Modelling Spatial & Temporal Urban Growth

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Modelling Spatial and Temporal Urban Growth
Modelleren van ruimtelijke en temporele stedelijke groei
城市扩张的时空建模

Doctoral Dissertation (2003)

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To my late mother and father
&
To my wife and daughter

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Chapter 1

Introduction

This research focuses on improving modelling methods and techniques to analyse urban growth as a complex phenomenon. The broader concept of urban development implies changes, growth or decline. The term includes the physical, socio-economic and environmental dimensions. Physically and functionally, urban development includes both new development and urban redevelopment. In contrast to decline, growth involves the transition into urban of non-urban activities and spaces. The physical aspects of urban growth are related to land cover, the functional to land use. Hence, temporal and spatial urban growth indicates the spatial and temporal dimensions of land cover/land use change at the level of the urban landscape.

The aim of modelling is to abstract and represent the entity being studied. Modelling can be conceptual, symbolic or mathematical, depending on the purposes of the specific application. In the domain of urban planning, modelling can be utilised for analysing, evaluating, forecasting and simulating urban systems to support decision-making. From the perspective of spatial science, modelling must take both the spatial and temporal dimensions of urban systems into account.

1.1 Relevance

1.1.1 Societal relevance

Spurred by economic development and the space technologies revolution (transport, communication and information), rapid urban growth and restructuring are expected over the next 10 to 20 years (Masser and Ottens, 1999). This will be characterised by urban redevelopment in the city centre, suburban expansion with new sub-centres, and leapfrog urban sprawl.

Urban growth has two contradictory facets. On the one hand, mega-cities act as engines of economic and social growth; on the other, most of this is being accompanied by both poverty and environmental degradation, e.g. encroachment on valuable agricultural land, increasing use of the private car and energy consumption, inner-city decline, premature write-down and under-utilisation of the existing built environment. The impacts of land use changes on environmental sustainability will become globally significant through their cumulative effects. This is considered to be one of the major global change issues (Vitousek, 1994).

Faced with the severe negative impacts, urban planners need to rethink the most important development policies and manage urban sprawl and urban growth more scientifically in the future. For instance, in the USA, urban sprawl has sparked off a national debate over land use policy that includes smart growth management and growth boundary measures (Brueckner, 2000).

In developing countries such as India (Thangavel, 2000) and China (Yeh and Li, 2001b), patterns of urban growth (compact or sprawling) have been studied in the context of their special social and economic circumstances. There is no universal solution. However, it is recognised that scientific management and planning should be based on a proper understanding of the spatial and temporal processes of urban growth. This is the major objective of modelling spatial and temporal urban growth.

1.1.2 Scientific relevance

Theoretically, urban growth modelling should be considered as an interdisciplinary field as it involves numerous scientific and technical areas, e.g. geographical information science (GIS), remote sensing (RS), urban geography, complexity theory, land use/cover modelling etc. Understanding urban growth and applying this knowledge for planning are both closely linked with these areas. Hence, a systematic and "holistic" perspective should be adopted in the process of modelling.

(1) Complexity

Complexity theory has become a hot topic across all scientific disciplines, especially in the 21st century (Batty and Torrens, 2001). Its overall objective is to define some general properties of the complex systems involved. It is applied in various disciplines and findings are exchanged. Its progress can provide many disciplines with philosophically innovative ideas, but it also needs new research, development and application. There is a growing body of literature that views the city as a complex system (Allen, 1997a; Batty and Longley, 1994; Portugali and Benenson, 1995).

Urban growth is in essence a complex subsystem; it involves multiple actors with differing patterns of behaviour at various spatial and temporal scales. It centres on understanding the dynamic interactions between the socio-economic and built environments and major natural environmental impacts. Complexity in the domain of urban growth can be divided into such classes as spatial, temporal and decision-making processes (as described in chapter 2 of this dissertation). Because of their size of operation, complex systems are difficult to understand without building models. Modelling spatial and temporal urban growth helps to identify the complexity hidden in its processes and provides urban development planning and land management with new theoretical concepts and methods.

(2) Land use change modelling

Under the umbrella of sustainable development (e.g. the International Geosphere-Biosphere Programme (IGBP), the International Human Dimensions Programme on Global

Environmental Change (IHDP) and NASA's Land Cover and Land Use Change Program), land use/cover change (LUCC) has attracted a great deal of attention. It spans the global, national, regional and local levels and is interdisciplinary in nature, with agricultural, ecological, landscape, forest and urban sub-themes. This research considers the complex interactions between land use/cover change and other systems, such as the impacts of change on ecological systems and vice versa. A systematic understanding of land use/cover change needs individual cases at different geographical levels and from a range of disciplines. Urban growth results from the transition from non-urban into urban land uses, both physically and functionally. In this land use/cover change, the human dimension is important. The outcome is a result of the interaction between natural and human systems. Land use/cover modelling aims at quantitatively specifying the mechanisms of the physical and functional transitions of the land system and interprets the causal effects hidden in its processes (Agarwal et al., 2000). Modelling spatial and temporal urban growth is a way of exploring the spatial and temporal patterns and processes of land use/cover transition at the level of urban landscape. They are able to provide quantitative evidence to aid decision-making in urban planning and sustainable land management.

(3) Geographical information science

Urban growth remains a major topic concerning GIS and remote sensing applications. Remote sensing and GIS have proved to be effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Masser, 2001). GIS has gradually shifted its emphasis from system-oriented to science-oriented (e.g. International Journal of Geographical Information Science). Apart from key techniques, GIS needs to incorporate broader and more fundamental scientific concepts in order to better understand geographical phenomena such as process, pattern, heterogeneity, scale etc. Urban growth is the projection of political, social and economic activities onto a land system at the level of the urban area. The spatial and temporal dimensions are major concerns of GIS and remote sensing. Modelling spatial and temporal urban growth enriches the spatial science of GIS. Methodological research into urban growth can contribute to improving current GIS, in particular its spatial analysis and modelling functions such as exploratory spatial data analysis and spatial econometrics (Goodchild, 2000).

(4) Urban geography

Urban geography is a branch of geographical science focusing on the urban context. Urban growth is one of its major concerns. Urban growth is not a universal process with similar attributes in all world regions but a set of complex phenomena conditioned by various cultural and historical forces in different places (Laurence and Edward, 1981). Systematic research on specific cases can be beneficial to local planning systems. Comparative studies are useful for better understanding differences and similarities. Empirical studies are a prerequisite for forming and confirming the theories of urban geography. Urban modelling, as a tool to quantify and analyse urban phenomena and issues, is an important methodology in urban geography as well. Progress in urban modelling is impacting on and has been impacted by the changes in society. When entering the information society, new opportunities and challenges coexist for urban modelling. New opportunities come from the advances in complexity science, computer techniques, remote sensing and GIS. New challenges originate from the emerging world economy and information society that are leading to the restructuring of urban economies. Systematic research on macro socio-economic processes and urban consequences will improve our insights into the new urban geography.

1.1.3 Practical relevance

Since 1949, Chinese cities have undergone two waves of urban growth, the first spurred by the rapid industrialisation from 1953 to 1965 and the second stimulated by land reform from 1987 onwards (chapter 3). Rapid spatial expansion has caused China's cultivated land per capita to decrease significantly from 1800 m^2 in 1949 to 1133 m^2 in 1995 (Zhang, 2000a). The massive loss of agricultural land has evoked the awareness of the central government. The phenomenon threatens its sustainable development strategy. In 1997, a country-wide project under the auspices of the China State Land Administration was implemented to monitor the dynamics of urban expansion in 100 municipalities. Landsat Thematic Mapper (TM) images acquired for 1989/1992 and 1996/1997 were used to examine the scope and the speed of urban expansion in this period (Ji et al., 2001). It can be predicted that an urgent follow-up task will be to model urban expansion for the purpose of decision-making in planning and management at various levels of government, based on the outcome of the monitoring exercise.

Urban sprawl (spreading urban growth) has become a hot topic in the urban planning and management practices of many countries in both the developed and the developing world. Individual case studies and further comparative research can be helpful in the sharing of experiences and lessons.

1.2 Research Questions

As described above, modelling spatial and temporal urban growth is at the intersection of such fields as complexity, land use/cover change, GIS/remote sensing and urban geography. It needs the inputs of new concepts, new methods and new techniques from these fields. Innovative scientific progress requires a multidisciplinary framework to integrate various lines of research and development. When looking at the development history of urban modelling, each progressive step was closely linked to those of other disciplines, in particular systems science, computer science and quantitative techniques (e.g. remote sensing and GIS) (details in chapter 2). Understanding urban systems is the first step to guaranteeing the success of modelling (Batty and Torrens, 2001; Cheng and Yang, 1998). Further, advanced modelling needs the physical support of computation power and case studies with sufficient data. With the rapid progress made in computer techniques and remote sensing, computation and data availability have proved to be less of a barrier for modelling that is focused on the spatial and temporal dimensions. Consequently, a major problem is how to (theoretically and methodologically) understand the complexity inherent in urban systems and their subsystems for the purpose of decision support.

1.2.1 Complexity modelling

Complexity theory is promising and actively pursued in academic circles, but is still quite new and insufficiently linked with reality and practice. The research line was initiated in logical and natural sciences such as mathematics, physics, chemistry and ecology. Currently, it gradually diffuses to the social sciences. As a pioneering research community, the famous Santa Fe Institute has published numerous papers exploring the applications of complexity in social sciences. Human geography, with a focus on the interaction between natural and human systems, has seen an increase in complexity analyses. The concepts in complexity theory have been widely employed for systematic thinking about complex geographical phenomena such as self-organisation, emergence, hierarchy, scale etc. Further, many modern methods for modelling complexity have been explored, e.g. fractals, chaos, self-organisation, fuzzy logic, cellular automata etc. (see details in chapter 2). However, urban growth research, a sub-field of urban geography, has not yet paid enough systematic attention to complexity. Batty and Longley (1994) reported a preliminary exploration of fractal methods for modelling the scale independence and spatial irregularity of urban growth. This research was detailed and expanded later by other scholars (Frankhauser, 2000; Makse et al., 1998; Shen, 2002a). Currently, numerous publications are reporting on the methodology of using cellular automata and multi-agent approaches to model urban growth patterns and processes (Benenson, 1998; Clarke and Gaydos, 1998; Li and Yeh, 2002; Ward et al., 2000a; Wu, 1998d). These studies show that modelling complexity is highly valuable in offering innovative thinking and methods for understanding urban growth. However, they are still insufficient when it comes to fully understanding and modelling the complexity inherent in urban growth. First, the complexity of the urban growth system is not clearly explained from the perspective of either system science or geographical science. Second, the methods of modelling need further extension and modification as required by practical urban planning. Consequently, among the major research questions are:

- What is the specific complexity of spatial and temporal urban growth?
- What are the strengths and weaknesses of modern methods in complexity understanding when applied to the urban growth system?
- How should appropriate methods for a specific case be selected and implemented?

These questions will be addressed in this study. In terms of systems science, urban growth is defined as a complex system; its complexity is elaborated in chapter 2. However, constrained by available data sources, only some aspects can be modelled in this research. The focus will be on structural and functional complexity, temporal complexity in comparative measurement, spatial complexity in patterns, and complexity in processes.

1.2.2 The spatial and temporal measurement of urban growth

Disorderly urban sprawl has been widely criticised in both developed and developing countries. The scientific planning and the management of urban growth need the quantitative measurement of growth patterns. With the progress of modern remote sensing techniques, earth-observation-based monitoring of urban growth has been widely accepted and implemented by national, regional and local governments (Chen et al., 2000; Quarmby and Cushnie, 1989; Ward et al., 2000b; Ji et al., 2001) because it is the prerequisite for comparing spatial and temporal change patterns. This change analysis can be performed with multi-temporal and multi-source imagery. Various methods have been put forward in recent literature (I-Shian, 1998; Shou, 2000; Yeh and Li, 2001b). These methods include spatial, statistical, economic and integrated indicators, often in a comparative analysis setting (details in chapter 4). However, few methods touch on the comparison of temporal growth patterns for one city. Here, the challenge can be stated in the following research questions:

- What is the proper definition of urban sprawl, in particular from the spatial perspective?
- How can temporal urban sprawl be measured?

1.2.3 Spatial and temporal pattern modelling

The concept of pattern has special definitions in different disciplines. In geographical terms, pattern refers to a "regular arrangement or logic ordering of objects in geo-space", the manner in which a phenomenon is distributed in time and space (see details in chapter 2). Space logic is called spatial pattern. In addition, a temporal pattern can be defined for changes over time (time logic). Various types of patterns have been studied in urban analysis, such as residential or settlement patterns (I-Shian, 1998), population and employment patterns (Ingram, 1998), land development patterns (Wu and Yeh, 1997), land use change patterns (Kiril, 1998; Yeh and Li, 1998), and transport/land use interaction patterns (Jun, 1999). These studies focus on the spatial patterns of physical and functional objects. Interpretation of both spatial patterns and their complexity in urban growth is still deficient, especially from an urban planning point of view. Recently, multi-scale analysis has attracted more and more attention in pattern modelling (e.g. Kok and Veldkamp, 2001; Stein et al., 2001; Walsh and Crawford, 2001). The concept "scale" is mainly interpreted as spatial extent and resolution, which is linked with hierarchy theory. Such a classification can facilitate a more detailed spatial data analysis. However, employing such different scales does not generally provide more powerful explanations of the patterns being modelled. Or rather, it only provides the same level of information for planning and management purposes. The multi-scale issue should be re-interpreted by linking it to planning rather than to data (details in chapter 5). The relevant questions include:

- What is the definition of multi-scale in the context of urban growth planning and management?
- How can spatial and temporal patterns of urban growth be modelled in a multi-scale framework?
- What are the spatial and temporal determinants of urban growth on the multiple scales?

1.2.4 Spatial and temporal process modelling

In the context of urban studies, process refers to the sequence of changes in space and time; the former is called a spatial process, the latter a temporal process (see details in chapter 2). It should be noted that strictly speaking spatial and temporal processes can not be separated in reality, as all geographical phenomena are bound to have a spatial and a temporal dimension. The process defined here does not include social and economic processes, which are the major driving forces of urban growth at macro scales. In recent literature it is stated that the urban development process is self-organising, stochastic, catastrophic and chaotic (see details in chapter 2), referring to the underlying mechanisms resulting in the complexity of the urban growth process. Therefore, a number of methods – self-organising, stochastic, catastrophic, chaotic and the mixed perspective respectively – have been explored and applied for process modelling. Examples include Markov chain stochastic modelling in land use/cover change (Petit et al., 2001; Weng, 2002), cellular automata modelling in the land development process (Wu and Webster, 1998; Li and Yeh, 2000), chaotic process modelling in rainfall-runoff (Sivakumar et al., 2001), and multi-agent modelling in residential dynamics (Benenson, 1998). Modelling processes, especially temporal processes, is much more difficult than modelling static patterns, as the modeller needs to consider dynamic interactions in space and time. The methods currently available can only model and interpret parts of spatial and temporal processes on varied scales, but many factors are still not incorporated, especially those dealing with complex dynamics. Moreover, most methods are not sufficiently linked with decision-making processes in urban development and planning – although this linkage should be the ultimate objective of modelling. Most authors focus on improving computational or mathematical algorithms from a primarily modelling point of view. Another major problem is the rudimentary or simplistic incorporation of the temporal component. This affects the comprehensive understanding of dynamic processes. Consequently, the major questions can be summarised as:

- How can urban growth process be conceptually understood?
- How can process modelling be linked with decision-making processes in urban planning?
- How can temporal processes be incorporated into modelling?

1.2.5 The transformation of Chinese cities

The transition of the economic system of Chinese cities has brought about major transformations in the physical and functional urban structures over the last five decades.

This transformation requires that the urban planning system be modified from a centrally planned economy to a transitional economy (Yeh and Wu, 1999) based on a sound understanding of the urban development process of Chinese cities. Previous studies regarding Chinese cities mostly concentrated on political, social and economic processes (see details in chapter 3). The studies on spatial patterns and processes were initiated in the period after the 1980s and focused on economically developed regions such as Shanghai, Beijing, Guangzhou and Shengzhen. Case studies of other cities are very rare and systematic research over longer periods is completely lacking. The empirical investigation of Wuhan city in this research will explore the following questions:

- How can the urban growth of Wuhan in the past five decades be evaluated?
- What are the spatial and temporal patterns and processes of Wuhan?
- How does the Wuhan case relate to other Chinese cities?

1.3 Research Objectives

Summing up, the general research question is: Where, when and how did the urban growth occur? This results in a focus on spatial, temporal and decision-making processes in this study.

The general objective of this research is to develop a theoretical framework and methodology for modelling spatial and temporal urban growth, in order to better understand the complexity inherent in urban growth systems and to generate and improve relevant knowledge for local urban planning. Five research objectives can be specified:

- Analysis of the complexity of the urban growth system and evaluation of the current methods available for modelling this complexity;
- Monitoring urban growth of a fast growing city in the developing world, based on remotely sensed imagery, and using modelling to evaluate its structural and functional changes;
- Development and demonstration of a quantitative method for comparative measurement of long-term temporal urban growth;
- Development and demonstration of an interpretable method for urban growth pattern modelling;
- Development and demonstration of a spatially and temporally explicit method for understanding the urban growth process.

