UNDERSTANDING URBAN GROWTH SYSTEM: THEORIES AND METHODS

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Abstract: Understanding the urban growth system is a prerequisite for modelling and forecasting future trends of urban land use/cover change and its ecological impacts. As urban growth involves various actors with different patterns of behaviour, we argue that scientific understanding must be based on elaborated complexity theory and a multidisciplinary framework. The theoretical analysis can provide a guideline for selecting modelling methods currently available in complexity modelling and in remote sensing and GIS environments. This paper first proposes a conceptual model for defining urban growth and its complexity, in which spatial, temporal and decision-making complexity are distinguished as separate domains. Second, this paper links the conceptual model with the major current methods of modern urban modelling, such as cellular automata, fractals, neural networks, multi-agent, spatial statistics etc. This confrontation enables the possibilities of various modelling methods to understand urban growth complexity to be indicated. Third, this paper evaluates the operational implementation of representative methods based on criteria such as interpretability, data need and GIS embeddedness.

Keywords: understanding, urban growth, complexity, modelling, methods

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1. INTRODUCTION

In the field of urban planning, one of the important subjects of concern is to predict the trend of land use transition. However, prediction without scientific understanding of the system under study implies a certain degree of uncertainty due to the numerous unknown factors involved.

To date, quite a number of models have been developed and applied in wide scientific areas. But most of them are criticised as being unsuccessful. This may indicate that most objects being modelled are not completely understood conceptually. Rakodi (2001) argues that one of the proposals for improving the quality of planning is an attempt to improve the understanding and analysis of the interrelated components of the urban development process in order to arrive at more appropriate priorities and sets of policies. It is persuasive that the big forward movement in remote sensing (RS), geographical information science (GIS) and system theories, especially the developing complexity and non-linear theories (the most promising science in the 21st century), is undoubtedly stimulating a new development wave of modelling. The reasons are threefold. First, complexity theory brings hopes for re-understanding the systems or phenomena under study. A recent resurgence of interest in complexity issues is evident as new theories and methods have mushroomed in the last few decades. Second, new mathematical methods create new means to represent and quantify the complexity. Third, remote sensing and GIS guarantee the availability of data on various spatial and temporal scales.

However, the complexity of urban growth and its impacts on urban development planning and sustainable growth management have not been systematically researched. Here, we attempt to answer these questions: What is the urban growth system? And why and how should the complexity of this complex system be understood? With this purpose in mind, this paper first proposes a conceptual model to define the urban growth system and then another conceptual model to project the complexity of the urban growth system onto spatial, temporal and decision-making process dimensions. Second, this chapter links the conceptual model with the major current methods of modern urban modelling. This confrontation makes it possible to indicate the possibilities of the various modelling methods to understand urban growth complexity. Third, this chapter evaluates the operational implementation of representative methods based on criteria such as interpretability, data need and GIS embeddedness. Finally, this chapter ends with some conclusions.

2. COMPLEXITY OF URBAN GROWTH

That the urban system is highly complex has become a well-recognised fact. Systems thinking has been widely accepted by urban planners and other decision-makers engaged in urban management and construction. When we consider urban growth as a system, in particular a complex system, we need to uncover the universal and unique characteristics that it shares with and distinguishes it from other complex systems. This exploration is conducted by answering four relevant research questions. The first question is: Where is urban growth occurring from a system perspective?

2.1 Complex system of urban growth

As far as the type of urban development is concerned, it consists of physical expansion and functional changes. The former refers to the change in space (transition from non-built-up to urban), the latter to the change in major activities (land uses). As a result, space and activity should be the basic elements of any systems defined for understanding urban growth. In figure 1, it is supposed that urban growth occurred in a specific period from time t_l to t_2; apparently the evolution of urban growth is closely related to three systems − ***P***, ***U*** and ***N***. ***U*** itself is a highly complex social and economic system, as the concentration of considerable urban activities present at time t_l shows. It offers current activities rather than space for urban growth to come. ***N*** is a typical physical and ecological system, including various ecological units (water body, forest etc.) and agricultural land. It primarily provides possible opportunities and potential for urban growth in space, instead of activities until time t_2. ***P*** is a spatial and conceptual system that results from a spatial planning scheme. It prepares organised space and activities for urban growth in the future. As the main topic of this research, new urban growth is treated here as an independent system within the specific period under modelling. Under such an assumption, urban growth ***G*** can be defined as a system resulting from the complex dynamic interactions (only from t_l to t_2) between the three systems ***(P***, ***U*** and ***N).*** The thin arrows in figure 1 refer to the interaction between the three systems, and the thick arrows to the contributions to urban growth made by the three systems. System ***P*** contributes planning control and requirements to ***G;*** system ***N*** contributes developable land, and system ***U*** contributes activities and stimulant factors to the growth of ***G***. A key to understanding urban growth is to understand the complex dynamic interactions. We can say the interaction is open, non-linear, dynamic and emergent. Urban growth is a self-organised system.

