, the early application of CA was recorded in cities of North America, specifically in the USA, and of China (*Table 2*). The examples of this early application were in Amherst and San Francisco Bay, USA, and in Guangzhou, China (Batty and Xie, 1994; Clarke1997). In the period after 1997, the increasing applications of CA in urban modelling in Europe and other Asian countries, such as in Japan, Korea, Malaysia, and Nepal have been observed (Guan et al., 2011; Naimah et al., 2011; Thapa and Murayama, 2011). In Nepal for instance, the combination of CA with the Bayesian approach has been successfully implemented to predict the future expansion of urban areas in Kathmandu.

Table 2. The number of CA urban model articles based on the regions (in absolute unit and percentage of total article for each period)

Year	North America		China		West 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	10	32	7	23	5	16	4	13	5	16
2008-2012	6*	17	11	31	9	25	8	22	2	6
total	24	27	31	35	14	16	12	14	7	8

--including Australia

** including South America and Africa

Figure 4 visualizes the content of *Table 2* in the Google Map interface. *Figure 4* visually suggests the imbalanced distribution of CA applications around the world with at least 50 percent of articles having mainly been implemented in cities of USA (North America) and China whilst the other 50 percent was spread across other regions. The high number of CA applications in USA and China was in strike contrast with the implementation of CA in cities of Africa, South America, and the rest of Asia, where it has been scarce. The spatial distribution of CA implementation reflects better with a research cluster in CA rather than the distribution of cities which are facing urban problems such as managing the unprecedented growth of their urban populations, the provision of basic infrastructures, or distributing urban services. With cities in Asia and Africa being the place of nearly 90 percent of the world's urban population in the next two decades (UN-HABITAT, 2010), CA urban modelling in these regions is crucially important, not only to explore the capability of CA in regions known with limited data availability, but also to bring a better understanding of the urban system in these cities with the hope to better anticipate the expansion of urban areas. The fact of spatial imbalance in CA's study area highlights the potential regions to be explored in the future within CA urban models.

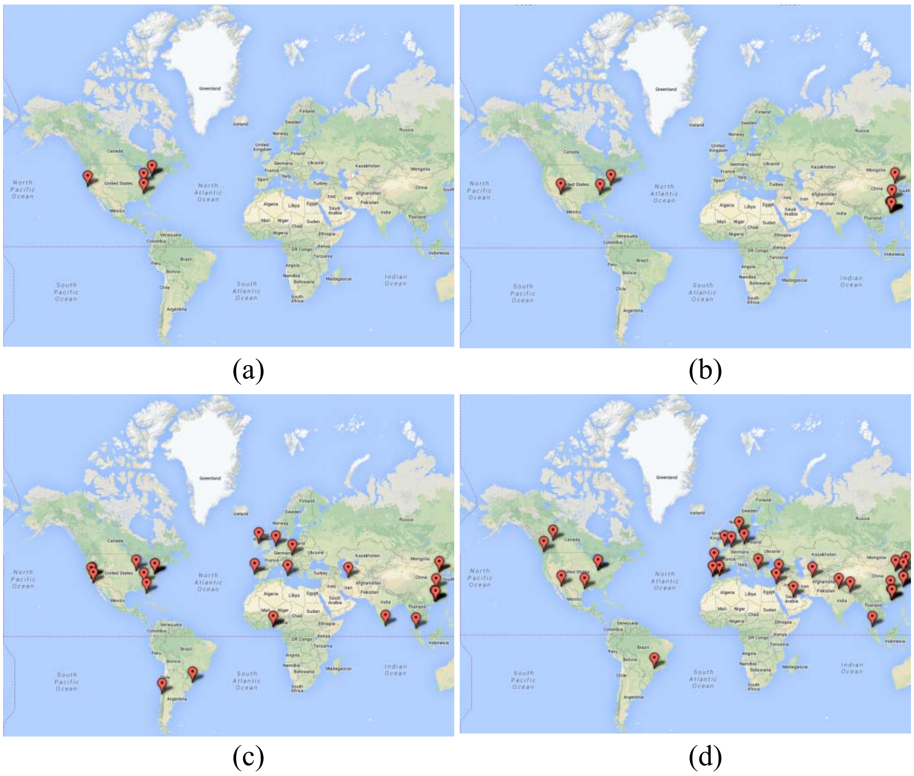

Figure 4. The implementation of CA urban growth modelling across the globe in different periods; (a) 1993-1997; (b) 1998-2002; (c) 2003-2007; (d) 2008-2012.
Similar images in colour are available online.