Due to the limited data and time available, methodological exploration forms the major focus of this research. A case study of Wuhan city in P.R. China is selected for testing the methodology to be developed. Methodology development is concentrated on each of the four specific complexity issues described above. System-level modelling (see chapter 7) is not the aim.

In this research, urban growth is defined as physical and functional changes due to the transition of non-urban to urban land. Urban land use restructuring or urban redevelopment is not the concern of the research. Moreover, owing to the unavailability of three-dimensional data this research only focuses on the horizontal dimension. The driving forces of urban growth originate from political and socio-economic processes, which are important for qualitative analyses of cause-effects at macro scale but are beyond the scope of this thesis. Ideally, process modelling should seek to predict or simulate future development. However, prediction is based on understanding. The focus of this study is on understanding urban growth. The impacts of urban growth on local ecological systems are not included in this research.

1.4 Methodology

This research is primarily methodological and theoretical in nature. The methodology is highly dependent on the concepts used, the methods selected and the data available. Concepts must be based on an understanding of the complexity of urban growth and the information requirement of urban development planning. The selected methods should be based on an evaluation of the techniques available in both complexity modelling and spatial analysis of GIS. This needs extensive literature review and the development of evaluation criteria for the selection of methods. Complexity study is much more successful, relatively speaking, in the areas of natural science, especially ecology. Perhaps the most promising approach has been the application of systems theory and ecological theory to the analysis of urban evolution and flows of material through the urban environment (Kropp, 1998). New concepts and techniques applied in urban modelling mark a dramatic shift from conceiving cities based on predominantly physical metaphors as machines for conceptualising cities to using biological metaphors for organisms (Sui, 1998).

As such, similar concepts can be borrowed from other relevant research areas such as landscape ecology. Data must be collected from primary and secondary sources. Aerial photography and SPOT imagery are the major primary sources in this research. Fieldwork and to an extent interviews for key information are also used to capture local knowledge. The flowchart displayed in figure 1.1 summarises the seven chapters that make up this study and their relationships.

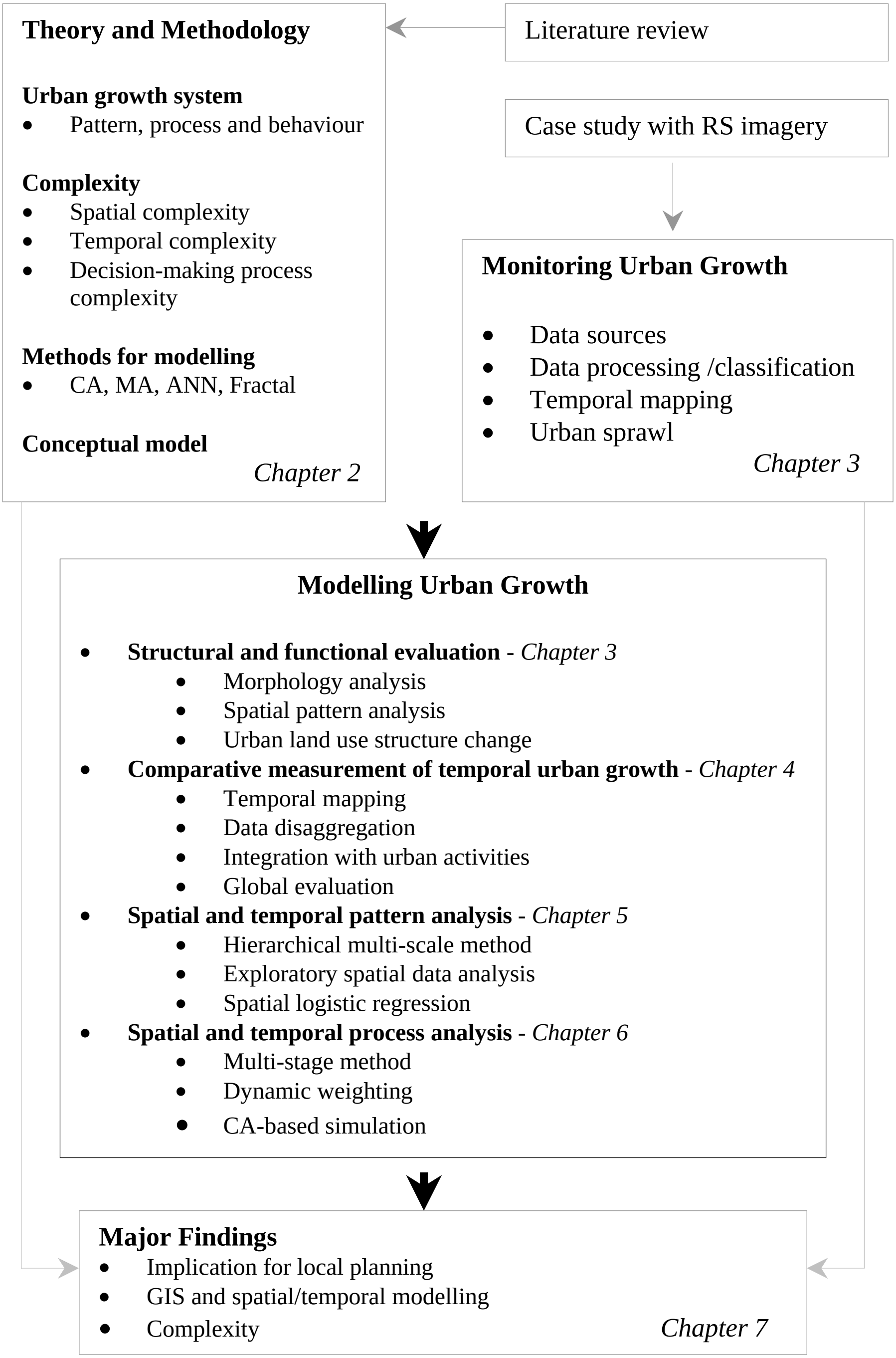

Figure 1.1 Flowchart of the research

1.5 Thesis Structure

The research comprises theory, methodology and application, which correspond to the three major sections of the thesis. Chapter 2 offers the theoretical framework for modelling. Chapter 3 deals with the data and modelling requirements for the case study area. As the core of this research, chapters 3 to 6 present four methods that are tested in pilot applications.

Chapter 1 provides a general overview of the research. This includes its relevance, the questions that are addressed, its research objectives and scope, and its methodology.

Chapter 2 provides the theoretical and methodological discussions that are relevant to this research. The theoretical section is dominated by the analysis of the urban growth system and its complexity; the former includes pattern, process and behaviour, the latter is divided into spatial, temporal and decision-making processes. The concepts of scale, hierarchy, heterogeneity, self-organisation, emergence etc. are elaborated in this discussion. Next, currently prevalent methods of modelling, such as neural networks, multi-agent, spatial statistics, fractals and cellular automata, are evaluated based on the operational criteria, e.g. data availability, interpretability and GIS linkage. This evaluation results in a conceptual model for the next four chapters.

Chapter 3 systematically monitors and evaluates the spatial and temporal urban growth of Wuhan city in P.R. China during the last five decades, using aerial photography and satellite images as the primary data sources. This chapter aims to improve local knowledge of urban growth in order to produce the data framework for the modelling exercise, and also to develop methods for modelling structural and functional complexity. After an introduction to urban development policies and urban master planning since 1949, urban growth patterns, including road networks and centres/sub-centres of Wuhan, are mapped for 1955, 1965, 1986, 1993 and 2000 and interpreted. Following this, the spatial and temporal patterns are quantitatively evaluated from the perspectives of annual growth rate, urban morphology, spatial pattern, master plan and land use structure change. The evaluation makes it possible to compare the Wuhan case with other Chinese cities for the purpose of identifying similarity and disparity. This chapter ends by identifying further modelling requirements, which is the starting point for the following three chapters.

Chapter 4 theoretically discusses the relevant definitions of urban sprawl and explicitly develops a method for comparatively measuring temporal urban growth. Incomparability of temporal measurement is one type of temporal complexity. We argue that urban sprawl is just a matter of relative degree and absolute space is not an adequate approach in temporal measurement. This chapter presents an innovative and interpretative method to integrate the physical aspect of urban growth with the socio-economic information of built-up areas, based on the concept of relative space. The method comprises four steps: temporalmapping, data disaggregation of socio-economic activities, integration based on spatial gravity, and global evaluation. In a case study of Wuhan city, this method is used to analyse urban sprawl in the periods 1955-1965 and 1993-2000.

Chapter 5 presents a preliminary multi-scale framework for spatial pattern modelling based on spatial hierarchy theory. This framework starts with a hierarchical conceptual model, which aims at theoretically linking planning hierarchy, analysis hierarchy and data hierarchy. Analysis hierarchy is the focus of this research, which addresses three scales: probability of change (macro), density of change (meso) and intensity of change (micro). The multi-scale analysis perspective seeks to distinguish spatial determinants on two different scales, which can provide deeper insights into urban growth patterns. Also a method is presented to implement the framework, based on the integration of exploratory data analysis and spatial logistic regression. This combination has served to improve interpretation. This framework is tested by analysing the urban growth of Wuhan city in the period 1993-2000. The scale-dependent and scale-independent determinants are found significant on two scales.

Chapter 6 presents an innovative methodology to understand spatial processes and their temporal dynamics on two interrelated scales (municipality and project), using a multi-stage framework and dynamic weighting concept. The multi-stage framework aims to model local spatial processes and global temporal dynamics by incorporating explicit decision-making processes. It is divided into four stages: project planning, site selection, local growth and temporal control. These four steps represent the interactions between top-down and bottom-up decision-making involved in land development for large-scale projects. Project-based cellular automata modelling is developed for interpreting the spatial and temporal logic between various projects forming the whole urban growth. Dynamic weighting attempts to model local temporal dynamics at the project level as an extension of the local growth stage. The methodology is tested with reference to the urban growth of Wuhan city, from 1993 to 2000.

Chapter 7 evaluates the findings of the study with reference to the research objectives set out above and offers discussion and suggestions for further research.

Chapter 2*

Understanding the Urban Growth System

Abstract

The rapid urbanisation and urban sprawl in particular in the developing world require a scientific understanding of complex urban growth patterns and processes. This knowledge is highly crucial to sustainable land management and urban development planning. Progress in modern remote sensing and GIS techniques has opened up great opportunities, and significant success has already been achieved in monitoring and managing fast urban growth. However, these techniques are still poor when it comes to supporting decision-making on sustainable development, as reasonable theories and methods have not been sufficiently and systematically developed to understand the complexity inherent in urban growth. 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 chapter 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 chapter 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 chapter evaluates the operational implementation of representative methods based on criteria such as interpretability, data need and GIS embeddedness.

Key words: understanding, urban growth, complexity, modelling, methods

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∗ Based on Cheng et al. (2003a) and Cheng et al. (2003b).

2.1 Introduction

Geography is not about collecting facts, expressed as a proposition in logic, but about understanding the causes – the processes in space and time which created these facts (Frank, 2000). The process is typically represented by the complex interactions between humanity and nature. Traditional differential equations were the only well-known formalism to describe processes that affect change in time and space (Frank, 2000). However, this method is only suitable for physical geography and not appropriate for topics from human geography. The latter has properties that distinguish it completely from the former. The importance of human geography is strongly linked with the risks of human decision-making at varied spatial and temporal scales. Over the last 20 years, complexity issues have deeply affected modelling approaches in geography (Occel, 2002).

In the field of urban planning, one of the important subjects of concern is to predict the trend of land use transition (Osaragi and Kurisaki, 2000). However, prediction without a scientific understanding of the system under study implies a certain degree of uncertainty due to the numerous unknown factors involved. This may result in risky decision-making in urban development planning and management. Wrong decision-making may cause severe economic and environmental losses, or even lead to large disasters. As a consequence, scientific decision-making has been the pursuit of urban development planning and management that is highly dependent on the reasonable understanding of the objects involved. Understanding needs modelling to analyse the complex relationships involved in the decision-making; it also needs an understanding of the properties of the problems being studied.

To date, quite a number of models have been developed and applied in wide scientific areas. But most of them have been criticised. 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.

Looking through the history of modelling, it is quite clear that its progress is dependent on the advances in other areas such as system sciences (including mathematics, physics and chemistry), computer science and techniques, and various application domains. Progress in system sciences and computer science has brought about a new revolution in quantitative geography. The "quantitative revolution" in economics, geography and the social sciences reached the planning profession in 1960s (Wegener, 2001). The emergence of "the old three system theories" (general system theory, information theory and cybernetics) and computer techniques in the 1940s spurred the first modelling revolution, which is based on structural linear equations but is not spatially explicit. Famous paradigms include the Lowry urban development model (Lowry, 1964), the spatial interaction model (Wilson, 1970) and the input-output model (Leontief, 1970). 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 (Wu and David, 2002). 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.

We argue that scientific understanding must be based on complexity theory and a multidisciplinary framework. In the field of urban analysis and modelling, perhaps the most promising approach has been the application of systems theory and ecological theory to the analysis of urban evolution and the flows of materials through the urban environment (Kropp, 1998). However, approaches that capture the complexity of large urban systems, and efforts to integrate the various themes are rare (Kropp, 1998). The application of complexity theory in urban analysis (qualitative or quantitative) has been increasing recently – for example deterministic chaos, stochastic dynamics, artificial life, ecological and natural evolutionary dynamics, evolutionary and genetic programming, cellular automata, percolation theory, cellular games, agent-based modelling, and neural networks. However, the complexity of urban growth and its impacts on urban development planning and sustainable growth management have not been systematically researched.

Here, within the framework of complexity theory and in the environments of remote sensing and GIS, 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 chapter 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 such as cellular automata, fractals, neural networks, spatial statistics, multi-agent etc. 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, it ends with some discussion and conclusions.

2.2 Complexity of Urban Growth

Modelling urban growth aims to support urban development planning and sustainable growth management. Scientific planning and management must be based on the proper understanding of the dynamic process of urban growth, i.e. from past to present to future. Such understanding enables planners to experimentally simulate "what-if" decision-making based on various scenarios. However, the dynamic process involves various socio-economic and physical and ecological components at varied spatial and temporal scales, which result in such a complex and dynamic system. Consequently, it requires a systematic perspective to understand this complexity.

2.2.1 Complexity

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. While the concepts of "complexity" themselves are not new, the application of these concepts to socio-economic processes is a relatively new phenomenon. Advocates of complexity theory see it as a means of simplifying seemingly complex systems. Complexity often results from the non-linear interactions among complex system components, which frequently lead to emergent properties, unexpected dynamics and the characteristics of self-organisation becoming the basic properties of complex systems.

Non-linear relationships and feedback among all components at the same and different scales often lead to instability and unpredictability in large complex systems.

Emergence (as a phenomenon that high-level behaviours emerge naturally out of low-level interactions) implies that the behaviour of the small part is different in isolation than when it is part of the larger system. This description is often summarised as "a whole that is greater than the sum of its parts or in simple terms, much coming from little". Thus the collective behaviour of a complex system is dependent on the behaviour of all of its parts.

For example, Portugali and Benenson (1997), who have intensively studied the theoretical aspects of socio-cultural emergence during recent years, show the emergence of different forms of cultural and economic segregation as a consequence of the interactions between individuals and the city environment at the local and global levels.

Self-organisation (the spontaneous emergence of macroscopic non-equilibrium organised structure due to the collective interactions among a large assemblage of simple microscopic objects as they react and adapt to their environment) implies that the system organises itself from within and structures are not imposed from the outside – in other words, owing to purely internal dynamics instead of any external force. It requires an interaction with its environment and non-linear relations between its elements.

In a self-organising system (SOS), the local actions and interactions of individuals are the source of the higher-level organisation of the system into patterned ordered structures with recognisable dynamics. Since the origins of order in SOS are the subtle differences among components and the interactions among them, system dynamics cannot be understood by decomposing the system into its constituent parts. Self-organisation theory suggests that insignificant local interaction behaviour can lead eventually to a qualitatively different global structure (Wu, 1998a; Batty, 1995), which constitutes the basis of cellular automata and multi-agents theory. SOS theory has been applied for explaining many urban phenomena, such as spatial economies (Krugman, 1996) and urban evolution (Allen, 1997b; Haken and Portugali, 1995; Portugali, 1999; Schweitzer and Steinbrink, 1998). Order in the spatial structures or urban systems emerges from the structured responses of multitudes of individuals to outside forces and constraints (Benguigui et al., 2001b).

A branch of self-organisation theory, synergetics, attempts to illuminate explicit relationships between the behaviour of individuals (micro level) and evolving patterns (macro level). The approach is based on concepts such as order parameters, which typically represent macroscopic patterns, and the so-called slaving principle showing the relation to microscopic structures (Daffertshofer et al., 2001). The initial goal of synergetics was to understand how the emergence of a macroscopic system, showing a high degree of order, may be explained by the microscopic behaviours (Tannier and Frankhauser, 2001). The principles have been gradually popularised and applied to socio-economic and ecological systems. Haken and Portugali (1995) applied a synergetic approach to explain the self-organisation of urban settlement, based on a framework of pattern recognition within which the interplay between the material pattern of cities and the cognitive pattern of cities were conceptualised and subsequently analysed.