Urban growth creates a new dynamic system, which comprises a quantity of projects constructed that are increasing with time from t_l to t_2. It is an open system. It imports a variety of regulation/decision-making, investment from higher organisations, external investors, inhabitants and managers. Its non-linearity is indicated in the following aspects. In the spatial dimension, new development density (population density or land conversion) decreases non-lineally with the distance from the city centre and sub-centres. This is mostly represented by a negative exponential function or an inverse power function. In the temporal dimension, new growth does not follow a linear trend but, in most cases, a logistic trend in certain periods. The interactions among a huge number of factors have proved to have the unknown non-linear relationship. The structure and function of each local project depend not only on its neighbouring projects but also its built-up environments, i.e. these new projects interact not only with each other but with developed areas, as well as spatially and temporally. These non-linear interactions result in globally ordered land use patterns. The order is typically indicated by large-scale spatial agglomeration or by clustered patterns. From this, we can infer that urban growth is a typical self-organised system where the three systems are treated as a whole.

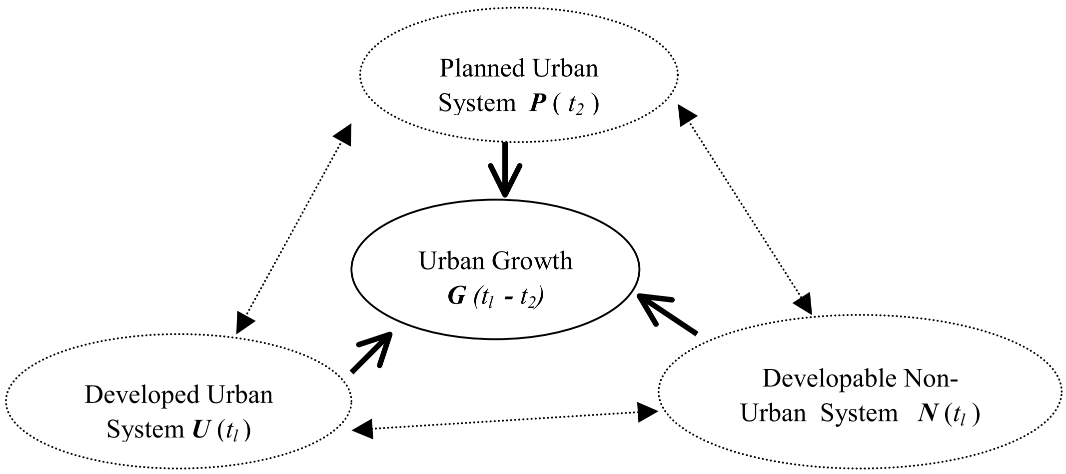

Figure 1 Where is urban growth occurring?

Second, we need to answer the questions: What should be understood in supporting urban development planning and management? And how can urban growth be represented for modelling purpose? Understanding urban growth can be summarised as five interweaving levels: policy, actor, behaviour, process and pattern. Policy is the level proven to be the most influential factor or driving force of urban growth on the macro scale. Pattern is the lowest level, which is a directly observable outcome. Process indicates the dynamics of urban growth, behaviour indicates the actions of the actors involved, and actors indicate the agents of behaviour. As a result, modelling has to follow a ladder: from pattern gradually to policy level. In the terms of hierarchy theory, understanding a single level must consider its lower and upper levels as they are comparatively closely linked. Consequently, to understand a process, one must take its pattern and behaviour into account. A pattern is the temporal snapshot of a process, and behaviour is the decision-making source of a process.

2.2 Projection of complexity in urban growth

Much of our understanding of explicit dynamic processes will coincide with our ability to understand complex systems in general. A third question is: What is the complexity of urban growth? or How should we look at its complexity?

(1) Sources and measurement of complexity

Urban growth consists of the various scales of new projects. Large-scale projects are characterised by heavy investment, long-term construction and the number of actors involved; examples include airports, industrial parks and universities. By contrast, small-scale projects are characterised by rapid construction, light investment and few actors; examples can be a private house and a small shop. Urban growth results in various land uses with different levels of social, economic and environmental values. This is a higher dimension of heterogeneity, indicated in the attributes of spatial objects. New development units are the spatial entities carrying heterogeneous social, economic and environmental activities.

Consequently, the functional differences between these projects, and also between them and the other three systems, create a massive flow of matter, people, energy and information. They are the sources of the complexity inherent in urban growth. Our observation or assumption is that the spatial, temporal and decision-making heterogeneity of urban growth results from socio-economic-ecological heterogeneity. Such heterogeneity may originate from self-organised socio-economic processes. The interaction between these categories of heterogeneity creates complex patterns, behaviours and processes of urban growth.