3.3 The number of factors in CA models

The average number of factors in CA models shows in general an increasing trend (*Figure 5*). Between 1993 and 1997, there were on average three factors in CA urban models and this doubled into seven factors in the 1998-2002 period. The number decreased slightly in the 2003-2007 period, but bounced back with nearly eight factors in every CA urban model in the years between 2008 and 2012.

While the increasing number of factors in recent CA models could be attributed to a number of reasons, the three concurrent reasons are the greater availability of data from sources previously limiting data sharing to the public, the shifting paradigm in CA modelling, and the advancement of computer power. In the recent application of CA during the 2003 to 2012 period (see Section 3.5), applications of CA have been made possible with increased data availability in categories such as social, economic, and demographic. Data gathering from socio-economic surveys previously missed the spatial information or came in a large spatial unit, for example the national-scale unit, constraining urban researchers to include these data in the CA model. Nowadays, these data have better, disaggregated spatial information which allows them to be linked with other urban driving factors and helps the analysis become more detailed (Irwin and Geoghegan, 2001).

Another reason could be attributed to a shifting paradigm in CA. In the 1993-1998 period, the urban growth models were intended to introduce CA to spatial researchers (Batty and Xie, 1994), thus using a simple model with few factors was considered as a way to gain attention and reach the objective of becoming one of the popular and versatile approaches in urban modelling. In a later period, the focus in using CA has been shifted to achieve a greater accuracy in reconstructing the configuration of the urban areas. It invites modellers from various backgrounds to perceive urban growth from their perspective, where involving non-spatial factors such as the *demography* and *economy* could lead to better accuracy in urban growth modelling (Batty and Xie, 1994; Clarke et al., 1997).

It is inevitable that the advancement of computer technology allows urban modellers to include more factors into the model with various weights representing the degree of influence of the factors on the urban growths. Complex spatial analysis that involves multiple factors to be simultaneously operated in a higher spatial dimension (i.e. the additional spatial dimension representing vertical development) or in a higher spatial resolution has been made possible with a stronger computer power than in the previous period where CA was initially adopted for urban research in the 1990s (Liu et al., 2012; Xian et al., 2005).

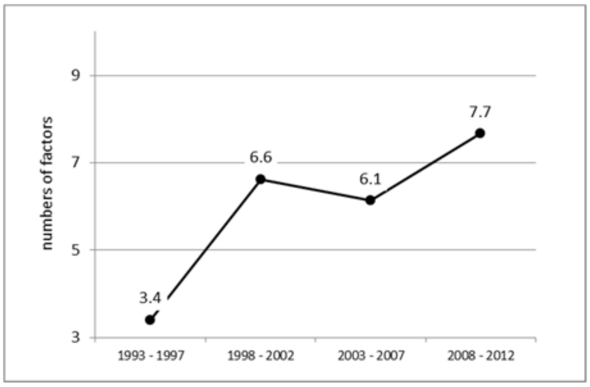

Figure 5. The average number of factors in urban CA models based on years.

The question whether the number of factors in CA urban models will continue to rise in the future remains open. We tend to agree with what Park et al. (2011) have argued, that the number of factors in CA models will reach a 'saturated level', where adding additional factors in CA models will give diminutive contribution in predicting urban growth. Indeed, the non-deterministic nature of urban growth means putting more factors in the model may not necessarily produce better prediction in urban growth (Itami, 1994; Syphard et al., 2005). Moreover, in the developing countries, data availability is still an impeding problem for urban modelling studies to proliferate (Barredo et al., 2004; Thapa and Murayama, 2012).

3.4 The selection of factors in different regions

The selection of factors for CA urban modelling across regions is presented in *Figure 6*. The various peaks in driving factors in *Figure 6* indicate that each region has unique driving factors affecting its urban growths. Among all driving factors, *road* was the most popular factor as indicated with the high peaks (above 75 percent) across all regions.