Complexity frequently takes the form of hierarchy, whereby a complex system consists of interrelated subsystems that are in turn composed of their own subsystems, and so on, until the level of elementary component is reached (Kronert et al., 2001). Hierarchy theory applies hierarchy to organise concepts and interpret various complexities. The theory examines closely the issues of scale, levels of organisation, levels of observation, and levels of explanation in a complex system characterised by hierarchical structures and interactions across levels. Hierarchy theory suggests that when a phenomenon is studied at a particular hierarchical level (the focal level, often denoted as Level 0), the mechanistic understanding comes from the next lower level (Level -1), whereas the significance of that phenomenon can only be revealed at the next higher level (Level +1) (Kronert et al., 2001).

The key to understanding hierarchical structure is scale. Scale is the central concept for describing and explaining the complex hierarchical organisation of the geographical world (Marceau, 1999). In a hierarchical system, higher levels (or smaller scale) set constraints or boundary conditions for lower levels. The latter operate much too rapidly to be of interest and can be ignored. In spatial analysis, the scope of scale can be threefold: spatial, temporal and decision-making (see chapter 5).

2.2.2 Complex system of urban growth

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?***

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), such as increasing the physical size of a built-up area, the latter to the change in major activities (land uses), such as residential or commercial function. Although the focus of this research is on the physical expansion, the functional aspects have to be taken into account in interpreting the causal effects of the former as both interact spatially and temporally. For example, the activities at a location may influence the change in space at another location; the activities in a period may impact on the change in space at another later period. As a result, space and activity should be the basic elements of any systems defined for understanding urban growth.

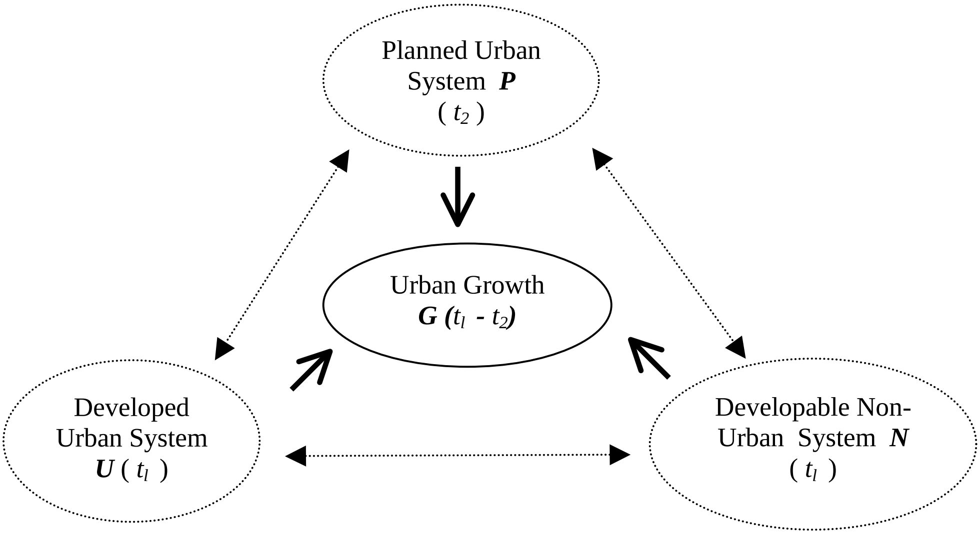

Figure 2.1 Where is urban growth occurring?

In figure 2.1, 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. Urban growth is a temporally relative term. New development units will be administratively transformed from rural management into an urban built-up area after a certain term has elapsed since birth. For example, in figure 2.1 urban growth, being the transformed area from t_l to t_2, will become a part of system ***U*** after t_2 from system ***N*** at time t_l. 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 2.1 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. In terms of physics, system ***U*** exerts "pull" forces on system ***G***, which is attracted by a certain scale of urban social and economic activities. Conversely, system ***N*** exerts "push" forces on ***G***, which is excluded by the limitation and requirement of ecological protection or sustainable agriculture. Hence, ***G*** results from the interaction between "push" and "pull" forces. ***We can say the interaction is open, non-linear, dynamic and emergent. Urban growth is a self-organised system.***

The major decision-making in urban growth is related to plans, policies and projects. Projects are special land use or development proposals initiated usually by various levels of actors. Projects evolve in the context of various levels of policy and plans. Urban growth creates a new dynamic system, which comprises a quantity of projects constructed that are increasing with time from t_1 to t_2. It is an open system. In the course of urban development, it incessantly exchanges matter, energy and information with external physical and ecological systems (water, land), other regions and cities. It imports a variety of regulations/decision-making styles, 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 (Clark, 1951) or an inverse power function (Batty and Kim, 1992). In the temporal dimension, new growth does not follow a linear trend but, in most cases, a logistic trend (Herbert and Thomas, 1997). The interactions among a huge number of factors have proved to have the unknown non-linear relationship, such as the famous interaction between transport and land use (Wilson, 1998).

The structure and function of each local project depend not only on its neighbouring projects but also its built-up environment, 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 a 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.

As a focus, this research only discusses the impacts of other systems on urban growth, as indicated by the one-way arrows (figure 2.1). In reality, the impacts of system ***G*** on ***N*** have been the major concern of landscape ecology, the interactions inside system ***U*** being the major concern of urban land use change. Therefore, urban growth involves landscape ecology (pattern and process), urban planning (decision-making) and urban geography (activities and behaviours). We need an interdisciplinary instrument to understand these complex relationships. Complexity theory is undoubtedly an ideal tool to construct conceptual frameworks systematically.

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?*** Traditional approaches to urban science as exemplified in the work of Christaller and others are based on the assumption that cities grow homogeneously in a manner that suggests that their morphology can be described using conventional Euclidean geometry. However, recent studies have shown that the complex spatial phenomena associated with actual urban systems are better described as a dynamic process consistent with growth in disordered patterns. The process of urban growth does not exist independently but rather coexists with pattern and behaviour. They interact mutually and comprise three interrelated conceptual subsystems that are crucial to the decision-making for urban planning and management. The work of Sui (1998) shows a need to understand urban form, process and policies in this new information society. When moving to urban growth, an emphasis should be given to pattern, process and behaviour.

As illustrated in figure 2.2, 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. From policy to pattern, the qualitative degree is decreasing and the quantitative degree is increasing. As a result, modelling has to follow a ladder (figure 2.2), from pattern gradually to policy level. This ladder works in the opposite direction to the real urban growth hierarchy. On the one hand, in the terms of hierarchy theory (see previous section), understanding a single level must consider its lower and upper levels as they are comparatively closely linked.

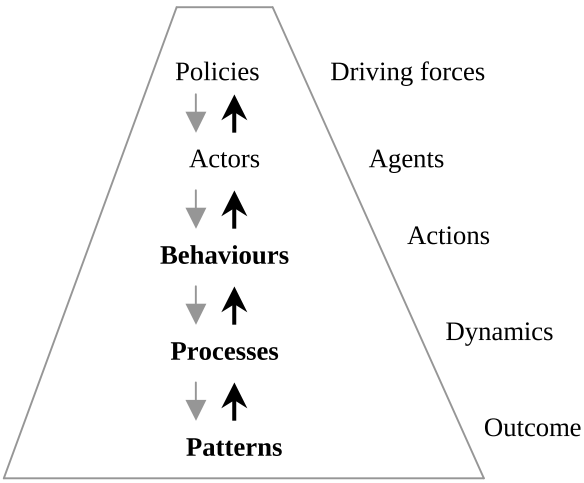

Figure 2.2 A ladder for modelling

Consequently, to understand a process, one must take its pattern and behaviour into account. On the other hand, as actor and policy are interrelated, they principally impact on the decision-making units and processes, and are linked with behaviours. Thus, process, pattern and behaviour are becoming the key levels for modelling urban growth. A pattern is the temporal snapshot of a process, and behaviour is the decision-making source of a process.

(1) Pattern

What is the definition of pattern? How to classify and distinguish the patterns of urban growth? The Oxford English Reference Dictionary defines pattern as "a regular or logic form, order, or arrangement of parts such as behaviour pattern". Two key components are stressed in the definition: elements and the logical ordering among the elements. As such, spatial pattern focuses on the spatially ordering and temporal pattern on the dynamic ordering, i.e. logically ordering described from the perspectives of space and time respectively. However, the concept "pattern" varies with discipline in academic circles. In spatial sciences, pattern refers to a "regular arrangement of objects", which may be explained in terms of structures, processes and systems. It refers to the manner in which a phenomenon is arranged in time and systems. In landscape ecology, patterns refer to the spatial configuration of discrete landscape elements, which can be of different geometrical nature.

To summarise, pattern is a relative term, which is dependent on a specific system under study. Pattern is based on defined elements of the system. In this sense, urban growth patterns can be viewed from two standpoints: one is on the urban growth system itself, the other is as part of a larger system (***G***, ***U***, ***P***, ***N***). The former only comprises new development units. The latter includes not only urban growth but also the three other systems ***U***, ***P***, ***N***. A development unit can be defined as any spatial entity that will be subject to change, albeit physical or functional, during the period to be modelled. The physical change means the appearance or disappearance of a new unit; the functional change indicates the new usage of a unit, such as change from industrial to commercial. The pattern in system ***G*** is called univariate as it focuses on the logic arrangement among the new development units. Landscape metric, point-pattern and spatial auto-correlation belong to this category, which contributes to the quantitative description of the spatial distribution of urban growth. In a larger system, elements include relevant spatial entities coming from three other systems, which stimulate or constrain the occurrence of new development units. They can be river, water body, railway line, slope, shopping centre, road network etc. Actually, this category aims to model the spatial relationship between ***G*** and ***P, N, U,*** instead of ***G's*** spatial distribution. It is called a multivariate pattern, which contributes to the quantitative description of interaction pattern between multiple systems.

Various types of "pattern" studies have been carried out in urban modelling, such as residential or settlement pattern (I-Shian, 1998), land use development pattern (Kiril, 1998; Yeh and Li, 1998), population and employment pattern (Ingram, 1998), development pattern of informal settlement (Mahmud and Duyar-Kienast, 2001), land development pattern (Wu and Yeh, 1997), and transport/land use interaction pattern (Susantono, 1998).

Wu and Yeh (1997) focus on the multivariate functional pattern (land use) between system ***G*** and ***P***, ***N***, ***U*** in a case study of Guangzhou city in China. They model not only spatial patterns but also temporal patterns in two periods. These models are very helpful in comparing and explaining the land development patterns under two distinct economic systems.

Pijanowskia et al. (2002) study the multivariate physical pattern (land cover) between system ***G*** and ***P***, ***N***, ***U*** in a case study of Michigan's Grand Traverse Bay. They explore how factors such as roads, highways, residential streets, rivers, the Great Lakes' coastlines, recreational facilities, inland lakes, agricultural density and the quality of views can influence urbanisation patterns in this coastal watershed. Artificial neural networks (ANNs) are used to learn the patterns of development in the region and test the predictive capacity of the model, while GIS is used to develop the spatial predictor drivers and perform spatial analysis on the results.

(2) Process

Space and time are well-known notions but in order to explain them they must be connected to other fundamental concepts such as change or process. Since relative space is inseparably fused with relative time, nothing in the physical world is purely spatial or temporal; everything is process. Change must be seen as a composite of processes that occur on a wide band of time scales in space. Therefore, the link between space and time is through the process itself, where specific processes determine specific temporal and spatial conceptualisation (Dragicevic et al., 2001). The process discussed here does not include the social and economic processes, which are the driving forces of physical and functional urban growth.

Process generally refers to the sequence of changes in space and time; the former is called the spatial process, the latter the temporal process. It should be noted that strictly speaking spatial and temporal processes cannot be clearly separated as any geographical phenomena are bound to have spatial and temporal dimensions or named a spatio-temporal process. Understanding change through both time and space should, theoretically, lead to an improved understanding of change and of the processes driving change (Gregory, 2002).

However, spatial processes are much more than any sequence of changes. Spatial process implies a logical sequence of changes being carried on in some definite manner, which lead to a recognisable result (Getis and Boots, 1978). Summing up, the key components of process are change and logical sequence. The former is defined by a series of patterns. The latter implies the understanding of process. In contrast with pattern, process contains a component of dynamics.

Pang and Shi (2002) propose a spatial system theory in which they define spatial process as a system containing two components: based on structure and movement (including add, delete, move, merge and subdivide operations). They actually correspond to pattern and sequence (a set of operations) of change. This is a generalised process for spatial modelling in GIS. However, it is not suitable for urban growth as urban growth only includes rural-urban land cover conversion and not decline in land use in the inner city.

In landscape ecology, fragmentation is a common process related to landscape change, affecting both its structure and function. It causes the division of landscape elements into smaller pieces. In this domain, landscape pattern comprises various patches, which represent the diverse structure and function of landscape elements. Fragmentation of patches or patch dynamics (Wu and David, 2002) can be utilised to explain the ecological process of landscape pattern change. It is a spatial process in system ***N***.

Landis and Zhang (2000) define spatial processes as those by which activities at one location affect or are affected by activities at another location. They identify four types of spatial processes that arise in urban activities: spatial diffusion and dispersal, exchange and transfer, interaction, and segmentation or percolation. The outcome of the spatial process refers to urban land use. Process is to understand the causal relationships of urban land use change; they are spatial processes in system ***U***. Arbia (2001) classifies the spatial processes of individual firms into a birth process (new firms) and a growth process (existing firms) and proposes a model of economic activities on a continuous space. This classification aims to analyse the economic behaviour of individual firms. It is not an explicit spatial process.

Benguigui et al. (2001a) described city growth as a leapfrogging process, based on population growth in a case study of the Tel-Aviv Metropolis. With reference to three case studies (Beijing, Shanghai and Guangzhou), Gaubatz (1999) generalised the urban development process of Chinese cities after land reform was initiated in 1987 into three aspects: production of urban plans, urban renewal, and privatisation of the housing and real estate market. These two definitions are only given as a specific requirement of the analysis, not in any systematic way.

According to hierarchical theory, processes – in particular spatial processes – may be divided into two levels: global and local. The former takes the whole study area into account, the latter only a neighbourhood. For example, Mendonca-Santos and Claramunt (2001) defined explicitly spatial processes on two scales (landscape and class or local) in order to explain the change in landscape patterns. At the landscape level (global), spatial processes are identified as fragmentation, perforation, diversification and simplification. And at the class level (local), spatial processes are characterised by expansion, contraction, stability, invasion, domination and succession. They argued that different levels (landscape and class) have a specific time scale: evolution process on a local scale is likely to happen in a faster mode than the ones identified at the landscape level.

To sum up, the classification of process is very complex, and dependent on the specific requirements of the analysis. The same patterns can be explained from the standpoint of different processes. In urban growth, when we focus on urban growth system ***G***, we may classify it as a spontaneous or self-organised process. The former is indicated by sporadic patterns and the latter is reflected by clustered patterns. This classification can be better linked to social and economic processes and also the decision-making processes of urban development planning. When we focus on the interaction between the three systems, we can define the process as leapfrog, space fill-in, dispersed, scattered, road-influenced, spread etc. This classification in particular considers the interaction of urban growth with developed urban areas from a global perspective.

(3) Behaviour

Urban growth results from direct or indirect decisions to alter the current uses of land at various levels. The analysis of urban growth necessarily asks who decides to change the transition, and where, when and why. The factors that are taken into account relate to the particular decision-making units and processes.

Behaviour refers to the decision-making of actors. Spatial behaviour focuses on spatial decision-making, temporal behaviour on temporal decision-making. The key components of behaviour are decision making and the actor. In spatial science, examples include way-finding, travel mode, site selection, and land use allocation.

The actors from the three systems $\boldsymbol{U}$, $\boldsymbol{P}$, $\boldsymbol{N}$ – individuals, households, businesses, developers, farmers, landowners, planners and governments – make decisions about their social and economic activities, and their spatial location and temporal scheduling, leading to changes in land cover and land use. These decisions affect, directly and indirectly, the physical and functional system $\boldsymbol{G}$ through the conversion of land, the use of resources, and the generation of interaction.

For example, the projects for commercial use make choices about scale, location, cost and transport. Households make choices about employment, location, housing type, travel mode, and other lifestyle factors leading to varied spatial behaviours. Developers make decisions about investing in development and redevelopment. Governments make decisions about investing in infrastructures and services and adopting policies and regulations. Decisions take place at the individual and community levels through the economic and social institutions. The actors interact in three sub-markets: the job market, the land market and the housing market. These actors also interact in non-market institutions, including governmental and other non-profit and non-governmental organisations.