As a first step towards decision-making support, quantitative measurement has a crucial role, affecting the accuracy of modelling and further the risks of decision-making. To effectively measure the complexity of a system remains an unsolved issue even in complexity theory. In urban growth, such complexity can be threefold (or projected onto): spatial measurement, temporal measurement and decision-making measurement, which correspond to the three categories of heterogeneity. Although numerous indicators are designed for the quantification required by any specific analysis based on remote sensing and GIS techniques, they are still not rich enough to understand all aspects of multiple complexity. A major reason is that conceptual understanding of any specific complex system is still limited at present.

(2) Spatial complexity

A frequently cited shortcoming of GIS and most spatial analysis tools is their difficulty in dealing with dynamic processes over landscapes. This is not because of a lack of people thinking about dynamic processes in space, nor is it from a lack of talent or technology. It has more to do with the fact that space is inherently complex, and dynamic processes often become complex when they are regarded in a spatial context. As a result, the first step to spatial modelling is to recognise the spatial complexity in the study. Spatial complexity may include spatial interdependence, multi-scale issues and structural or functional complexity.

Spatial dependence is defined as a functional relationship between what happens at one point in space and what happens at a neighbouring point. In urban growth, spatial dependence is indicated by the impacts of neighbouring sites on land conversion of any site – which is the result of a causal relationship among neighbouring entities, e.g. interaction. The impacts can be twofold: positive (stimulation) or negative (constraint) from three systems (***U***, ***P***, ***N***). Examples of positive impacts may include transport infrastructure or developed urban area; in particular low density fringe growth is highly dependent on transport infrastructure. Examples of negative impacts may be steep terrain and non-developable land such as deep lakes. The complexity lies in the following facts:

- The impacts are determined by an unknown number of factors and their spatial relationships are non-linear;
- The intensity of spatial dependence or neighbourhood size is spatially and locally varied;
- Land conversion includes probability (occurred or not), density (scale), intensity (floor number), function (land use) and structure (shape or morphology); each may have distinguished spatial dependence.

Urban growth involves a number of hierarchical structures. In the spatial dimension, ***U*** includes different levels of shopping centres and road networks; system ***N*** includes different levels of ecological units; system ***P*** contains different levels of urban planning (general plan, district plan and zoning plan). As a result, urban growth ***G*** may be related to more complex spatial hierarchies as interacting with three systems. From the perspective of land development, urban growth can be divided into different scales of projects. Patterns and processes have components that are reciprocally related, and both patterns and processes, as well as their relationships, change with scale. Different patterns and processes usually differ in the characteristic scales at which they operate. Spatial complexity resulting from the multi-scale issue lies in the following facts:

- Urban growth pattern, process and behaviour and their relationships are spatially varied with different scales;
- The relationships between scale and varied level of urban development planning and land management are still fathomless;
- The spatial framework supporting multi-scale modelling is impacted by numerous institutional factors, especially in developing countries.

In spatial science, structure is the physical arrangement of ecological, physical and social components, and function refers to the way the components interact. Urban growth involves both; structure is more linked with pattern and function rather than with process. The representation or semantics understanding of a spatial system is diverse. The spatial representation of structure and function may influence the spatial understanding of urban growth pattern and process. Its complexity lies in the following:

- The self-organised process of urban growth has complex spatial representation and understanding;
- The interaction between pattern and process is dynamic and non-linear.

(3) Temporal complexity

Urban growth means only increasing the number of new units transformed from non-urban resources. Urban growth is largely controlled or impacted by its economic development scale and environmental protection strategy. Or rather it is controlled by the systematic co-ordination between the three systems. For example, when system ***N*** is not influential and strong, more arable land might be encroached upon. Economic development is not predictive, in particular in the long term, due to numerous uncertain factors. The non-linear interactions between the three systems lead to a non-linear curve of urban growth. The non-linearity results in the fact that patterns, processes and behaviours of urban growth are temporally varied, i.e. temporal scale is a highly influential factor for understanding its dynamic process. In the longer term, urban growth might be considered uncertain and unpredictable or even chaotic. Urban systems are rather complicated and their exact evolution is unpredictable. It means its development process is sensitive to unknown initial conditions such as war, natural disaster, and new policies of the central government. These conditions are often not predictive, particularly in quantitative terms. If the system of interest is chaotic, prediction of the values of all system variables is possible only within a usually short time horizon, owing to limited information production.

The temporal scales of various decision-making are also different. Large-scale projects such as shopping centres or industrial parks frequently take a few years, much longer than small-scale constructions such as a shop. It is likely that various levels of actors have various temporal scales of decision-making behaviour. Local government needs to have a series of procedures, such as public participation or interviews with local people, to support their democratic decision-making. Individuals or households are able to make much quicker decisions as such a decision-making process is simple and the criteria for their decision objectives are also fewer.