In North America, most of the CA urban models used factors such as *slope*, *road, water bodies,* and *land genetic.* These are factors similar to the input of the popular CA model in the USA; the SLEUTH, a CA urban model developed by Clarke et al. (1997). The SLEUTH model has been opted for as the preferred model for urban growth and frequently used in urban growth models within and outside the USA (Feng et al., 2012; US-EPA, 2000).

In China, the CA urban models implemented a wider variety of factors than the models in North America, as indicated with more peaks and less flat lines in the dotted line of *Figure 6*. The factors that appear more frequently in the articles in China – apart from *road* – are *major towns, land genetic* and *highway*. *Existing developed area*, *railway*, and *water body* also appear in the CA articles.

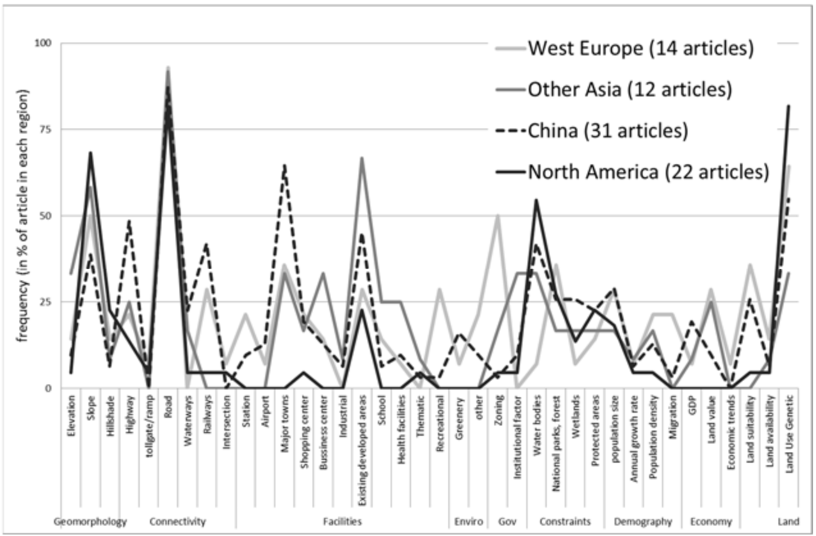

Figure 6. Summary of factors in CA urban growth models based on regions.

In other Asian countries, *existing developed areas* emerged as a key driving factor in CA urban models. In this region, people tend to live near the already developed areas to experience the benefits of the existing infrastructure and proximity to their workplaces (Maithani, 2010; Thapa and Murayama, 2011). In most Asian cities in developing countries, faced with unreliable public transportation and facilities, typical urban development near existing urban areas is common practice (Hudalah and Firman, 2012).

In West Europe, *land suitability* and *zoning* were amongst the most frequently used factors in the CA model. In West Europe, limited land availability could be a constraint for urban development for every country, thus highly competitive land markets is inevitable (Ligtenberg et al., 2004). Zoning, as an instrument to control and regulate land development, was strictly imposed by various local governments in West Europe to ensure the most suitable use of land. Zoning was also an important strategy to maintain the balance in land distribution for supporting non-urban activities, for example securing land parcels for food crops (Hansen, 2010).

3.5 The variety of urban growth factors over time

Figure 7 displays the frequency (number of appearance) of factors in CA urban growth models over the period between 1993 and 2012. *Figure 7* suggests that *road* was constantly used in CA urban models over the entire analysis period (1993 – 2012). The high appearance of *road* as an input in CA urban model corroborates with what Sante et al (2010) found where *road* is indeed the main driving factor in many urban studies. The highly appearing *road* was followed by *land genetics* and *slope* as the most frequently used factors in CA models.

Looking into the details of every period, the period of 1993 to 1997 was notable with few peaks above 25 percent and more flat lines, indicating that in this period the CA employed a limited number of factors in the model, with *road, existing developed areas,* and *land genetic* appearing more in the models. In the later period, between 1998 and 2002, more peaks were observed (above 25 and 50 percent) with the following factors - *major towns*, *water body*, and *protected areas* - as the leading factors in the CA urban models. In the periods of 2003 to2007 and 2008 to 2012, the selection factors include groups of factors relating to the *environment, demography,* and *economy*; these are the factors that appear less frequent in the previous periods.