A variety of decision making and diverse actors create disparate spatial and temporal behaviours in the urban growth process. Urban growth is highly impacted or controlled by the major actors of urban construction, planning and management. Urban spatial structure can be described as a cumulative and aggregate order that results from numerous locally made decisions involving a large number of intelligent and adaptive agents. The behaviour of these agents is subject to their rules of action based upon new information. The local behaviour of multiple decision-makers can eventually lead to qualitatively different global patterns. Due to the number of actors involved in urban growth, the spatial behaviour of urban growth falls into various levels: individual behaviour, planners' behaviour, developers' behaviour etc. Spatial behaviour regarding urban growth includes site selection behaviour and spatial spread behaviour (such as scale, density, intensity). Temporal behaviour contains the speed of growth.

Decisions are made under constraints (space and time), and they reflect the attitudes, values and beliefs of people and of society. Therefore, behaviours are individually subjective and stochastic but follow global regulation in statistical terms. Meanwhile the basis for making decisions may change over time.

For instance, previous studies regarding the urban growth of Chinese cities (Gaubatz, 1999; Fung, 1981; Wu, 1998b) have shown that because of the determinant role of the state budget the state and work units were the main urban developers in the period before 1987. Urban planning principally contributed to site selection for industrial projects. Since the land reform initiated in 1987, however, with the retreat of state work units from urban construction, the comprehensive management of local governments and the new land-leasing system, the right of controlling urban space has been transferred from work units to local governments and then to external developers (Wu, 2000a). More actors are involved in the decision-making, with more vague functions (Han, 2000; Jiang et al., 1998; Zhang, 2000b). As a result, to understand the urban development process, the roles of various actors and their behaviour should be taken into account. Wu (1998b) argues that, in order to explain the complicated spatial structure and process of Chinese cities, one must understand the two points: capital and its movement, social actors/agents and their functions/roles.

2.2.3 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 (Box, 2000). 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

Contemporary urban growth is characterised by dispersal and decentralised patterns, especially in the USA (Gordon and Richardson, 1997). Restructuring has involved the decentralisation of jobs, services and residences from traditional urban centres to suburban settings and "edge cities" within expanded metropolitan areas (Garreau, 1991). The new urban regions are multi-centred, with more than one core (Fishman, 1990). This trend is the result of a variety of heterogeneity.

Kolasa and Pickett (1992) gave a more conceptual definition of heterogeneity: "a system is heterogeneous in time and/or space if a specific temporal interval and/or different location is characterised by different values". Homogeneity and heterogeneity can be defined as the "border" between individual levels of hierarchy.

Systems of any interest are composed of heterogeneous agents and objects, indeed their very richness comes from such heterogeneity (Batty and Torrens, 2001). Socio-economic events have an explicit heterogeneous spatiality and temporality. Their structure and function are defined in and by space, as well as in and by time, such that no two locations are alike. Maintaining heterogeneity may be critical for the movement of energy, matter and information within different social contexts. Or rather, heterogeneity is the source of complexity of any system.

In the field of landscape ecology, increasing attention is given to the importance of spatial heterogeneity in understanding the relationship between pattern and process (Turner, 1989). Hierarchical patch dynamic models are being developed to incorporate the effects of spatial heterogeneity on ecosystem dynamics. An increasing hierarchical order is often accompanied by an increase in heterogeneity (Kronert et al., 2001).

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. In 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. For instance, a university accommodating many people has a high social value but a low economic value. Conversely, a sewage treatment plant accommodating few workers has a low social and economic value but a high environmental value. As a result, each unit of new development is assigned different values. They are the spatial entities carrying heterogeneous social, economic and environmental activities.

Consequently, urban growth comprises a large number of varied scale projects. The functional differences between them, and also between the new units 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. For example, the self-organised process to some extent can be explained by scale economy, multiple nuclei etc. The integration or 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 plays 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. In the published literature, although numerous indicators are designed for the quantification required by any specific analysis such as proximity, accessibility, and density 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

Classic location theory utilises micro-economic concepts such as perfect competition and perfect rationality; but the over-simplified economic and spatial landscape it assumes is not sufficient to explain existing spatial processes where location choices depend on relationships rather than on an individual actor's choices (Besussi et al., 1998).

A frequently cited shortcoming of GIS and most spatial analysis tools is their difficulty in dealing with dynamic processes over landscapes (Box, 2000). 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 its distinct 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, such as large-scale new development zones, key-point industrial zones or parks, middle-scale new residential areas, and small-scale shops. 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 various levels 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.

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. Scale issues are inherent in studies examining the physical and human forces driving land use and land cover changes (Currit, 2000). An understanding of how processes operate at various spatial scales and how they can be linked across scales becomes a primary goal when investigating these complex phenomena (Marceau, 1999).

In spatial science, structure is the physical arrangement of ecological, physical and social components, and function refers to the way the components interact (Zipperer et al., 2000). 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

In the time dimension, the physical size of a city is increasing continuously, with a functional decline in some parts, such as the inner city. However, urban growth means only increasing the number of new units transformed from non-urban resources. In different countries, regions and cities, the speed, rate and trend of urban growth are very distinct. In developed countries (e.g. the USA, the UK), urban growth may be much more gentle than that in rapidly developing countries such as China and India. 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. This results in patterns, processes and behaviours of urban growth that 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 (Yeh and Li, 2001a). This means its development process is sensitive to unknown initial conditions such as war, natural disaster, and new policies of the central government. These conditions can not often be predicted, particularly in quantitative terms. If the system of interest is chaotic, the prediction of the values of all system variables is possible only within a usually short time horizon.

Generally, urban growth is in a state of disequilibrium, especially in most rapidly developing cities. In such cases, uncertainty becomes predominantly important, because in these systems spontaneous growth or any surprising changes that depart from observed past trends, indeed any form of novelty or innovation, open up the path of system evolution. This can be illustrated by the so-called "evolutionary drive", showing how the error-making of a particular type of individual in an initially pure population eventually diversifies the characteristics and behaviours of the population. This indicates that the urban development process contains stochastic components to a certain degree.

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 different 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 because their 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 of various periods. Such comparisons enable planners to modify or update their planning schemes in order to adapt to the changing environment. However, these comparisons are subjective and depend 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 in the following ways:

- 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

Quantitative geographers increasingly recognise that spatial patterns resulting from human decisions need to account for aspects of human decision-making processes (Fotheringham et al., 2000). In particular, the urban spatial structure is viewed as a result of interlocked multiple decision-making processes (Allen and Sanglier, 1981a). Decision-making complexity is indicated in the unit and process of decision-making, and the 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. For example, in China, decision-making in an industrial park project may include investment sources, site location, development scale, time scheduling. Actors may include central government, local government, foreign investors, local developers and work units. 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 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. Their differences are indicated in the various actors and the criteria for respective decision-making. Consequently, decision-making in 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.

(5) An example in transport and land use interaction

The pattern of urban development principally results from the accumulative effects of transport/land use interactions at different spatial and temporal scales. The term *interaction* implies *a feedback* mechanism between transport and land use systems. The land use system supplies the transport system with estimates of the location and volume of travel generators. The transport system affects the land use system through the notion of accessibility, often in a temporally lagged manner. As an integral part of such accessibility, changes in travel costs become part of the mechanism used to relocate labour, residence and other urban economic activities. Many empirical studies have shown that the interactions are complex, bi-directional, and difficult to sort out due to spatial and temporal scaling factors. In the temporal scale, the interactions can be distinguished and summarised as follows (Hanson, 1995):

- Short-term effects of land use on transport;
- Medium-term effects of transport on employment location;
- Long-term effects of transport on housing location.

The implication is that transport system changes, notably major infrastructure investment in new highways or rail transit lines, will need time to affect urban land use patterns. Once introduced, such land use patterns may also, but within shorter time frames, induce further changes in urban travel demand.

At the spatial scale, on the one hand, the link between transportation and land use may be stronger only when transport costs are significant, or when transport or development decisions significantly affect accessibility. These conditions are generally met in two very different circumstances: *heavily congested downtown areas and rapidly growing suburban areas*. On the other hand, the impact of highway investments today, with a mature highway system, may not be the same as in earlier periods. They have a decreasing impact.

2.3 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?***

In one philosophical tradition, understanding means the construction of models (Newell, 1997). There are a number of ways of classifying models of urban growth. For example, in terms of system completeness, models can be system-level or specific-level. The former takes all components of urban systems into account; the latter focuses only on a specific phenomenon or problem by using a limited number of components in the system under study, such as residential dynamics. In terms of dimension, they can be divided into spatial models, temporal models and spatio-temporal models. Different dimensions distinguish focus or emphasis and requirements of data. In terms of analysis objectives, they can be pattern models, process models and behaviour models. With the general purpose of understanding the complexity of urban growth, we hereby attempt to classify them as cellular automata modelling, multi-agent modelling, neural network modelling, fractal modelling etc., according to the methods available for modelling complexity and non-linearity.

2.3.1 CA-based modelling

Cellular automata (CA) are dynamic discrete space and time systems. A classic cellular automaton system consists of a regular grid of cells, each of which can be in one of a finite number of *k* possible states, updated synchronously in discrete time steps according to a local identical interaction rule.

The idea of CA is closely associated with that of microscopic simulation in which the behaviour at a local scale gives rise to an emerging global organisation (Webster and Wu, 2001). Global structure in a CA system is often seen to emerge out of purely local interactions between cells. This is attractive because it matches our intuitive sense that much human spatial activity is not centrally planned or organised, but arises from the responses of various actors, residents, developers, planners, politicians and local circumstances (O'Sullivan, 2001). It also holds out some promise of deeper insight into the enduring mystery of the relationship between processes at the micro level and the macro level of geographical and economic activity.

As an effective bottom-up simulation tool, 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. By mimicking the manner in which macro-scale urban structures may emerge from the myriad interactions of simple elements, CA offer a framework for the exploration of complex adaptive systems (Torrens and O'Sullivan, 2001). CA represent a modelling approach quite different from top-down and macroscopic approaches (Webster and Wu, 2001).

CA have many advantages for modelling urban phenomena, including their decentralised approach, the link they provide to the complexity theory, the connection of form with function and pattern with process, the relative ease with which model results can be visualised, their flexibility, their dynamic approach, and also their affinities with geographical information systems and remotely sensed data (Torrens and O'Sullivan, 2001). Perhaps the most significant of their qualities, however, is their relative simplicity.

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

The first type links CA with complexity and GIS theory, e.g. CA theory (Batty and Xie, 1994; Childress et al., 1996; Couclelis, 1997; Itami, 1994; Wolfram, 1984), map dynamics (Takeyama and Couelelis, 1997), CA calibration (Li and Yeh, 2001; Wu, 2002), graphbased CA (O'Sullivan, 2001), Voronoi-based CA (Shi and Pang, 2000), event-based CA (Gronewold and Sonnenschein, 1998) and fuzzy CA (Wu, 1998d). In complexity, many contributions come from other areas such as informatics, biology, physics and ecology. They use abstract models for exploring such general properties of complex systems as emergence, self-organising criticality and chaos. As regards the spatial complexity of the urban systems, 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 type links CA to theoretical urban studies, e.g. urban development patterns (Batty, 1998), self-organising competitive location theory (Benati, 1997), polycentric structure (Wu, 1998a), emergent urban form (Xie and Batty, 1997), land use dynamics through their life cycles (Batty et al., 1999b), real estate investment simulation (Wu, 1999), and urban socio-spatial segregation (Portugali et al., 1997). In these studies, transition rules are linked with urban theories to test theoretical hypotheses by using simulated or real data. Published literature has shown that this is a very promising direction, although little explored, which may bring new 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, prediction and planning based on 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 (White and Engelen, 1993, 2000), the prediction of future urbanisation patterns (the San Francisco Bay and Washington/Baltimore corridor) (Clarke and Gaydos, 1998) (Gold Coast in Australia) (Ward et al., 2000a), Spanish cities (Silva and Clarke, 2002), long-term simulation of sprawl in the Ann Arbor Region (Batty et al., 1999a), land development process simulation (Guangzhou) (Wu and Webster, 1998), identification of diffused city (central area of Veneto region) (Besussi et al., 1998), urban form planning (a city in Guangdong, China) (Yeh and Li, 2001a), regional-scale urbanisation (Li and Yeh, 2000), urban development density (Yeh and Li, 2002), urban development plan (Chen et al., 2002), landscape dynamic (Soares-Filho et al., 2002), urban expansion based on population density surface (Wu and Martin, 2002), and suburban expansion of a peripheral municipality (town of Amherst, in metropolitan Buffalo, NY) (Batty and Xie, 1994).

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 span various spatial and temporal scales. They have adequately shown that CA offers a flexible and advanced spatial modelling environment that has not 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 by Clarke and Gaydos (1998). The latter aims to aid the decision-making process of land conversion in urban growth (Wu, 1998c) or to simulate the fuzzy behaviour of decision-making in agricultural land encroachment (Wu, 1998d). Second, these applications focus on the simulation of spatial patterns rather than on the interpretation or understanding of the spatio-temporal processes 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.

2.3.2 Agent-based modelling

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

An agent-based model is one in which the basic unit of activity is the agent. Usually, agents explicitly represent actors in the situation being modelled, often at the individual level. Agents are autonomous in that they are capable of effective independent action, and their activity is directed towards the achievement of defined tasks or goals. They share an environment through agent communication and interaction, and they make decisions that tie behaviour to the environment.

From the perspective of modelling, 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. Multi-agent models can locate agents and other resources of the environment in space and thus include the effects of space on the behaviour of the agents and the effects of the agents on the environment (Frank, 2000).

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 (Haklay et al., 2001).

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 (Batty, 2002; Epstein and Axtell, 1996). 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 (Kerridge et al., 2001) and relocate householders (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. This 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 has been 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 a micro scale, such as a single large-scale project.

2.3.3 Spatial statistics modelling

Traditional statistical 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), multiple regression (Theobald and Hobbs, 1998) and logistic regression (Wu and Yeh, 1997; Wu, 2000b) have been 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. They 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 Guangzhou between 1978 and 1992, based on a series of aerial photographs. They found that the major determinants of land development have changed: from distance from the city centre to closeness to the city centre; from proximity to inter-city highways to proximity to city streets; and from more related to less related to the physical condition of the sites etc. 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. The major reason is that spatial and temporal data often violate basic assumptions such as the normal distribution, appropriate error structure of the variables, independence of variables, and model linearity (Olden and Jackson, 2001). Two alternatives are frequently adopted. One is incorporating spatial sampling into traditional analysis (Atkinson and Massari, 1998; Dhakal et al., 2000; Gobin et al., 2001). 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 (Griffith and Layne, 1999; Haining, 1990), spatial econometrics (Anselin, 1988), local spatial analysis (Ord and Getis, 1995) and geographically weighted regression (GWR) (Fotheringham et al., 2000).

2.3.4 ANN-based modelling

An artificial neural network (ANN) is a system composed of many simple processing elements operating in parallel, whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes. The development of a neural network model requires the specification of a "network topology", a learning paradigm and a 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). According to published literature on its various applications, its strength lies in prediction and performing "what-if" types of experiment (Corne et al., 1999).

In the geographical sciences, recent ANN applications include spatial interpolation (Rigol et al., 2001), transport planning (Shmueli, 1998), transport and land use interaction (Rodrigue, 1997), land cover classification (Foody, 2002), image classification (Skidmore et al., 1997), urban change detection (Liu and Lathrop, 2002), and land cover transformation (Pijanowskia et al., 2002).

Shmueli (1998) used an ANN model to test whether or not there is a connection between socio-economic and demographic variables and travel activities. Skidmore et al. (1997) found that the neural network did not accurately classify GIS and remotely sensed data at the forest type level. Kropp (1998) applied a self-organising map (SOM) ANN model to classify 171 cities into four dimensions that represent all relevant features of the system and assess their sensitivity to change. As a form of non-linear dimension reduction, SOM successfully provided an effective tool to identify cities that are susceptible to perturbations of human-nature interactions. 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 show 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, make it of limited value for modelling the urban growth process.

2.3.5 Fractal-based modelling

Benoit Mandelbrot, who coined the term in 1975, defines a fractal as "a set for which the Hausdorff-Besicovitch dimension strictly exceeds the topological dimension (Mandelbrot, 1967; Mandelbrot, 1982). Fractals were originally used for natural objects such as coastlines, plants and clouds or ill-defined 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 has shown that planned and designed spatial objects such as urban forms and transportation networks can also be treated as fractals (Batty and Longley, 1994; Frankhauser, 2000; Shen, 1997; Shen, 2002a; Vicsek, 1991). It is considered that fractal dimension is one of the few concepts that are directly relevant to the problem of urban complexity (White and Engelen, 1993; Yeh and Li, 2001a).

The complexity represented by fractals is measured by a fractal dimension of a real number rather than an integer at various spatial dimensions. The fractal dimension may provide a less ambiguous approach to analysing the spatial structure and phenomena than current complexity measures. It is thought that a comparison between conventional density measures and the fractal dimension index gives more insight into the usefulness of fractal dimensions for modelling urban form, growth and development.