From the perspective of urban planning and management, understanding the dynamic process of urban growth includes the temporal comparison in various periods. Such comparison enables planners to modify or update their planning schemes in order to adapt to the changing environment. However, the comparison is a subjective analysis depending on numerous fuzzy criteria. As a complex system, urban growth involves a certain degree of unpredictability, phases of rapid and surprising change, and the emergence of system-wide properties. Temporal complexity is specifically indicated as follows:

- Patterns, processes and behaviours of urban growth are temporally varied with scale;
- The dynamic process of urban growth is non-linear, stochastic or even chaotic in the longer term;
- Temporal comparison of urban growth is subjective and fuzzy.

(4) Decision-making complexity

Decision-making complexity is indicated in the unit and process of decision-making, and actors or decision-makers. The decision-making unit and process of large-scale projects are relatively more complicated than those of small-scale ones. They involve more actors or decision-makers. However, a small shop only needs the decision-making of one private developer. Large-scale projects are limited in quantity and their decision-making is more certain and well planned if compared with others. The latter are large in quantity and their decision-making is more uncertain, dynamic and less organised. However, the collective behaviours of small-scale projects can be emergent, which are controlled or guided by various management and urban development policies. From the perspective of self-organising theory, all of these small-scale and large-scale projects are spatially and temporally self-organised into an ordering system. The decision-making behaviours of different functions of projects are also disparate, e.g. commercial and residential. Remarkably, the differences are indicated in the various actors and the criteria for respective decision-making. Consequently, the decision-making for urban growth is a completely multi-agent, dynamic and stochastic system.

As discussed above, urban growth involves various levels and scales of decision-making, from individual land rent to a government's master plan. Each actor has a distinguishing domain of decision-making and profit pursuit, which are frequently in conflict. The interactions between these actors are spatially and temporally varied. This is a typical multi-agent system spanning broad spatial and temporal scales.

Understanding the dynamic process of urban growth must be based on the linkage with the decision-making process as the final users of modelling are the various levels of decision-makers. However, the interaction between these actors is in essence non-linear, dynamic, and self-organised. The ability to realistically represent the behaviour of the key actors depends on the level of aggregation at which actors and their behaviours will be represented in the model. Real decision-makers are a diffuse and often diversified group of people who will make a series of relevant decisions and trade-offs over a period of time. Their decisions will depend on a broad range of characteristics, such as site characteristics, locational conditions and legal constraints. Furthermore, in the real world the costs and benefits of alternative decisions are both distributed and valued differently among these decision-makers. In addition it is important to note that these actors also learn through time. Hence, the interaction between the spatial, temporal and decision-making processes is much more complicated. Summing up, decision-making complexity is specifically indicated as follows:

- Decision-making for urban growth is a multi-agent dynamic and stochastic system;
- Its spatial and temporal projection is a self-organised process;
- Decision-making behaviours are subjective and fuzzy.

3. COMPLEXITY MODELLING

This section is going to answer the fourth question: How can the complexity of urban growth be modelled (understood) and what are the strengths and weaknesses of each method from the perspective of complexity described above?

There are a number of ways of classifying the models regarding urban growth, such as in terms of system completeness, dimension, and objectives of analysis. Moving towards the general purpose of understanding the complexity of urban growth, we hereby attempt to classify them as cellular automata modelling, multi-agent modelling, spatial statistics, neural network modelling, fractal modelling etc., according to the methods available for modelling complexity and non-linearity.

3.1 CA-based modelling

As an effective bottom-up simulation tool, cellular automata (CA) first offer a new way of thinking for dynamic process modelling, and second provide a laboratory for testing the decision-making processes in complex spatial systems. CA represent a modelling approach quite different from top-down and macroscopic approaches.

The many applications of CA can be classified into three types: complexity and GIS theory, theoretically artificial urban study, and empirical case study. These researches have proved the great potential of CA for discovering the complexity (in particular spatial complexity) of urban system or its subsystems.

The first links CA with complexity and GIS theory, e.g. CA theory (Couclelis, 1997) and map dynamics (Takeyama and Couelelis, 1997). As regards the spatial complexity of the urban system, as Torrens and O'Sullivan (2001) argue, CA models have been used to explore the self-organising properties of urban systems and experiments with fractal geometry and feedback mechanisms. However, there remains room for connecting that work with studies in other disciplines. Indeed, many aspects of complexity studies remain relatively unexplored by urban CA. In GIS, they attempt to develop more advanced spatial analytical functions based on CA modelling or they try to expand CA from raster data structure to another format. This direction still shows an increasing trend.