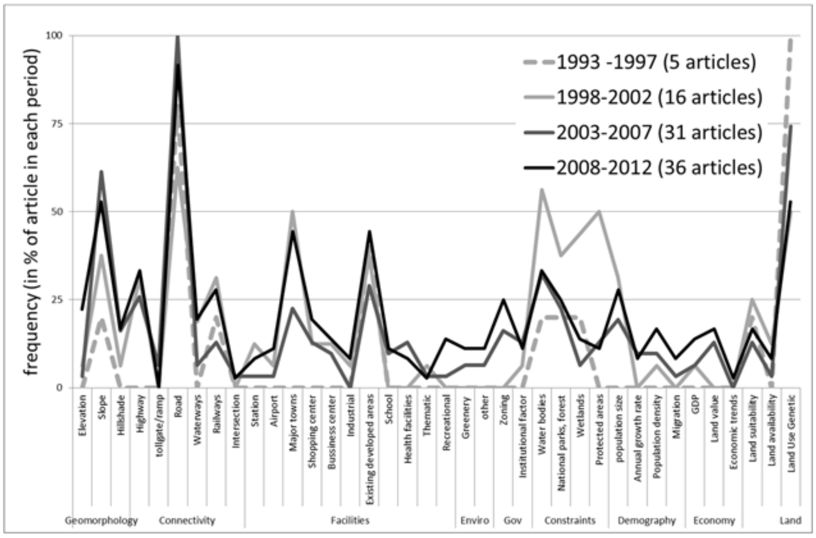

Figure 7. Summary of factors in CA urban growth models based on the periods.

4. DISCUSSION AND CONCLUSION

Unlike previous reviews, which oriented the focus of studies on the different types of CA models, the present study focuses on investigating the spatial location of *driving factors* in CA urban growth models and the temporal variability of these factors during the 1993 to 2012 period.

The results show that the number of factors in CA urban models between 1993 and 2012 has steadily increased. In the early 1990s, CA urban models incorporated less than five factors, such as *road, slope*, and *land genetic.* In the last decade, the number of factors in CA urban models has increased to more than seven factors with the addition of socio-economic factors such as *population size*, *migration* and *GDP*. The increasing factors in CA models stem from the influence of research from, for example, economy, demography, or social disciplines that view urban growth as a result of combined physical and non-physical factors. In the early development of CA urban models, the social, economy, and demography factors were considered to be macro-level, thus were generally considered as external and constant factors in the models. With the inclusion of these factors by urban researchers from various disciplines, the understanding of urban changes and its system has become richer as the newer era of urban modellers perceive the urban changes as more than a result of physical factors (i.e. *slope*, *hillshade*). The inclusion of more factors in CA models has been reported to produce a better variation in the micro-scale of urban changes than if the modellers include the physical factors alone (Lauf et al., 2012).

As CA modelling was born from a complex system developed alongside the rise of computer power (Batty and Xie, 1994), it is unavoidable to perceive that the increasing number of factors in CA urban model is linked to the exponential growth of computer power that enables rich information from various factors to be processed simultaneously in the model. Initially, in the 1980s, the socio-economy and population factors were externally determined outside the CA model using standard regression or predetermined models (Chen et al., 2002) because it was intractable to do processing simultaneously inside the CA model. However, in the recent development of CA urban models, analysis can be done endogenously inside the CA model or seamlessly coupled with spatial analysis within GIS applications. The tight-coupling analysis of CA and GIS allows the spatial analysis, the transition rules, and the influence of neighbouring cells in CA to be performed and visualised in a single computer application. The demand for more powerful computing seems to be inevitable as more complex analysis, such as the following: (i) the repulsion-attraction as an effect from the neighbourhood cells, (ii) the combination of macro-meso-micro scale factors, and (iii) the uncertainties that require the simulation to run multiple times, dictate future research in CA models (Liu et al., 2012; Xian et al., 2005). These analyses and simulations, whilst currently can be done by parallel computing, will be handy and practical if they can be done in a single computer.

Despite reports on the increasing accuracy when using more factors, it remains unclear whether the effort to obtain the data and fine-tuning the relative weights within the factors is worth the accuracy gained from this effort (Clarke, 2004). In the face of complex urban systems, where each urban element interacts with other elements, the intention of urban modelling is not merely to mimick the pattern of urban growth, but to understand the processes underlying the growths. Thus, using fewer factors could be beneficial to help explain the larger process and mechanism in the urban system without losing the generality (or replicability) of the model. Urban researchers should measure their effort to obtain the necessary data for input in CA models with the expected accuracy from the analysis and consider whether their effort is worthwhile in terms of improving their understanding of the urban system being analysed.