Cities are similar in a variety of ways, central place theory being the clearest demonstration of this principle (Batty and Longley, 1994). Fractal models give us a very different perspective on studies of urban density. This book explains how the structure of cities evolves in ways which at first sight may appear irregular, but when understood in terms of fractals reveal a complex and diverse underlying order. Recent studies have shown that the complex spatial phenomena associated with an actual urban systems are 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 the 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 the urban population. It is thought that a comparison between 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. But Makse et al. (1998) criticise the DLA model for generating only one large central place or cluster, whereas a real urban area is formed by a system of central places spatially distributed in a hierarchy of cities. They 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 used to measure the similarity between real and simulated spatial patterns created by cellular automata (Yeh and Li, 2001a). But it should also be noted that fractal measures of spatial complexity are difficult to interpret due to the fact that the same value of the 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.

2.3.6 Chaotic and catastrophe modelling

Catastrophe theory (Clarke and Wilson, 1983) and the theories of bifurcating dissipative structures (Allen and Sanglier, 1981b) 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-term behaviour arises in deterministic dynamic systems because of their 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 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) 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.

Sprott et al. (2002) tested the phenomena of SOC in the field of landscape ecology, based on a simple cellular automata model. They found that spatial distributions and temporal fluctuations in global quantities show power-law spectra, implying scale-invariance, the characteristic of self-organised criticality when a system evolves into a self-organised system.

2.4 Evaluation of Modelling

2.4.1 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, e.g. the Lowry model was designed in 1964 and first introduced into the process of urban planning by using aggregated data. 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 from the 1960s to 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. They proved inadequate to reflect the complex, dynamic and non-linear factors inherent in urban systems or subsystems (Lloyd-Jones and Erickson, 1997; Sui, 1998), and were of limited value in supporting planning decision-making.

Consequently, the new challenge requires that the 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. Famous examples including TransSim and UrbanSim (Waddel, 2002) indicate the current trends of urban modelling. 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.

2.4.2 Criteria of evaluation

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

(1) Data requirements

Questions of urban growth have attracted interest among a wide variety of researchers concerned with modelling the spatial and temporal patterns of land conversion and understanding the causes and consequences of these changes. 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 (see chapter 4) 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 in the long term also seriously limits our capacity to understand the driving forces and processes controlling these changes (Petit and Lambin, 2001).

As illustrated in figure 2.1, 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); and 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 studies have widely utilised remote sensing imagery as inputs to their modelling.

(2) Linkage with GIS

GIS first came to fame in the early 1980s as a technique for geo-referenced data input, data storage, data processing, data retrieval, and data output, with simple data models and a few spatial analysis functions. The first GIS provided only limited decision-making capacity, due to insufficient spatial modelling functions. The inability to incorporate urban models and to more directly support policy-making processes are two main deficiencies of the current geo-spatial technologies and tools (Nedovic`-Budic`, 2000). The integration of both did not take place until the late 1980s. GIS can 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 complex dynamic and non-linear processes, and therefore the capacity of interpretation is crucial. Compared with logistic regression, the Markov chain model lacks explanatory power as the causal relationships underlying the transition studies are left unexplored. The transition probabilities are estimated as proportions of cells that have changed state from one point in time to another. This approach remains a useful way of estimating these probabilities despite the development of procedures for estimating transition probabilities on the basis of more complex scientific consideration. ANNs have a greater predictive and non-linear power than traditional approaches. However, their property of "black box" provides little explanatory insight into the relative influence of the independent variables in the prediction process. This 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 some 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.

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 the city level (Wu and Webster, 1998) and the regional level (White and Engelen, 2000). In contrast, MA is only applied on the household (Bernard, 1999) and family (Benenson, 1998). The MA approach deals with decisions posed to people more frequently (Benenson, 1998). 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.

2.5 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 a macro scale than on a 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 a limited number of 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; Bura et al., 1996; Wu, 1998a). The poor interpretation capacity of most models (such as CA, fractal and ANN) means that they are less used for practical applications than traditional or spatial statistics such as logistic regression and geographically weighted regression (GWR).

The conceptual modelof the strategy adopted in this research, as illustrated in figure 2.3. Here, the complexity that can be modelled depends on four factors: the demand from urban development planning and growth management, the data that is available from multiple sources, the concepts from other relevant disciplines, and the theories and methods from complexity science. These concepts are based on the theories of complexity and need models to test theories. Methods need data for implementation. The advanced theories and methods discussed above have great potential for understanding urban growth complexity. As the result of the dynamic interactions, urban growth modelling involves numerous variables from three systems ***P***, ***N***, ***U***. This is a basic principle for the models in the later chapters. Their interpretation needs to be linked to the experiences of other disciplines such as agriculture, landscape, ecology and environmental science. Consequently, a multidisciplinary framework is advocated to incorporate the concepts for developing new methodologies for understanding urban growth. In this research, four types of complexity regarding urban growth will be modelled. These are complexity in structure and function (chapter 3), complexity in temporal measure (chapter 4), complexity in pattern (chapter 5) and complexity in process (chapter 6). The specific concepts, methods and data of each model will be elaborated in these four chapters. The major methods for modelling include fractal for structural complexity, landscape metric for functional complexity, data disaggregation and spatial auto-correlation for temporal measures, exploratory data analysis and spatial statistics (logistic regression) for pattern complexity, and cellular automata for process complexity.

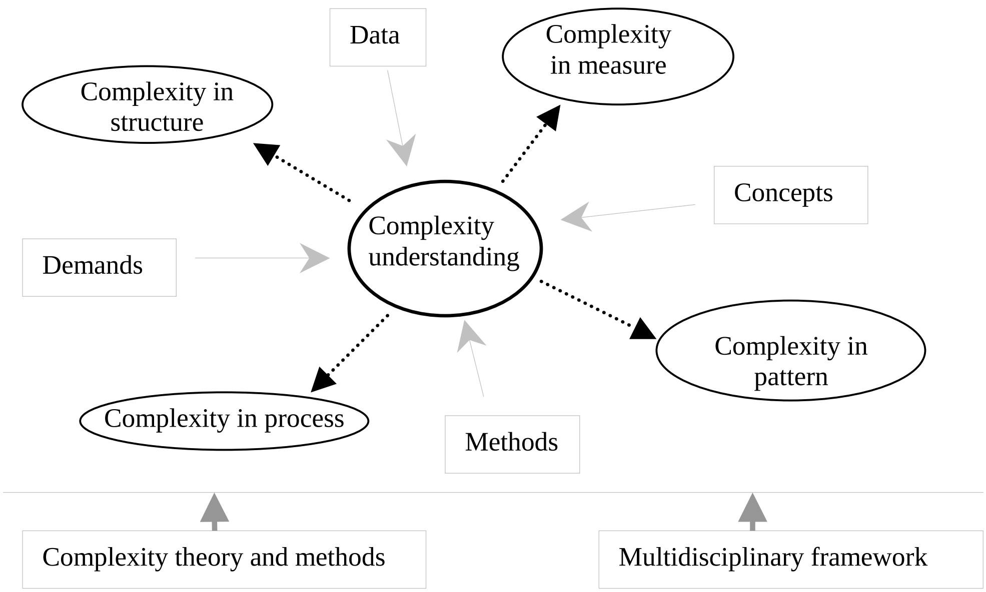

Figure 2.3 A conceptual model for the strategy adopted in this research

Chapter 3*

Monitoring & Evaluating Urban Growth in Wuhan 1955-2000

Abstract

The transfer from a planned to a market economy is presenting a challenge to Chinese urban planning, which requires a change of planning methods and techniques from blueprint to process-oriented planning. These changes create a need to monitor and evaluate spatial and temporal urban growth as a first step to understanding this dynamic process under various socio-economic conditions. The rapid advances in remote sensing and geo-information science and techniques make urban growth studies more feasible than before. This chapter systematically presents a methodology for monitoring and evaluating structural and functional changes for a rapidly growing city. With the aid of fractal and landscape metrics approaches, this methodology primarily comprises morphology analysis, urban land use structure change and spatial pattern analysis. As a case study, Wuhan city has undergone a series of major physical and socio-economic changes over the last five decades. Although it partially shared common development with other Chinese cities, the changes also had specific features. So far, a systematic study on the temporal urban growth of Wuhan has not been published in academic literature. In this research, temporal mapping is carried out for the five years 1955, 1965, 1986, 1993 and 2000, based on aerial photographs, SPOT images and other data sources. This study reveals temporal variations in the spatial urban growth process.

Key words: urban growth, monitoring, evaluation, Wuhan, structure and function

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∗ Based on Cheng et al. (2001) and Cheng et al. (2003c).

3.1 Introduction

Owing to the transformation from a centrally planned economy to a transitional economy, Chinese urban planners are facing a huge challenge to modify the urban planning system (Yeh and Wu, 1999). The new urban planning system should be based on understanding the urban development process of Chinese cities in transformation. This issue is attracting more and more attention of not only Chinese scholars but also international urban researchers (e.g. Chan, 1994; Gaubatz, 1999; Hsu, 1996; Khakee, 1996; Kirkby, 1985; Laurence and Edward, 1981; Victor, 1985; Wu, 2000a; Wu, 2001; Wu and Yeh, 1997; Xu, 2001; Yao, 1998; Zhang, 2000b).

These studies have four main distinguishing features. First, the urban development process of Chinese cities is differentiated into two periods: before and after 1978 or 1987 (Gaubatz, 1999; Laurence and Edward, 1981; Victor, 1985; Wu and Yeh, 1997). This means that the economic reform in 1978 and the land reform in 1987 are the key factors impacting the urban development process. It shows that changes in urban landscape systems are driven by complex political, social and economic systems.

Second, most studies focus on the impacts of relevant policies or actors on urban development, such as the interplay between state and market on urban development in Shanghai (Han, 2000), foreign investment on urbanisation in the Pearl River Delta (Victor and Yang, 1997), foreign investment on the real estate industry (Jiang et al., 1998), the roles of local government in urban sprawl in China (Zhang, 2000a), the effects of foreign investment and changing urban governance on urban restructuring in Shanghai (Wu, 2000a), the relations between investment sources, development organisation and planning regime and the changing urban landscape in Guangzhou (Wu, 1998b), the urban planning transition before and after land reform (Yeh and Wu, 1999), and the impact of the housing reform (Chen, 1996; Wang and Murie, 1999; Wu, 1996).

Third, some studies use population data as the indicator of urban growth (Hsu, 1996; Shen, 2002b) in descriptive analyses, particularly when analysing a longer period, e.g. since 1949. Generally population statistics are generally more easily available than geo-spatial information, as most detailed spatial information could only be used after the 1980s when GIS was introduced in government organisations. Most studies regarding spatial development do not cover the period before 1980. A systematic analysis of 50 years of urban growth has not yet been done for Chinese cities.

Finally, the selected studies are mostly located in economically strong regions or mega-cities such as Guangzhou, Shanghai, Beijing and Shenzhen. This geographical focus prevents a complete understanding of the urban growth processes of Chinese cities.

These pioneering studies have focused on some determinant policies such as investment structure, industry structure, housing commercialisation, land leasing, urban planning, decentralisation of decision-making and the main development actors such as the state, local governments, developers, employers and investors, all of which are changing the spatial form of Chinese cities. They provide valuable evidence for further comparative study and guidelines for specific applications to other cases and even to new planning schemes. However, the main concern of urban planning and urban spatial systems at the urban landscape level must be recognised and linked with various policies. Political, social, economic and institutional variables finally have to be projected onto landscape systems when they are implemented. Moreover, with the rapid advances in remote sensing and geographical information science and techniques (GIS), modern satellite imagery, together with traditional aerial photography, has become available, with rich multi-resolution and scales, as a data source for monitoring urban development processes (Masser, 2001). By using GIS, it is technically feasible to integrate large quantities of data for further spatial analysis related to urban development.

For example, Ji et al. (2001) report on a project carried out in 1997 under the auspices of the China State Land Administration to monitor the dynamics of urban expansion in 100 municipalities throughout China. Most of the 100 cities were selected from eastern, southern and coastal regions. Landsat Thematic Mapper (TM) images acquired for 1989/1992 and 1996/1997 were used to examine the scope and the speed of urban expansion in this period. They also indicate that the monitoring of land use changes will be carried out every two years in China by targeting specific areas of interest. SPOT and other higher spatial resolution images are being considered for the future work.

So far, Wuhan city has not been systematically studied, especially not regarding its urban spatial and temporal growth. The cities considered in the former studies are quite different in local social, economic and political environment from Wuhan. For this reason, systematic research on Wuhan could be beneficial to the whole Chinese planning system as urbanisation is not a universal process with similar attributes in all world regions, but a set of complicated phenomena conditioned by various cultural and historical forces in different places (Laurence and Edward, 1981). Comparison of Chinese cities helps to form complete images of the urbanisation process in China.

Given these considerations, this chapter analyses and evaluates the urban growth of Wuhan over the last five decades. It is divided into six sections. Following the introduction, a brief overview of urbanisation in China since 1949 is presented in section 2. This serves as background information for the Wuhan case studies. Section 3 deals with the methodologies of systematic evaluation, including morphology analysis, spatial pattern analysis and land use structure change. Section 4 focuses first on monitoring and mapping temporal urban growth, based on a time series of multiple data sources, and then the evaluation of this temporal growth is described from multiple analytical perspectives. The final section of the chapter discusses these findings with reference to other Chinese cities (e.g. Guangzhou) and to modelling.

3.2 Urban Growth in China

3.2.1 Urbanisation since 1949

In the last century, two great events brought earth-shattering changes to China. The first was when the Chinese Communist Party came to power and a new type of government was born in 1949. The second was when China initiated its economic reform and embarked on an "Open Door" policy in 1978, which led to land reform in 1987. These events had a profound impact on China’s urbanisation in the period 1950-2000. The urbanisation level (the ratio of non-agricultural population to total population) of China increased from 11% in 1949 to 22% in 1983 to 28% in 1993 and to 36% in 2000 (China Population Statistical Yearbook, 2001). Chinese cities can be classified according to a five-level hierarchy (Yao, 1998) based on the magnitude of the non-agricultural population: super-mega (>2 million), mega (1-2 M), large (0.5-1.0 M), middle (0.2-0.5 M) and small (<0.2 M). There were five mega-cities in 1949, 13 in 1978 and 37 in 1998.

Rapid urbanisation creates opportunities for new urban development. However, it has also brought about serious losses of arable land; this occurred in other developed countries such as the USA, and in the UK before 1950 (Firman, 1997). China has the lowest farmland acreage per capita at 800 m^2 in 1994 (Yang, 1996). During the period 1991-1997, the area taken up by urban expansion was 1,200,000 ha; but these figures probably underestimate the actual situation, as land taken by the expansion of rural villages is not included (Ji et al., 2001).

3.2.2 Urban development policies

The process of urbanisation reflects the urban development policies of a specific period. Four different policies can be identified for the periods: 1949-1960, 1961-1977, 1978-1987 and 1988-2000 respectively (Kirkby, 1985; Leaf, 1995; Young and Deng, 1998).

(1) The 1949-1960 period

The first phase (1949-1952) is called the national economic recovery phase. In this phase the central government adopted a series of policies to expropriate and take over enterprises from the defeated *Guomingdang* government. This facilitated a rapid recovery of the national economy. However, urban development was restricted by a shortage of capital, which seriously limited investment in housing and urban infrastructure.

During the 1953-1957 phase, the government implemented its first five-year plan. Soviet-style industrialisation became the goal for the country’s economic development (Young and Deng, 1998). Urban development principally consisted of the construction of new factories, new power generation facilities and transportation projects that directly supported industrial production (Laurence and Edward, 1981). At the same time, inner-city redevelopment projects in the major industrial cities were planned, although few were realised (Kwok, 1981). Many major cities in China, particularly those with heavy investment from the central government *(Zhongdian chengshi*), underwent a very high rate of spatial expansion. Many cities increased their original area several times over between 1949 and 1957 (Fung, 1981).

The period (1958-1960) is called “The Great Leap Forward” (GLF). During this period, large city projects were drastically reduced in scale, concentrating on individual public buildings, such as exhibition halls and hotels (Kwok, 1981).

(2) The 1961-1977 period

This period can be divided into two parts: the readjustment period (1963-1965), and the “Cultural Revolution” (1966-1976). In 1961, severe economic recession interrupted the policy of industrial construction. The period between 1962 and 1965, the period of recovery from the Great Leap Forward, was followed by the "third-front" development (*san xian jian she*), which lasted from the 1960s to the early 1970s. During this period, the investment focus of the state shifted from mega-cities such as Shanghai and Wuhan to mountain areas such as Sichuan, Guangxi and Yunnan for the purpose of national military defence. Consistent with the strategic thinking, the government also adopted a policy of urbanisation “to control mega-city, develop medium/small-size city”. Consequently, the development and expansion of large cities was reduced drastically while small and medium-sized cities experienced continuous development (Kwok, 1981). In most mega-cities, apart from public buildings and small-scale factories, there was virtually no urban construction. Land development was restricted to small projects (*Jian Feng Cha Zhen).* As the development emphasis was put “first on production, second on living consumption”, house construction was stopped after 1958. By the late 1970s, many Chinese inner-city neighbourhoods were dilapidated, inadequately serviced and overcrowded (Gaubatz, 1999).