The second links CA with theoretical urban studies, e.g. urban development pattern (Batty, 1998), self-organising competitive location theory (Benati, 1997), and urban socio-spatial segregation (Portugali et al., 1997). In these studies, transition rules are linked with any urban theories to test any theoretical hypothesis by using simulated or real data. Published literature has shown that this is a very promising direction, although little explored, which may bring new research means for developing and interpreting new urban theories. One of the manifold potential uses of CA in urban theoretical research is the generation of novel city-like phenomena from theoretically informed components (Torrens and O'Sullivan, 2001).

In the third class, CA works as a spatial decision support system for simulation, predication and planning based on any real case study areas. This is a category of practice-oriented research where data availability and quality largely affect the application of CA on various scales (regional, metropolitan and town). Examples include urban land use dynamics, the prediction of future urbanisation patterns, land development process simulation, urban form planning etc.

In these applications, classic CA have been modified to incorporate urban theories and the understanding of specific practical issues of the study area. These applications spanned various spatial and temporal scales. They have adequately shown that CA offers a flexible and advanced spatial modelling environment that has never been available before.

However, of the complexity of urban growth, first they principally touch on spatial and decision-making complexity, with little about temporal complexity. The former includes pattern-oriented growth simulation, such as shown Clarke and Gaydos (1998). The latter aims to aid the decision-making process of land conversion in urban growth (Wu, 1998) or to simulate the fuzzy behaviour of decision-making in agricultural land encroachment. Second, these applications focus on the simulation of spatial pattern rather than on the interpretation or understanding of the spatio-temporal process of urban growth. CA models are constrained by their simplicity, and their ability to represent real-world phenomena is often diluted by their abstract characteristics (Torrens and O'Sullivan, 2001). As a consequence, there are many tasks waiting for further exploration of urban growth complexity based on CA.

3.2 Agent-based modelling

Multi-agent (MA) systems are designed as a collection of interacting autonomous agents, each having their own capacities and goals that are situated in a common environment. This interaction might involve communication, i.e. the passing of information from one agent and environment to another.

From the perspective of modelling, the multi-agents also have attractive features (White and

Engelen, 2000): (1) as a tool to implement self-organising theory such as a straightforward way of representing spatial entities or actors having relatively complex properties or behaviours; (2) an easy way to capture directly the interactive properties of many natural and human systems, as well as the complex system behaviour that emerges from this interaction. Agent-based simulation is ideally suited to exploring the implications of non-linearity in system behaviour and also lends itself to models that are readily scalable in scope and level. The approach is useful for examining the relationship between micro-level behaviour and macro outcomes.

It is important to realise that agents are not necessarily either spatially located or aware. In many models, spatial mobility is not considered at all, although sometimes the term "space" appears as a metaphor for "social distance". The implications of the outcomes of such models for actual, physical spatial outcomes are not generally considered, because in most agent-based models the researchers' main concern is understanding how individual behaviour leads to global outcomes in a generic sense, rather than in the modelling of the real world per se.

Agent-based models of this kind have only recently made their appearance in the social sciences (Batty, 2002), largely due to advances in computation and data that enable individual objects or events to be simulated explicitly, and to date most applications have been to theoretical situations. For the urban system MA are excellent tools for representing mobile entities in urban environments, e.g. people, households, vehicles etc. They have been used in urban contexts to simulate pedestrian movement in dense urban environments and relocate householders (e.g. Benenson, 1998).

Benenson (1998) reported a multi-agent simulation model of the population dynamics in a city, in which inhabitants can change their residential behaviour depending on the properties of their neighbourhood, neighbours and the whole city. The agent in this model is characterised by its economic status and cultural identity and these two properties differ in nature. This model is based on an artificial city, which is used to test some urban theories such as social segregation. The most substantial application of agent-based models in the socio-economic domain is the monumental TranSims. TranSims is a hybrid, lying somewhere between more traditional transport gravitation-interaction models and a full-blown real-time agent-based simulation. It currently models the activities of up to 200,000 individual travellers, which is where the model departs from previous transport planning models (Haklay et al., 2001).

Consequently, current applications of MA mainly focus on abstracted theoretical research or micro-behaviour simulation. There is no report that MA are applied solely for understanding urban growth on a certain scale. However, it can be inferred that MA are an ideal tool for understanding decision-making complexity of urban growth at micro scale, such as a single large-scale project.

3.3 Spatial statistics modelling

Traditional statistic models, e.g. Markov chain analysis, multiple regression analysis, principal component analysis, factor analysis and logistic regression, have been very successful in interpreting socio-economic activities. Markov chain (Lopez et al., 2001), logistic regression (Wu and Yeh, 1997) have been reported as being widely used for modelling urban growth with varied strengths and weaknesses.

Lopez et al.(2001) report a model for predicting land cover and land use change in the urban fringe, a case study in Morelia city, Mexico. The authors conclude that the most powerful use of the Markov transition matrices seems to be at the descriptive rather than the predictive level. Linear regression between urban and population growth offered a more robust prediction of urban growth in Morelia.