In terms of the spatial distribution of the study area, CA urban models have been dominantly applied in cities of North America (largely and historically in USA), China, and West Europe. In the remaining part of the world like Asia and Africa, the applications remain sparse. The numerous applications of CA models in North America, China, and West Europe may reflect more on the leading research clusters than the locations where managing urban growth is the crucial issue. Cities with a population of more than 10 million (megacity) like Delhi, Mumbai, Kolkata (India), Jakarta (Indonesia), or in West Africa, will grow tremendously fast and they are facing a serious threat to their sound and sustainable urban futures (UN-HABITAT, 2010). It is in these regions that it is crucially important for CA urban modelling to be developed and applied. Not only to address, but also to mitigate the unwanted impacts of urban growth by visualizing possible urban growth and designing urban strategies to cope with the projected urban growth. The future study areas of CA should be re-oriented toward addressing the urban problems in these megacities.

Apart from its contribution in improving the knowledge on the *driving factors* commonly used in CA urban models, this study provides a list of factors for urban modelling which contributes to the study of urban growth as a reference point to select and define the urban driving factors for CA modelling. While the list is not exhaustive, factors in *Table 1* could serve as pointers for early urban modellers or practitioners to select which factors should be selected as starters in the model. Knowing that different urban regions in the world exhibit unique characteristics, they can then adapt the selection of factors to the region where the CA model is being implemented (see *Figure 6*).

In the course of reviewing the factors, it was noticed that the *human behaviour factor* was starting to gain attention in the CA models. While considered to be one of the most influential factors impacting urban growth (Thapa and Murayama (2011)), the *human behaviour factor* was generally overlooked on the CA articles or was not well represented (Benenson, 1999). Lauf et al. (2012) mentioned that the *human behaviour factor* improves the variability, adapting to the stochastic nature of predicting urban changes, and improving the dynamic presentation of the spatial changes. However, a sceptical view on the inclusion of *human behaviour factors* in urban modelling exists. The supporters of the sceptical view argue that the requirement to define and develop the human agent including its inter-relationship with the physical factors inevitably cause the data requirement to grow exponentially (Batty et al., 2012). With this data-hungry requirement, the inclusion of the *human behaviour factor* in CA urban models will face a challenge, in particular, in the cities of the developing countries where data availability and accessibility to the public is still limited. A demonstration of the inclusion of human behaviour factors in CA modelling with case studies in the locations where data is lacking should be a target for any urban growth studies in the future.

The other reason for the increasing inclusion of the *human behaviour factor* in CA models could be attributed to the changing paradigm within CA urban modellers. Pattern-based models have dominated the studies of CA urban modelling in the last three decades (70s, 80s and 90s). In this paradigm, the main target of CA urban modelling was to mirror the spatial configuration of cities, whilst in the later period (year 2000 onward), the pattern-process paradigm started to rise. In the later paradigm, the modellers aim to find the relationship between the spatial patterns (size, direction, magnitude of urban growth) that configure the city with the process underlying the urban growth. In this regard, taking into account the *human behaviour factors* supports the main hypothesis of a pattern-process paradigm where humans are considered to be the major cause of urban growth (Irwin and Geoghegan, 2001). A new school of urban modelling based on cellular automata and human (agent) behaviour will emerge in future urban modelling practice.

This review investigated the driving factors of urban growth in CA urban modelling from two aspects, the time and geographic locations of the case studies. The reader might find the two aspects of analysis in this study were too narrow to cover the consideration in CA urban modelling. As the paper orients itself for the early urban researcher, this paper offers simplicity in the CA concept with the hope to attract more young and early urban researchers, with little background and experience in spatial modelling, to involve themselves in developing a better understanding of urban growth changes. It is worth noting that the selection of *factors* 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 analysed in the current research, a task to be explored in future studies. The analysis and claims in this paper were drawn from the selection criteria defined in Section 2.1, from which the 88 articles were selected for review. It highly possible that selected works highly relevant within this study were missed in the selection list, thus affecting the conclusions drawn in this study. Readers should regard the findings in this study as complementary to one of a comprehensive review.

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