(3) The 1978-1987 period

China's economic reform in 1978 and in particular the urban economic system reform in 1984 offered most Chinese cities an opportunity to adjust their economic structure. The tertiary sector was given more emphasis. The previous order “secondary, primary, tertiary” was re-ranked as “tertiary, secondary and primary”. The revival of the tertiary sector resulted in rapid economic development. Supported by rapid local economic growth, the rate of urban expansion speeded up. Residential construction by work units also started after 1978. Previous studies of Guangzhou, Beijing and Shanghai (Gaubatz, 1999) indicate that the mega-cities reduced the share of industrial enterprises in the central city area during the 1980s. Despite various housing reform schemes, the state work unit system continued to play an indispensable role in housing provision (Wu, 1998b). Most Chinese cities undertook massive renewal projects within older urban districts during the 1980s and 1990s (Gaubatz, 1999). In Guangzhou city, over 98% of the land developed was converted from agricultural land use; and industrial, government, institutional and community facilities were the dominant types of land development during the period 1979-1987 (Wu and Yeh, 1997).

(4) The 1988-2000 period

While the first wave of direct foreign investment in China (1980-1991) was related to industrial growth, the second wave, beginning in 1992, has also been directed towards infrastructure and land development (Gaubatz, 1999). After the successful experiment of land management reform in the Shenzhen Special Economic Zones (SEZ) in the early 1980s, the paid transfer of land use rights was accepted by the First Session of the Seventh People's Congress in 1987. Following this, the State Council announced "Regulations on land use tax collection in cities and towns" in 1988. This land reform first brought the land value concept into urban development of Chinese cities through the so-called land leasing system. Land was solely owned by the central government but administered by local governments or municipalities. Land use rights can be transferred through organised negotiation, open auctions and competitive bidding. Land lease terms vary with land use type, for example 70 years for commercial and 50 years for residential use.

Since 1991, when the central government approved the first group of 27 new high-tech development zones in mega-cities such as Beijing and Wuhan, land leasing and land development have been hot topics state-wide, stimulated by the land reform. The State Land Administration Bureau reported that the number of new development zones at city level was 117 in 1991 but reached 2700 in 1993 (Huang, 1995). In most cases, these zones are designated for the expansion of particular sectors of the economy and designed to promote specific and specialised activities such as special economic technology, high and new technology, tariff-free zones and foreign investor zones. These developments indicate a new land development pattern Most zones are located at some distance from the often crowded and fully developed existing urban centres. They are characterised by comprehensive development (Yeh and Wu, 1999), resulting in the emergence of large peripheral residential communities, and development zones and sub-centres through discontinuous, low-density and leapfrog development (Wu, 1998b).

Although China has opened its land market and also had established a commercial real estate industry in 1988, it was not until 1992, when Deng Xiaoping made his famous speech during his tour of south China, that the pace of economic reform was speeded up and the real estate market was reformed to attract more domestic and foreign investments. The real estate industry soon became the leading industry in China (Jiang et al., 1998). Inner cities in China became huge construction sites. Investment in commercial housing increased from 27% of the total urban housing investment in 1991 to nearly 60% in 1994; at the end of 1995 there were more than 23,000 real estate development companies working in China (Wang and Murie, 1999). The new land development pattern, based on real estate (Yeh and Wu, 1999), led to another component of the new urban landscape (Wu, 1998b). Urban restructuring involved the emergence of new business districts. In Shanghai, new clusters of high-quality commercial housing were constructed. Industrial growth in this period was dominated by high and new technology spatially concentrated in new development zones. Shi (2000) explored the land use change mechanism by studying the case of Shenzhen, based on images from 1980, 1988 and 1994. His findings show that the external driving forces are the rapid growth of population, foreign investment and the development of tertiary industry based on real estate, while mediating forces are the transportation network, topography and existing land use patterns.

3.2.3 Urban development planning since 1949

Urban planning practice in post-1949 China can be divided into four main stages corresponding to the periods defined in the previous section:

- Physical planning evolving from industrial site planning in the 1950s;
- Turbulent urban planning during the political turmoil (1960-1978);
- Recovery and establishment of the urban planning system (1978-1989);
- The new urban planning system since the 1989 City Planning Act in a transitional economy (1989-present).

Planning doctrines used in the former Soviet Union dominated Chinese urban planning before 1987. The strategic emphasis was on industrial construction. The first step was to facilitate the site selection for projects, the next step to construct self-sufficient communities centred around state-owned factories or government centres or institutes. These communities or "work units" (*Dan wei*) provided as many services for working and living as possible. For instance, a typical university contained teaching facilities, laboratories, kindergartens, primary to high schools, dormitories, dining halls, apartments, hospitals, gas stations, post-offices, open markets, barber’s shops etc, which were clustered together and walled but administered as a single work unit. Spatial organisation based on work units enabled people to reduce their travel demands. In most cases, land development was organised by the work units spontaneously rather than by urban planning, because they obtained most of their financial support from their superior departments instead of local government. Growth was accomplished largely through the expansion of these small independent cells (Gaubatz, 1999). This project-specific pattern was valid until the introduction of the land market. In this sense, urban planning was only an extension of the economic plans of local and central government. As Yeh and Wu (1999) noted, urban planning was perceived as a tool to realise the socialist ideology of planned development and to "translate" the goal of economic planning into urban space. The industrial location trend was to disperse activities widely throughout the city to foster the work unit ideal by achieving the integration of housing and factories and urban- and district-level self-sufficiency (Gaubatz, 1999). Development control was not carried out by urban planning but through the so-called "capital construction procedure".

Economic reform challenged the local planners to plan new development zones. In most cases, the zones are meant for the expansion of particular sectors of the economy and designed in order to promote these specific and specialised activities (Gaubatz, 1999). They are often planned for specific companies. For instance, the Zhuankou development zone in Wuhan is designed for car manufacturing and is a joint-venture enterprise between the local government and the French Citroen car manufacturer. The Wujiashan Taiwanese Development Zone in Wuhan, as its name suggests, is financed by Taiwanese developers. The 1989 Urban Planning Act was a major event in the history of urban planning in China. Planners were authorised by law to inspect the compatibility between construction and the plan and empowered to stop building or require the units to follow certain planning permit procedures.

The introduction of the land market (since 1987) challenges planners to organise urban restructuring as their main task. Deng Xiaoping's tour of south China speeded up the pace of land development to attract more foreign investment. However, the concurrent decentralisation of decision-making, the increase in development actors and conflicts among developers, local residents and government are increasingly weakening the role of urban planning in urban development. Land development based on the market principle frequently leads to the delay of planning schemes as local governments acquiesce in the face of the unreasonable demands of developers. The inconsistency between planning and construction is making urban planning much more involved in the process of political decision-making. Traditional blueprint planning has proved unable to deal with the complex dynamic changes in the cities. Therefore, new forms of process planning, strongly based on urban studies, information, negotiation and management, have become dominant. The planning practice that can be observed in some cities, including Wuhan, indicates that Chinese urban planning is still in the transition phase from a planned to a market economy.

3.3 Methodology

Urban growth involves complex physical, social, economic and ecological processes. As a consequence, the interpretation and evaluation of urban growth based solely on qualitative knowledge is difficult if not impossible. Physical or ecological processes lead to changes in landscapes, and the socio-economic processes to changes in land uses. Therefore, analysing urban growth should take both (physical and functional) into account and should also be based on quantitative modelling.

Individual indicators are only able to explain a specific aspect of the processes. In most cases, urban indicators are closely related and also complementary. As socio-economic systems are in essence complex, we argue that the non-linear interaction between a number of spatial and temporal indicators can be expected to improve the capacity for interpreting the systems under study. Or rather, in terms of self-organising theory, the interactions between these indicators can lead to global emergence, i.e. increased capacity for interpretation. The spatial indicators used in this study quantify the structural and functional complexity inherent in urban growth systems. Structure is the physical arrangement of ecological, physical and social components, and function refers to the way the components interact (Zipperer et al., 2000). Adolphe (2001) defined four urban structure variables – urban form, land use intensity, land use heterogeneity, and connectivity – for analysing the influences of ecological conditions on an urban-to-rural gradient. Structural and functional complexity is indicated in the aspects of urban form, morphology, land use and master planning for the urban growth system. A proposed methodology is displayed in figure 3.1, which is based on monitoring temporal urban growth from remotely sensed imagery. This methodology consists of several steps: data collection from multiple sources, data processing such as image fusion and digitising, temporal mapping, evaluation based on spatial indicators and comparisons. The main quantitative analysis includes morphology analysis, spatial pattern analysis and land use structure change. Fractal analysis, regression analysis and landscape metrics are selected as analytical methods.

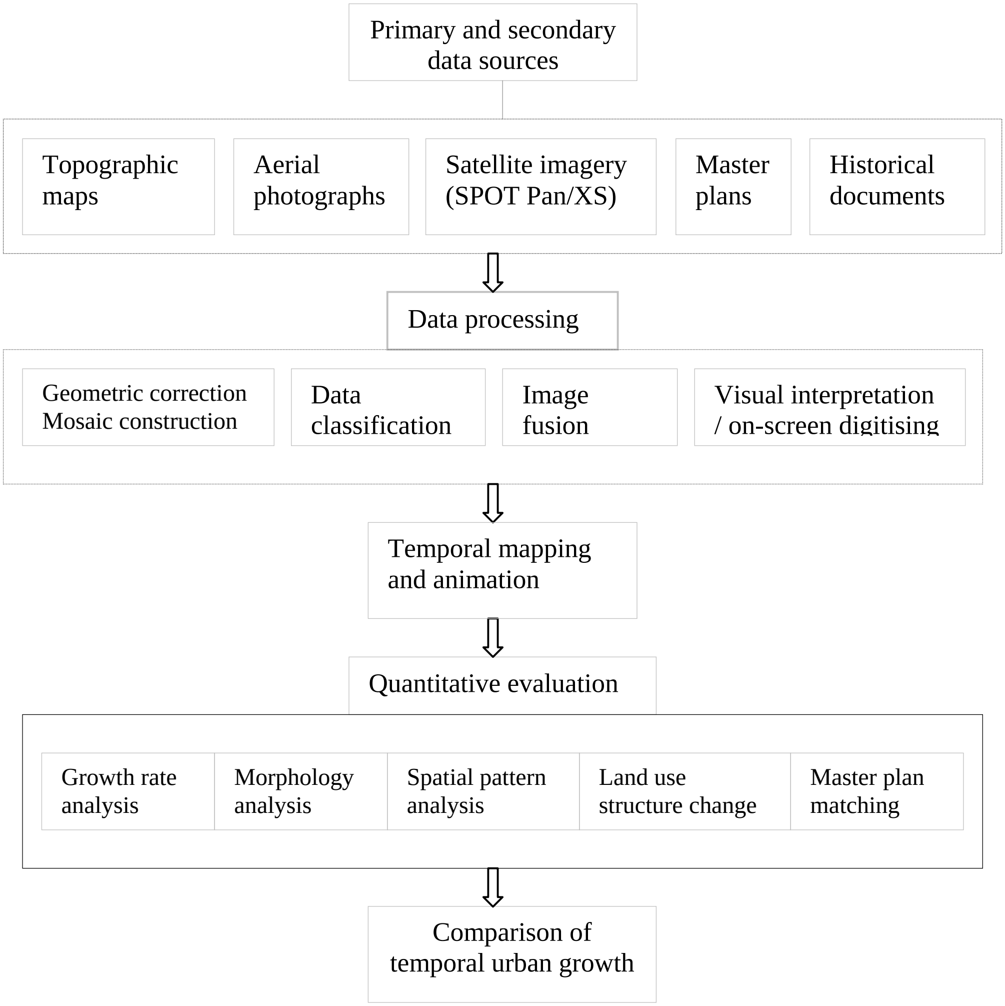

Figure 3.1 Flowchart of the methodology proposed

3.3.1 Urban morphology analysis

There are three classic theories of urban morphology: the concentric area theory (an urban pattern of concentric rings with different land uses and a central business district), the sector theory (the concentric zone pattern modified by specific development along transportation corridor), and the multiple nuclei theory (patchy urban pattern formed by multiple centres of specialised land use activities) (Carter, 1995). These theories structure urban morphology from a primarily static viewpoint. All of them are less well suited to analysing the more complex urban spatial evolution we witness today.

Recently, the spatial indicator approach has been introduced to describe urban morphology. For example, Adolphe (2001) proposed a simplified spatial modelling of urban morphology complexity. He defines a set of indicators of the environmental performance of urban fabrics: density, rugosity, porosity, sinuosity, occlusivity, compacity, contiguity, solar admittance and mineralisation. This model has been embedded in a GIS model called the "morphologic urban model" and applied to the analysis of existing urban fabrics. This method provides multiple viewpoints to quantify the geometrical properties of urban systems. However, this method is also static and not suitable for temporal evaluation. Moreover, local urban planners have extensive qualitative knowledge of the spatial morphology of dynamic growth, which would benefit from further quantitative confirmation based on GIS. Here, we propose a subjective method to confirm the dynamics of urban development axes based on local knowledge. Development axes represent the trends of new development in a specific period. Linear regression analysis is used to test the relevant hypotheses.

3.3.2 Spatial pattern analysis

Numerous studies show that a fractal approach to analysing a landscape may generate promising indicators of its structural complexity. It reveals morphological patterns of a higher order, and the approach provides a tool for modelling the spatial heterogeneity and complexity of landscape structure and processes of change. Recently, an increasing volume of analytical urban modelling has shown that planned and designed spatial objects such as urban forms (Makse et al., 1998) and transportation networks (Kim et al., 2003; Shen, 1997; Shen, 2002a) can also be treated as fractals.

However, it should be noted that fractal measures of spatial complexity still lack adequate interpretation capability for urban spatial patterns because the same value of a fractal dimension may represent different forms or structures. Consequently, the values can be more significant when they are used for the purpose of comparative analysis, such as different urban land use patterns (Batty and Longley, 1994), urban growth patterns (Batty and Longley, 1994), simulated and observed patterns (White and Engelen, 1993; Yeh and Li, 2001a), and transport network patterns (Kim et al., 2003; Shen, 1997).

From the perspective of geo-computation, fractal measures focus on the global scale of geographical space and only use its geometrical information. It is a global measure like spatial auto-correlation. Another difficulty in applying fractal measures is the selection of appropriate fractal dimensions, as more than 10 different notions of dimension have been acknowledged by mathematicians: *topological dimension, Hausdorf dimension, correlation dimension, self-similarity dimension, box-counting dimension, capacity dimension, information dimension, Euclidean dimension, Bouligand dimension, space-filling dimension*, and *Lyapunov dimension*. They are all interrelated. Some of them make sense in certain situations, but not at all in others. Self-similarity is only defined for strictly self-similar objects, i.e. deterministic fractals. However, in practice, most real fractals in nature and in the man-made world display self-affinity rather than strict self-similarity. These fractals should be measured according to their stochastic properties, applying statistical methods such as regression analysis.

Compared with the capacity dimension mentioned above, where the spatial objects are assumed to be spatially homogeneous, the information dimension is more powerful for modelling the spatial distribution of complex spatial objects as the heterogeneity of spatial distribution is taken into account. It is based on the concept of Shannon's information theory. This algorithm is easy to implement in a GIS environment. A common procedure is to partition the whole study area into a finite set of rectangles or squares. No difference between using rectangles or squares has been reported. Supposing that the total length and width of a study area are represented by *L* and *W* respectively; the *n*th partition is corresponding to create a grid with $n \times n$ pixels, each with length L/n and width W/n. Generally, the minimum partition is a 3 × 3 grid (i.e. n=3). This grid layer will be overlaid with the layer to be modelled. C_{ij} means the grid element in the *i*th column and *j*th row. The probability of C_{ij} can be indicated by the value P_{ij} as follows (equation 1).

$$P_{ij}(n) = \frac{N_{ij}}{N}, I(n) = -\sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij}(n) * \ln P_{ij}(n) \qquad (1)$$

Where N_{ij} means the measure of the studied spatial objects in C_{ij}. For example in urban growth, it is the number of cells in C_{ij} occupied by new development units; in road networks, it could be the length of road located in C_{ij}. N is the total measure. I represents the total information capacity corresponding to the spatial partition n, which implies the measure of spatial distribution. The information dimension can be estimated by the following linear regression equation (equation 2):

$$I\,(\mathrm{n}) = D_0 + D * \log(n) + e_n \qquad (2)$$

Where e is the error term, D_0 is the regression constant or intercept and D is the fractal dimension based on the least-square method. Generally, D is between 1 and 2. When D=0, all spatial objects are concentrated on one point; when D=2, it indicates a homogeneous spatial distribution; when D approaches the value 1, the objects cluster to a curve or line like a river or a road. The larger D is, the more homogeneous the spatial distribution of the studied spatial objects is.