Wu and Yeh (1997) apply logistic regression for modelling land development patterns in the two periods 1978-1987 and 1987-1992, based on a series of aerial photographs. They found that the major determinants of land development have changed significantly during the two periods. This demonstrates that various factors are changing their roles in the process of land development. This research has shown that logistic regression has a stronger capacity for interpreting urban development based on the probability of land conservation.

However, traditional statistics are criticised as being ineffective in modelling spatial and temporal data. A major reason is that spatial and temporal data often violate basic assumptions such as normal distribution, appropriate error structure of the variables, independence of variables, and model linearity. Two alternatives are frequently adopted. One is incorporating spatial sampling into traditional analysis. The other is developing new statistics based on spatial relationships such as spatial dependence and spatial heterogeneity. New methods for analysing spatial (and space-time) data include spatial data analysis, spatial econometrics, local spatial analysis and geographically weighted regression (GWR).

3.4 ANN-based modelling

The development of an artificial neural network (ANN) model requires the specification of a "network topology", learning paradigm and learning algorithm. Unlike the more commonly used analytical methods, the ANN is not dependent on particular functional relationships, makes no assumptions regarding the distributional properties of the data, and requires no a priori understanding of variable relationships. This independence makes the ANN a potentially powerful modelling tool for exploring non-linear complex problems (Olden and Jackson, 2001).

Shmueli (1998) used an ANN model to test whether or not there is a connection between socio-economic and demographic variables and travel activities. Rodrigue (1997) provided an overview of a parallel transportation/land use modelling environment and concluded that parallel distributed processing offers a new methodology to represent the relational structure between elements of a transportation/land use system and thus helps to model these systems. He also considered that sequential urban modelling does not represent complex urban dynamics well, and he proposed a parallel network (back-propagation algorithm) model to simulate the spatial process and spatial pattern of integrated transport/land use system.

In urban growth, Pijanowskia et al.(2002) integrated ANN and GIS to forecast land use change, where GIS is used to develop the spatial predictor variables. Four phases were followed in their research: (1) design of the network and of inputs from historical data; (2) network training using a subset of inputs; (3) testing the neural network using the full data set of the inputs; and (4) using the information from the neural network to forecast changes.

These applications have actually shown that ANN is an ideal method of understanding non-linear spatial patterns, on which short-term prediction may be based. However, the major drawbacks of ANN, including its black-box and static nature, result in a deficiency in modelling the urban growth process.

3.5 Fractal-based modelling

Fractals were originally used for natural objects such as coastlines, plants and clouds or illdefined mathematical and computer graphics. These are essentially spatial objects whose forms are irregular, scale-independent and self-similar. Recently, however, increasing analytical geographical analysis and analytical urban modelling have shown that planned and designed spatial objects such as urban forms and transportation networks can also be treated as fractals (Batty and Longley, 1994; Shen, 1997).

These studies have proposed that the complex spatial phenomena associated with actual urban systems are rather better described using fractal geometry consistent with growth dynamics in disordered media (Makse et al., 1998). Makse et al. (1998) proposed and tested a model that describes the morphology of cities, the scaling of the urban perimeter of individual cities, and the area distribution of city systems. The resulting growth morphology can be understood from the interactions among the constituent units forming an urban region, and can be modelled using a correlated percolation model in the presence of a gradient. Shen (1997) applied a box-counting fractal dimension to calculate the fractal dimension of 30 urban transportation networks and then further tested the relationship between the fractal dimension and urban population. It is thought that a comparison between the conventional density measures and the fractal dimension index would give more insight into the usefulness of fractal dimension in modelling urban form, growth and development. Road network density is closely tied to many other parameters of urban development, such as population, urban growth, land use etc. The fractal dimension of a transportation network may also be used as an indicator of the complexity of the network.

Diffusion limited aggregation (DLA), a physical model used to describe aggregation phenomena, has been applied to describe urban growth (Batty and Longley, 1994). The growth of an urban area simulated through DLA can generate a fractal structure similar to that of real cities. Makse et al.(1998) also propose a correlated percolation model which could predict the global properties (such as scaling behaviour) of urban morphologies. The model is better able to reproduce the observed morphology of cities and the area distribution of sub-clusters and can also describe urban growth dynamics. But this model studied the impact of urban policy on growth only from the perspective of interactions among dependent units of development.

A considerable number of studies report that fractal analysis can be applied for measuring the similarity between real and simulated spatial patterns created by cellular automata (Yeh and Li, 2001). But it should be noted that fractal measures of spatial complexity of urban spatial patterns are only difficult to interpret due to the fact that the same value of fractal dimension may represent different forms or structures. It is also limited in urban process modelling as the temporal dimension is not incorporated in modelling.

3.6 Chaotic and catastrophe modelling

Catastrophe theory and the theories of bifurcating dissipative structures attempt to model urban changes. But they have been pitched at the traditionally macro level and thus it has been hard to develop coherent explanations of the kind of changes emerging from the smallest scales which subsequently restructure the macro form of the system (Batty, 1998).

Chaos theory effectively means that unpredictable long-time behaviour arises in deterministic dynamic systems because of the sensitivity to initial conditions. For a dynamic system to be chaotic it must have a "large" set of initial conditions that are highly unstable. No matter how precisely you measure the initial conditions in these systems, your prediction of its subsequent motion goes radically wrong after a short time. The key to long-term unpredictability is a property known as sensitivity to initial conditions. A chaotic dynamic system indicates that minor changes can cause huge fluctuations. As a result, it is only possible to predict the short-term behaviour of a studied system, especially for socio-economic systems such as cities. Although, chaos theory is able to explain the complex temporal behaviour of urban growth from a theoretical research viewpoint, the temporal scale of data available from urban growth is too limited to uncover its long-term behaviour.

Self-organised criticality (SOC) is a universal phenomenon occurring across a broad range of disciplines. It is thus a powerful interdisciplinary approach for understanding system complexity in a more general framework. Batty (1998) fundamentally applied the concept of SOC to explain the temporal urban development pattern by using the cellular automata technique. He suggested that real cities in their evolution over time display this characteristic, which has not yet been tested in his research. Wu (1999) modified a simple sand-pile model from SOC theory to explain the urban development process resulting from real estate investment through cellular automata simulation.

4. EVALUATION OF MODELLING

4.1 Review of urban modelling history

Planning is a future-oriented activity, strongly conditioned by the past and present. Planners have always sought tools to enhance their analytical, problem-solving and decision-making capabilities. Consequently, urban modelling should be able to assist planners in looking to the future. It should facilitate scenario building and provide an important aid to future-directed decision-making.

Urban modelling bloomed in the late 1950s and throughout the 1960s in both the USA and Western European countries. However, with the massive transformation from an industrial to an informational economy, urban modelling gradually faded away as a dominant planning and decision-making paradigm in the late 1970s and through most of the 1980s (Sui, 1998). Modelling techniques in the 1960s and till the 1980s were dominated by a-spatial, static, linear, cross-sectional, deterministic approaches, such as regression analysis, mathematical programming, input-output analysis and even system dynamics. However, they have proved inadequate to reflect the complex, dynamic and non-linear factors inherent in urban systems or subsystems (Sui, 1998). Consequently, a new challenge requires that a focus of modern urban modelling be shifted from macro to micro, from aggregate to disaggregate, from static to dynamic, from linear to non-linear, from top-down to bottom-up, from structure to process, from space to space-time, due to the unpredictability, instability, uncomputability, irreducibility and emergence that exists in the process of urban evolution. The time and space dimensions need to be incorporated into the urban modelling process by further integrating with GIS and complexity and non-linearity theories.

4.2 Criteria of evaluation

A major distinction among methods can be drawn on the basis of their purpose and the objective of their study. Purpose can be descriptive, explanatory, predictive, prescriptive. The major criteria for evaluating the operation of various methods are data, linkage with GIS, and interpretability.

(1) Data requirement

Aided by new spatial data capture technologies such as very high-resolution remote sensing satellites and global positioning systems (GPS), relatively accurate and comprehensive digital data sets of metropolitan areas collected and maintained by public agencies are now becoming widely available (Longley, 1998). Remote sensing potentially provides a strong data-source framework within which to monitor change and understand urban growth, e.g. frequently used Landsat TM, SPOT, IRS and even IKONOS imagery. Nevertheless, it is well known that classified urban land cover does not bear a spectrally identifiable correspondence with urban land use as urban land use is defined by a social purpose and not a set of physical quantities. Remote sensing data are useful for providing outline descriptions of urban form but are less helpful in understanding the functional characteristics of urban growth.

Spatially and temporally explicit models at fine levels of spatial and temporal resolution – the individual parcel level – are increasingly being developed as the required computational and technological infrastructure improves continuously and as data at this level become available. However, in the developing world, poor data infrastructure has been a major barrier in implementing some advanced methods of modelling. Socio-economic attributes based on various levels of spatial statistical units and parcel-based land ownership are still not available or accessible to the modelling community. Our inability to monitor land cover changes in a consistent way over the long term also seriously limits our capacity to understand the driving forces and processes controlling these changes.

As illustrated in figure 1, understanding urban growth involves pattern, process and behaviour. However, current data infrastructure only offers pattern and partial process with spatial data at limited spatial and temporal scales. Consequently, urban growth modelling remains dominated by macro spatial models (pattern and process); the spatial behaviours linked with micro-scale functional data and temporal complexity based on higher temporal resolution data are still in the state of theoretical research. This situation is even worse in the developing world. Fractal, CA, ANN and logistic regression have widely utilised remote sensing imagery as the input to their modelling.