3.3.3 Urban land use structure change

Land use is the projection of complex urban socio-economic activities on a land system. The structural and functional characteristics of land use reflect the outcomes of socio-economic processes. Landscape metrics or indices can be defined as quantitative indices to describe structures and patterns of a landscape based on information theory. It is an ideal means for describing and quantifying the degree of heterogeneity (Kronert et al., 2001). From the perspective of geo-computation, landscape metrics characterise the geometrical and spatial properties of mapped data.

The landscape index can be applied for describing structures and changes in urban land use. Herold et al. (2002) used landscape metrics to describe urban land use structures and land cover changes that result from urban growth, based on the spatial information from digitally classified aerial photographs of the Santa Barbara, CA urban region. The results show a useful separation and characterisation of three urban land use types: commercial development, high-density residential and low-density residential.

Table 3.1 Landscape metrics selected and their description

Metric	Abbreviation	Description
Mean patch size	MPS	Average size of all patches in one or all land use
Patch size coefficient of variance	PSCV	Standard deviation of patch size divided by MPS
Edge density	ED	Total length of one or all land use divided by total area
Mean shape index	MSI	Average perimeter to area ratio for all patches
Area weighted mean shape index	AWMSI	Average perimeter to area ratio weighted by area
Mean patch fractal dimension	MPFD	Average fractal dimension of land use patches
Area weighted MPFD	AWMPFD	Average fractal dimension weighted by area
Shannon's diversity index	SDI	Richness of land use types (only landscape level)
Shannon's evenness index	SEI	Distribution of area among all patches (landscape)

The landscape metrics have two components: composition and configuration. The former is a non-spatially explicit characteristic such as evenness, dominance and diversity. The latter measure, e.g. shape, edge and neighbourhood, reflects the patch geometry or geographical location. To quantify change in urban structural and functional complexity, selected metrics (table 3.1) at the land use level include MPS, PSCV, ED, MSI, AWMSI, MPFD and AWMPFD. At the landscape level, two additional metrics, SDI and SEI, have been selected. The mean patch size (MPS) gives direct information on the landscape configuration and its fragmentation. Patch density (PD) and the patch size standard deviation (PSSD) values yield information about the density and the size of built-up areas, as well as their spatial aggregation for each cover type. PSCV measures the relative variability about the mean (variability as a percentage of the mean), not the absolute variability. This is the well-established coefficient of variation.

The fractal dimension describes the complexity and the fragmentation of a patch by a perimeter/area measure. The area weighted mean patch fractal dimension (AWMPFD) measures a different dimension of urban land use structure. This metric averages the fractal dimensions of all patches by a higher weighting of larger patches. Edge density (ED) (the number of adjacencies between distinct land use classes per hectare) is a fragmentation index where the effect of spatial extent is concerned. The metrics attempt to quantify the irregularity and complexity of the shapes in the pattern (Saura and Millan, 2001) as an expression of the spatial heterogeneity of a landscape mosaic. As an indicator for patch shape complexity, MPFD approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted plane-filling perimeters.

3.4 Case Study

3.4.1 Location

The geographical position of Wuhan is 30° 33'N and 114° 19'E. Its climate is sub-tropical, characterised by a humid monsoon. It is located in central China and on the middle reaches of the Yangtze River, the third longest river in the world. Wuhan is in the eastern part of Hubei province and is its capital (figure 3.2). Its topography is dominated by relatively flat land between 22 and 27 m above sea level. Wuhan is nicknamed "Water City" (*Jiang cheng*), as not only do two rivers (Yangtze and Han rivers) intersect here but the city is also surrounded by a number of lakes. As the Yangtze River and the Beijing-Guangzhou railway line cross here, Wuhan is a focal point for water, railway and other traffic in China.

Wuhan is a combination of three towns: Wuchang, Hanyang and Hankou. Wuchang was named *Jiangxia* some 1600 years ago. In the area of Hanyang a castle was built during the Han Dynasty (206 BC-222 AD). Development of what is now Hankou began during the period of the south-north dynasties (420-589 AD). It was situated next to Hanyang before the Hanshui River changed its course during the Ming Dynasty (1368-1644 AD), separating it from Hanyang. By the 13^{th} century, Wuchang and Hanyang had developed into commercial and handicraft towns. In the 1700s, Hankou was already a major inland river trading port.

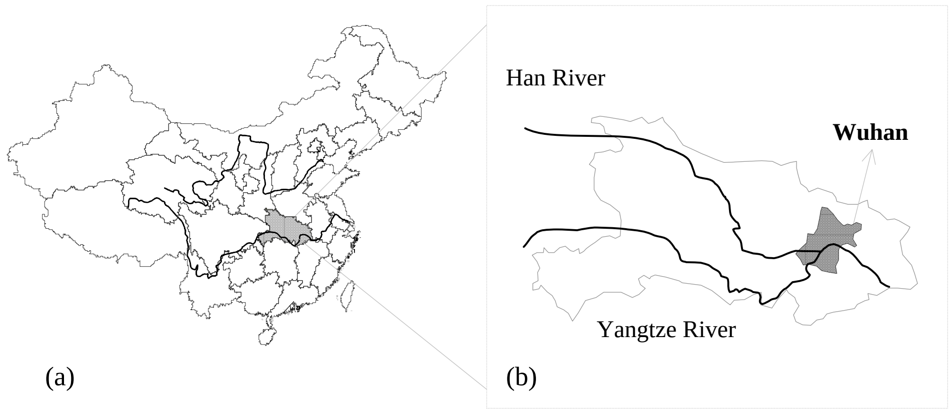

Figure 3.2 Location of Wuhan city: (a) Hubei in China; (b) Wuhan in Hubei

Around 1900, the three towns functioned in specific areas, i.e. Hankou in commerce, financial services, trade, transportation, regional services, entertainment and information services; Wuchang in institutional and educational activities; and Hanyang in the industrial steel and machinery sector. The population density of Hankou town ranked second among Chinese cities after Shanghai. Between 1840 and 1949, the population of the three towns expanded from 0.2 to 1.2 million and the city area, including the suburban areas, expanded from 20 to 941 km^2 (Pi, 1996).

Until 1840 Wuhan was the city "along the Han River". Later, Wuhan became the city "along the Yangtze River". This transition was a result of its opening to the world after 1840, which converted the city into a centre of not only domestic but also international trade due to its convenient water and ground transportation system with good connections to the surrounding areas.

3.4.2 Monitoring urban growth 1955-2000

(1) Data sources

Remotely sensed imagery is a widely recognised primary source for urban growth monitoring. Before the 1970s, high-resolution satellite images were not commercially available and the military controlled aerial photography. Unfortunately some of them do not cover the whole study area and the aerial photographs of 1955 have sub-optimal map scales. The SPOT images were captured in the best seasons for Wuhan city, from September to November. The land use map of 1993 was created by the Wuhan Bureau of Urban Planning and Land Administration through the support of various districts and considerable fieldwork. This is considered to have the best accuracy for this research. Secondary sources include topographic maps, traffic and tourist maps, master plan schemes, a sub-district boundary map and historical documents. Table 3.2 lists the various data sources with a time span of nearly half a century.

Table 3.2 Data sources

Source (year)	Scale/Resolution	Coverage
Aerial photographs (1955)	B/W 1: 25,000	100%
Aerial photographs (1965)	B/W 1: 8,000	70%
SPOT (Sept. 1986)	Pan / XS, 10/20m	100%
SPOT (Oct. 1995)	Pan / XS, 10/20m	80%
SPOT (Nov. 2000)	Pan / XS, 10/20m	100%
Topographic maps (1973)	1:50,000	100%
Topographic maps (1993)	1:10,000	100%
Land use map (1993)	CAD format	100%
Master plan 1996-2020	GIS file (shp)	100%
Master plan 1954, 1988	1:100,000	100%
Sub-district boundary in 1993	GIS file (shp)	100%

(2) Processing of aerial photographs and images

The aerial photographs of the three periods were scanned at a resolution of 1200 dpi. As no flight parameters, ground co-ordinates (including elevation) or large-scale topographic maps of the flight period were available for this set of aerial photographs, it was impossible to remove radial and tilt distortions from the scanned photographs. No ortho-rectification was performed on the images because of the very flat aspect of the terrain in this city.

The topographic maps of 1993 with the scale 1:10,000 are ideal sources of ground control points. The original SPOT images have been rectified using some 50 points (for the aerial photographs even more) systematically chosen and evenly distributed over the images to guarantee enough points in the centre and corners of the images. A second-order polynomial model was chosen for the image rectification and resampled using the nearest-neighbour algorithm. The root mean square error (RMSE) is strictly limited to 0.3 pixels for SPOT images. Due to their smaller scale, the aerial photographs of 1955 have a lower accuracy of RMS, which is about 5 pixels. The projection system of WGS84 NORTH with Zone 50 was selected for Wuhan.

Image fusion is the combination of different digital images in order to create a new image by using a certain algorithm. Image fusion is preferable to both higher spatial resolution and wider spectral information for the effective visual interpretation of images. With a fused image the interpreter has the benefit of both, without looking at two different images. Image fusion was implemented to comprehensively integrate the spectral information from SPOT XS (three bands) and the spatial information from SPOT PAN (10 m). Before fusion, accurate co-registration is vital for the accuracy of fusion. A map-to-image strategy is applied for SPOT PAN, based on the topographic maps. Subsequently, the image-to-image method is used for the geo-referenced registration of SPOT XS. Adequate ground control points guarantee the accurate position match of two images. Among the three techniques (multiplicative, principal component, brovey transform) in ERDAS, the multiplicative method was chosen for the fusion, as being better for highlighting urban features.

Before interpretation and digitising, the fused images are transferred into RGB images as colour composites and then a supervised classification (maximum likelihood) is made to identify pixels with land cover change. Visual interpretation (with local knowledge) is carried out to remove any errors of the automated classification exercise.

(3) Data classification

Urban area

In the course of interpretation, the first difficulty encountered was the definition of spatial attributes for digitising. For example, some enterprises or villages administratively belonged to neighbouring counties even though they are large-scale or near to the city area. Therefore the urban area should be clearly defined in geo-space. The concept of urban land can be described according to its physical and functional aspects. "Urban" in functional terms means activities. In physical terms, it relates either to density or to land use. The technique of remote sensing (satellite images and aerial photographs) focuses on the latter, with the assistance of fieldwork. “Developed areas” comprise all areas of continuous development that are covered by bricks and mortar, such as buildings and transportation features.

It can be argued that the administrative boundary is not an ideal definition as it rarely coincides with the physical extent of urban growth, and large urban agglomerations commonly include a number of separate authorities (Kivell, 1993). It is more appropriate to apply population size threshold, to use continuously developed areas and the residual urban definition from agricultural surveys.

In the case of Wuhan city, in particular during the last five decades, different urban development policies have been carried out. Therefore a uniform definition does not exist. According to historical records, the modification (in most cases it was expansion) of administrative boundaries frequently followed urban sprawl. Consequently, the administrative boundaries in a later period can be used for the spatial extent of urban areas. For example, when digitising the urban areas of 1955, the boundary of 1965 can be used as a reference. Of course, continuously developed areas are the basic concept when monitoring urban growth.

Land use/land cover

Land cover or form is essentially the nature of the elements in the landscape, such as the types of buildings, structures or open spaces. Information on land cover is discernible from remotely sensed imagery. Land use can broadly be defined as the level of spatial accumulation of activities such as production, transaction, administration and residence with highly dynamic relationships between them. Urban land use reflects the nature of social and economic activities in an area, as well as interactions with other areas (Rodrigue, 1997). It results from the complicated interactions between the land system and the social-economic systems. Land use/land cover information is fundamental for understanding the spatial and temporal dynamics of urban development, which is the basis for urban development planning and sustainable land management. In this research, land use data for 1955 and 1993 will be utilised for measuring temporal urban sprawl (chapter 4) and land cover data for 1955, 1965, 1986, 1993 and 2000 will be used for the modelling exercises (chapters 3 to 6).

The selection of a land use classification scheme depends on various factors such as the collected data, the local planning system and the purpose of the application. The National Land Use Standard Classification (NLUSC) has been promoted in China since 1992. It has 10 major classes, 46 groups and 73 subgroups. The local land use classifications used before 1992 were not nationally uniform and underwent many revisions.

The following land use classification was adopted for the land use map of 1993, which was already in digital format (CAD format) and is produced by the urban planning organisation. It was also applied to the 1955 aerial photographs. Here, the class "public facility" includes both commercial and institutional aspects. The main land use categories are:

- Residential; Industrial; Warehouse; Public facility (commercial, institutional etc.);
- Utility; Inter-city transport uses; Special uses (military),Water;
- Green; Town/Villages; Agricultural.

With the improved spatial resolution, SPOT data are commonly used to produce land cover maps at the urban-rural fringe (Jensen, 1996). It is possible to make a 1:50,000 land cover map. Here, land cover is classified as urban built-up, agricultural, water body and protected area (green, sands, special uses), which were principally extracted for the periods 1986 and 2000. Land cover for 1965 was derived from aerial photographs. Technically, more land cover types can be classified. For example, Gao and Skillcorn (1998) report a test based only on SPOT XS to identify the land cover at selected urban-rural fringes as residential, industrial and commercial, other urban or built-up, pasture and cropland, orchards and horticultural, mixed forest, bays and estuaries, forested wetlands or mangrove forests, transitional, and barren land. The accuracy of classification could reach 76.2% in the winter and 81.4% in the summer.

Road classification

There is not a universal standard for road classification as it varies not only between different countries but also with different periods of urban development. Moreover, an accurate characterisation of roads is also not available as it is determined by quite a number of indicators such as traffic volume, road width and structure, which are difficult objectively to collect. In China, before 1992, only three types (major roads, secondary roads and tertiary roads) were in existence and used for urban planning. But since 1992, four types (expressways/freeways, major roads, secondary roads and tertiary roads) have been adopted in transportation and urban planning as quite a few higher-quality highways have been constructed. In this research, to remove the ambiguous definition in road classification, only two classes (major and minor) are used to identify their impacts on urban development. The identification of major roads is based on the local classification available from master plans and tourist maps, which play a role in the decision-making on urban development. Some interviews with local planners were also necessary for further confirmation.

Centre /sub-centres definition

Most mega-cities in the world are undergoing a shift from a monocentric to a multi-nuclear spatial structure. This results in a demand to define, rank and even identify spatial (sub-)centres in the urban area. Compared with the road classification mentioned above, the spatial definition of city centres and sub-centres is much more ambiguous. First of all, the activities and buildings typical of the city centre cannot always be clearly defined. Centre components could be shopping, administration offices, institutional offices, banking, hotels, hospitals, parks etc. These components have not only different magnitudes but also various scales. Second, the boundaries of centres are not crisp but fuzzy. Consequently, in theoretical terms, a reasonable classification might be based on the comprehensive evaluation of information with reference to features such as density, intensity and diversity. Thurstain-Goodwin and Unwin (2000) report on a research project that tried to define a surface of city centres based on an Index of Town. The definition of centres in this research follows local knowledge, including maps and planning schemes. Some local planners were also interviewed to confirm the definition.

Master plan classification

The major master plan implemented in Wuhan includes the 1954 scheme approved by the State Planning Commission, the 1982 scheme approved by the State Council, the 1988 scheme approved by the Wuhan municipal council and the 1996 scheme approved by the State Council. During these periods the land use classification of the planning schemes underwent numerous modifications (WBUPLA, 1995). In 1954, urban land use was classified into industrial, warehouses, residential, hospitals, schools and green areas. In 1982 the classification was industrial, residential, warehouses, universities and green areas. In 1988 the classes included industrial, warehouses, residential, commercial/trade, universities and green areas. In 1996 the classification was extended to residential, low-density residential, commercial and residential, commercial, banking and trade, offices, education and research, culture, hospital and recreation, green areas, industrial, warehouses, external transportation, railways, infrastructure, waters etc. The modifications indicate a shift in urban development from industry-oriented to service-oriented, as more detailed sub-classes related to the tertiary section are included in the new scheme.

(4) Visual interpretation

While aerial photographs for land use mapping have been used for many decades, there is also ample experience in the use of satellite images with low (Landsat, Thematic Mapper) and medium resolution (SPOT) for land cover mapping. Many researchers have developed automatic solutions for land use classification based on digital imagery, but there are many aspects which remain unsolved, such as image understanding and pattern recognition. For urban areas, where urban land use systems involve complex social and economic activities, visual interpretation is still the most reliable method for classification.

As the interpretation of an image or photograph is to some extent subjective, a time series of urban growth mapping should be carried out by one person (in this case the author) to guarantee comparability. Manual interpretation provides a comparable interpretation of sequential images when consistent interpretation criteria are applied throughout the research by the same analyst. Before digitising, a minimum mapping unit should be determined for the various scales of the data sources.