(2) Linkage with GIS

It has been proved that GIS could provide limited decision-making only at data level, due to insufficient spatial modelling functions. The inability to incorporate urban models and to more directly support the decision- and policy-making processes are two main deficiencies of the current geo-spatial technologies and tools. The integration of both did not take place until the late 1980s. GIS could provide the urban modeller with new platforms for data management, spatial analysis and visualisation. Loose, close and tight coupling strategies are frequently adopted. At present, ANN and CA have been integrated into GIS such as the ArcView extension (spatial modeller: ANN, fuzzy logic and logistic regression) and IDRISI (CA). Open source software development is becoming popular, such as UrbanSim, which has a free environment for users to develop or modify their own models. Such progress has opened up more opportunities for the applications of these advanced methods of modelling.

(3) Interpretability

Urban growth modelling aims to understand the dynamic and non-linear processes, and therefore the capacity of interpretation is becoming crucial.

Compared with logistic regression, the Markov chain model lacks explanatory power as the causal relationships underlying the transition studies are left unexplored. Transition probabilities are estimated as proportions of cells that have changed state from one point in time to another. This approach appears to remain the handiest way of estimating these probabilities despite the development of procedures for estimating transition probabilities on the basis of more complex scientific consideration.

ANNs exhibit greater predictive and non-linear power than traditional approaches do. However, its property of "black box" provides little explanatory insight into the relative influence of the independent variables in the prediction process. The lack of explanatory power is a major concern in spatial pattern analysis because the interpretation of statistical models is desirable for gaining knowledge of the causal factors driving spatial phenomena. Traditional statistical approaches can readily identify the influence of the independent variables in the modelling process and also provide a degree of confidence regarding their contribution.

Olden and Jackson (2001) concluded that where the underlying data structure and assumptions are met for a particular traditional statistical technique, there is no reason to believe that major differences will exist between traditional approaches and ANNs. However, ANNs were shown to be superior to regression approaches for non-linearly distributed data.

The cellular automata (CA) and multi-agent (MA) approaches overlap to some degree; CA is sometimes considered to be a type of multi-agent system White and Engelen (2000). Comparatively, CA focuses on a smaller scale such as city level or regional level. In contrast, MA is only applied on a much larger scale, such as household and family. The MA approach deals with decisions posed to people more frequently. CA models focus on landscapes and transitions, agent-based models focus on human actions. CA are most suitable in urban simulation contexts for representing infrastructure. MA are better used to model population dynamics.

MA differ from CA in their spatial mobility: agents can be designed to navigate (virtual) spaces with movement patterns that mimic those of humans, while CA are only capable of exchanging data spatially with their neighbourhoods. Additionally, agents can be given functionality that allows them to evolve over time, altering their attributes and behaviour with the help of artificial intelligence. Comparatively, MA are based more on abstract cellular space as micro data are difficult to access. However, MA applications to urban studies have not been as widespread as those of CA, despite offering the advantages for urban simulation.

5. CONCLUSIONS

From the literature and the evaluation above, it can be seen that some methods are still in the theoretical stage or applied for artificial city analysis, and need very good data infrastructure. Some methods are more effective on macro scale than on micro scale. Each method has its strengths and weaknesses, and respective data requirements and application domains. The selection of methods should depend on the demands of the analysis, the feasibility of the techniques and the availability or limitation of the data framework.

First, as discussed above, urban growth involves three different systems ***P***, ***N***, ***U***. To model their dynamic interactions at varied spatial and temporal scales, current methods of modelling are not adequate to understand all the complexity inherent in urban growth described in the previous sections. Hence, only limited complex phenomena can be modelled.

Second, physical data are becoming more readily available, particularly on the macro-scale now, due to the low price of satellite imagery in recent years. On this macro-scale, socio-economic data are much easier to access as aggregated data are based on annual statistics. This results in the fact that urban growth modelling focuses mainly on spatial complexity understanding such as CA-based dynamic simulation, ANN-based pattern analysis and fractal-based morphology analysis. The difficulty in accessing micro-scale socio-economic data and higher-resolution (spatial and temporal) data limits the understanding of temporal and decision-making complexity in urban growth. Chaos theory and the MA model have not been widely applied for planning practice. The theoretical experiment based on artificial cities is also a feasible modelling means (Batty, 1998). The poor capacity of interpretation of most models (such as CA, fractal and ANN) results in the fact that they are less selected for practical applications than traditional or spatial statistics such as logistic regression.

Summing up, these advanced methods provide great potentials for understanding urban growth complexity. However, they still have a long way to go as limited by data infrastructure and also by their own drawbacks. Being a theoretical exploration, the simulation based on artificial cities is an attractive means.

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