An on-screen digitising approach using the ArcView package was selected for visual interpretation because of the easy conversion of data between the ArcView and ERDAS formats. First, in the case of fused images, two map files (non-urban and urban land use in 1993) were created respectively to be backcloths for assisting visual interpretation. The changed areas are directly digitised from the images. The procedure can be divided into two stages. Stage one is to make a supervised classification identifying possible cells with land cover change. This approach generally leads to some misinterpretation, with too many cells detected. Stage two eliminates errors and assigns the right land cover attributes. But, in the case of aerial photographs, the low accuracy of geo-referenced rectification makes this approach ineffective. The interpreted change has to be digitised on the backcloth, i.e. the land use map of 1993. The minimum mapping unit can be one 10 × 10 m cell, which is the same as the resolution of SPOT PAN. It is very important to go through the relevant background materials regarding the development process of the study area. The book *Wuhan Record of Urban Construction* (ECWLR, 1996), which describes in detail the history of urban construction from 1949, provides a rich secondary source of information for interpretation, especially for the years 1955 and 1965. It is unfortunate that the larger-scale aerial photographs of 1965 do not cover the whole city. They can be supplemented by the scale 1:50,000 topographic map of 1973 despite its lower resolution. It results in a coarse land use classification (urban/non-urban) rather than a detailed one, which can originally be extracted from aerial photographs.

From the viewpoint of the temporal comparison, some layers have a certain degree of fuzziness in their definitions, especially when the study area is large and the period is long. For instance, the construction of roads may occur in a different phase of the period to be modelled. Their construction time should be taken into account. In this research, a major road (linked with the Third Bridge over Yangtze River) was completed in early 2000, which can be clearly seen in the SPOT images of 2000. However, this major road was not included in the Major Road layer as it did not have any impact on urban development in the period 1993-2000. This observation is confirmed by the very limited land cover changes surrounding the road. Other layers are spatially interpreted following similar procedures.

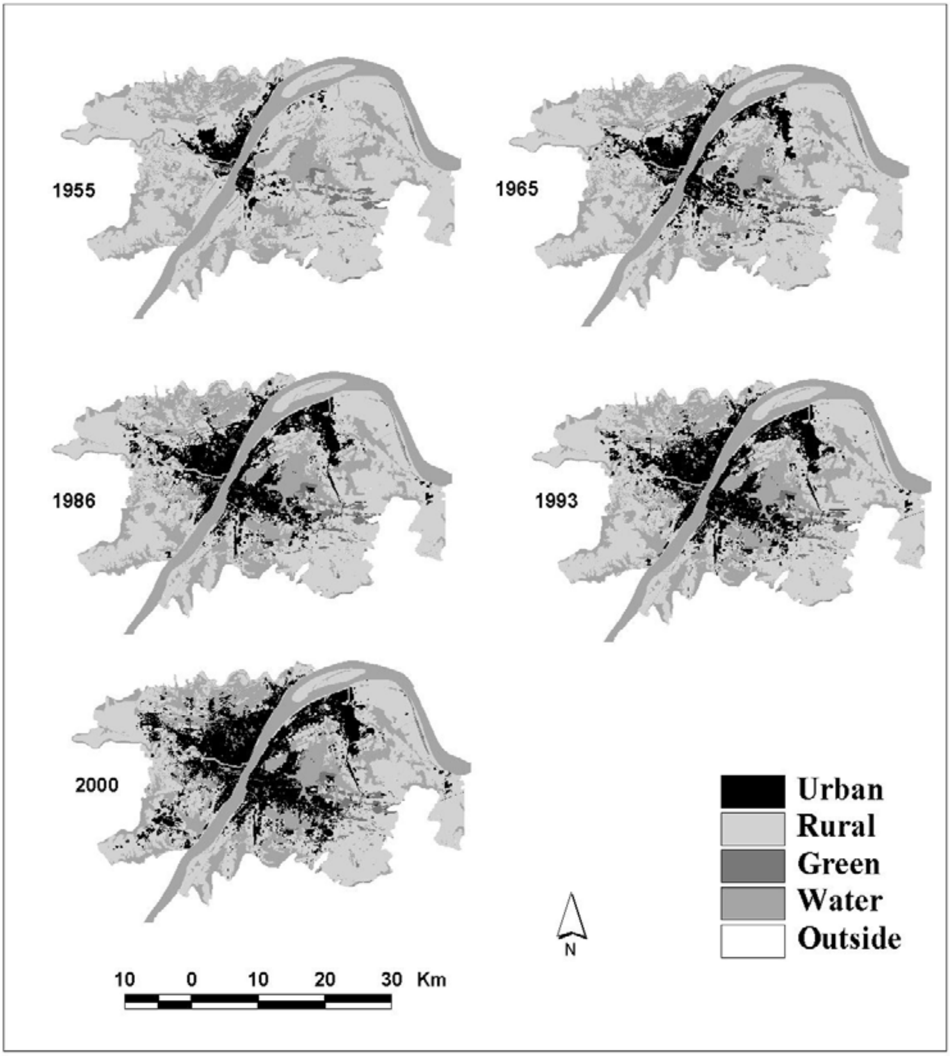

Figure 3.3 Temporal urban growth in five years

(5) Temporal mapping and animation 1955-2000

Animation is an excellent tool to present the time dimension in landscape change. It can also be used in interactive data exploration (Ogao and Kraak, 2002). Most animations consist of a set of sequential images, often one for each particular time slice, and the animations display them in a fixed sequence. Figure 3.3 maps the temporal urban expansion of Wuhan, spanning nearly five decades. Figure 3.4 shows the changing road network and city centres/sub-centres. These maps enable us to explore the spatial patterns of urban growth. The animations can be seen on the homepage http://www.itc.nl/personal/jianquan.

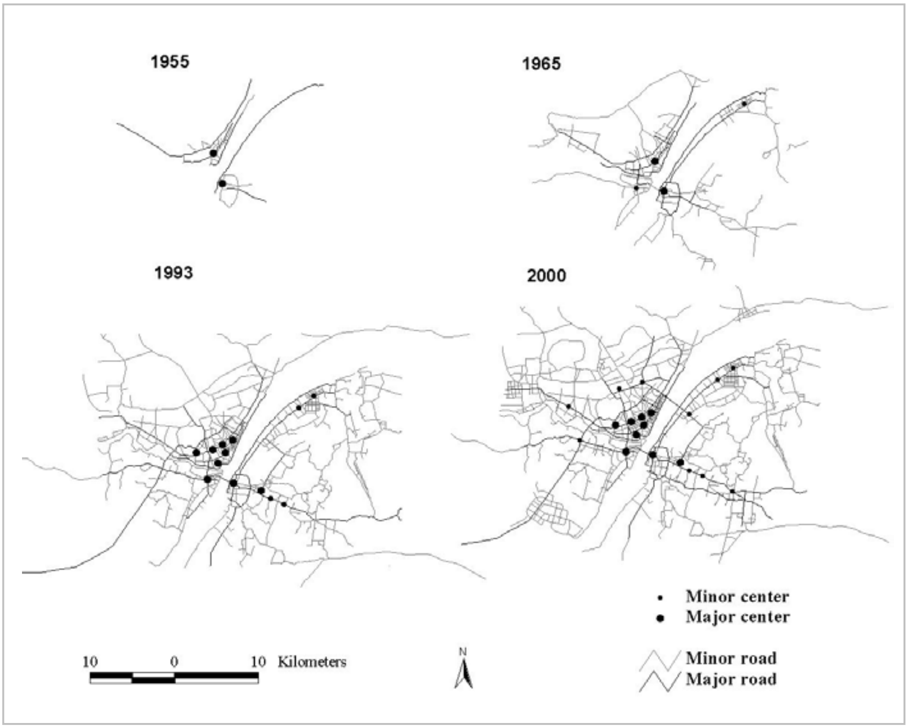

Figure 3.4 Temporal mapping of road networks and centres/sub-centres

1955 - 1965

Large-scale new development started after 1953, with the beginning of the first five-year plan (1953-1957). During that period Wuhan was selected to be one of the key industrial cities that received considerable investment from the central government. Assisted by experts of the former Soviet Union, a master plan was drawn up in 1954 (figure 3.11) for locating the new industrial projects, and quite a few major key projects were completed or started. In 1956, based on the master plan for 1954, Wuhan municipality made a more detailed “Wuhan urban construction 12-year plan 1956-1967”, as required by the National Economic and Social Development 12-year plan (WBUPLA, 1995).

In 1958, when the second five-year plan (1958-1962) and the famous Great Leap Forward development began, Wuhan city proposed an ambitious industrial development scheme comprising 200 projects. This scheme conflicted to some extent with the construction capacity available in 1956. The overheated construction resulted in serious imbalances and a decline in the national economy. Hence, at the end of 1958, the local construction committee made reasonable adjustments to the project scheme, which then centred on 12 industrial zones with a reduced number (from 196 to 118) of industrial projects (figure 3.5). The overall investment was also reduced from 3437 million to 1996 million yuan (*renminbi*) (ECWLR, 1996). The modified scheme was approved and implemented immediately. However, consecutive three-year natural disasters (1959-1961) seriously slowed down the planned urban construction.

In 1961, local government developed a series of policies for economic recovery and started to further reduce the planned industrial expansion. By 1965, the planned projects were mostly completed; about 13 industrial zones had been built. The major projects included the first road-rail bridge over the Yangtze River (1957 in operation), Wuhan Iron and Steel Company (1959 in operation), Qingshan Thermoelectric Plant (1959, no. 1 project in operation), Wuhan Heavy Machine Tool Factory (1956-1958), Wuhan Boiler Plant (1956-1960), Wuhan Integrated Meats Processing Factory (1958 in operation), Hanyang Steel Factory (1958 under construction) and Wuhan No. 2 Textile Factory (1965 under construction), as well as universities such as the famous Huazhong University of Science and Technology (1954 under construction). Other projects included the Wuhan department store (1959 in operation) and Wuhan theatre (1959 in operation). In this way, Wuhan became a famous industrial city and a centre of education and scientific research.

These large-scale developments resulted in discontinuous urban sprawl. Most large-scale factories were located in the northeastern part of the city (figure 3.3), which became an independent steel town (i.e. Wuhan Steel Company, known as *Gangcheng*). It was almost isolated from the other developed areas. This can be explained by two factors. The first is the proximity to the Yangtze River for ship transportation. The second is the availability of large-scale developable land. From figure 3.4, it is clearly seen that the right bank of the Yangtze River is covered with a higher percentage of water bodies, making it difficult for major construction around the developed areas. The spatial link between the new town and old city (in Wuchang) was established by two parallel main roads, i.e. the *Heping* road completed in 1958. Several railway lines were constructed to link the new town with the port and the major railway stations. The construction of new major roads and railway lines was also meant for a few key heavy industrial factories such as the Wuhan Heavy Machine Tools Factory and the Wuhan Boiler Factory, which were located close to the major roads. On the left bank of the Yangtze River (Hankou and Hanyang towns), new development was close to the already developed areas as many of the old factories were already located there. They comprised a middle scale of factories built by state and local governments. From figures 3.3 and 3.4 it can be seen that the factories were built near the old or new railway lines, most of the warehouses being located on the banks of the Yangtze River and near railway lines.

In addition to industrial development, around 24.2 ha of new housing was constructed before 1958 (ECWLR, 1996). Rapid urban growth in this period led to the addition of two commercial centres (figure 3.4). One was located in the "town of steel" (Q*ingshan*), centred around the *Qingshan* department store constructed in 1958. The other was located in Hanyang town.

1965-1986/93

After 1965, when state investment in the region was reduced, the urban development of Wuhan city slowed down. Further, disturbed by the 10-year Cultural Revolution (1966-1976), economic development in China as a whole was in disorder. Urban construction was dominated by small-scale local industrial projects which were built by the municipality and lower levels of organisations such as sub-district committees. Land development was restricted in a sporadic pattern (*Jian Feng Cha Zhen).* Moreover, in 1971, 17 work units were relocated to *Yangxin* county and another 19 to *Xianning* county, Hubei province, as required by central government. However, these units had to move back to Wuhan in 1973.

By the end of 1975, 12 industrial zones had been completed. As a result, 23.7% of the total population (2,437,000 in the seven urban districts) and approximately 279,000 employees were settled by these industries in 1975 (ECWLR, 1996). According to local records, the majority of the industrial sites completed in the 1965-1993 period were constructed before 1986. Based on the urban development map of 1986 (1986 in figure 3.3), a coarse map (1986 in figure 3.5) is drawn to display the spatial distribution of the zones. The largest zone with code 1 is *Qingshan* steel town in the northeastern corner. The three zones with codes 7, 8, and 9 located in Hanyang town are spatially clustered, whereas the three zones with codes 10, 11 and 12 in Hankou town are much more spread out. The three zones with codes 2, 3 and 4 in Wuchang town are mixed with other land uses. These patterns reflect the planning of the period. The planning doctrine at the time was that the three towns, except for the steel town, should have different functions: industrial for Hanyang, institutional for Wuchang, and commercial for Hankou. At the same time, as the development emphasis was put “first on production, second on living”, house construction almost stopped in this period.

After 1978, the primary sector in the Wuhan suburbs was restructured. In 1980, Wuhan became an open city to the outside world. From 1978 to 1990, local government started to pay attention to the development of housing, facilities and infrastructure to compensate for the imbalance caused by overemphasising industrial development. For example, some 30 clustered or planned residential areas larger than 5 ha were constructed in 1975-1990, totalling 404 ha (ECWLR, 1996). Wuhan was also listed in 1990 as ranking eighth in the whole of China for its provision of urban infrastructure resources (John, 1996).

In 1984, Wuhan was approved by the Chinese government as a pioneer of economic system reform in cities. It then acquired more freedom through the “single planning city system”, which made the city directly responsible to Beijing. Local reform started with the opening of the communication and circulation markets. The economic structure of Wuhan city was adjusted and made more modern and rational. These new policies stimulated the rapid development of tertiary activities, which had been decreasing since 1949, such as the *Hanzhenjie* small-goods market that was becoming a facility that served several surrounding provinces.

The master plan approved by the State Council in 1982 needed to be revised to satisfy the new market economy. The revised version was implemented in 1988, when Wuhan planned the Donghu New Technology Development Zone (DNTDZ) and the Wuhan Economic Technology Development Zone (WETDZ) to attract more foreign investment and stimulate more rapid economic development. The DNTDZ was approved by the State Council in 1988. The WETDZ started construction in 1993 with the establishment of a national car manufacturing unit in co-operation with French companies. Another national project, the Yangluo electric power plant, began operations in 1991. These state investment projects were located in the outer belt, occupying a large amount of agricultural land.

But in the 1980s, the emphasis of national state investment was put on coastal cities and preferential policies were shifted there. Relatively, Wuhan urban development was much slower than in open coastal cities or Special Economic Development Zones such as Shenzhen. As a result, despite rapid urban sprawl, its development density is still very low due to limited investment sources.

Figure 3.4 shows that a couple of new major roads were constructed in the new developed areas of Hankou and Wuchang towns respectively. These roads were planned or completed before the new developments. However, due to the change of industry structure, traditional industry, in particular heavy industry, was gradually losing its position. The demand for railway transportation decreased, and the railway network did not change after 1986. However, the development of industrial sections spurred the building of new commercial centres as these sectors came in operation around 1986. One was located in Qingshan town and others were located in Wuchang.

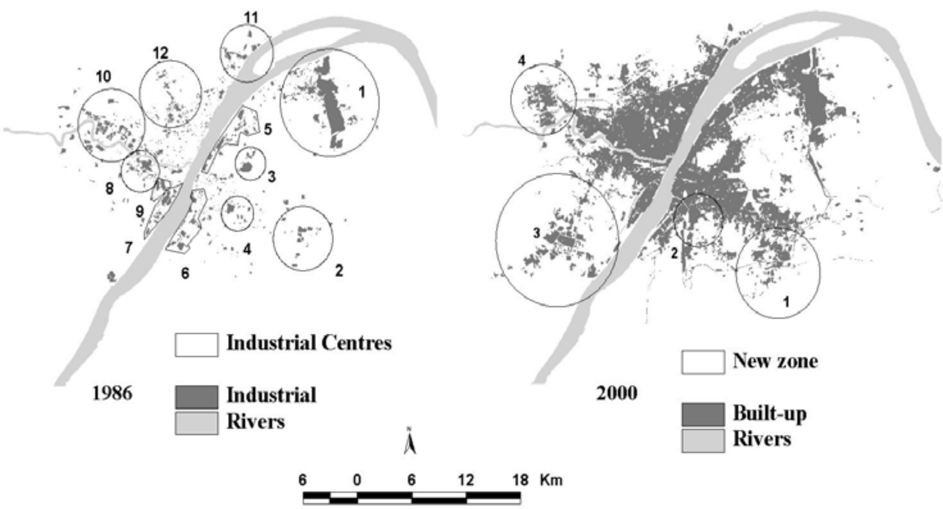

Figure 3.5 Industrial zones in the two periods

Official reports (ECWLR, 1996) indicate that housing construction stopped in the period 1959-1978 and started again after 1980. The average living area per person increased to 6.09 m^2 in 1990 from 4.05 m^2 in 1980.

Summing up, the growth pattern in the period was characterised by relatively slow industrial development. In the 19 years, urban development was dominated by inward and outward fill-in along development axes such as the Yangtze and Han rivers and major roads.

1993-2000

In Wuhan, new types of development characterised by high-tech zones were planned at the end of the 1980s, but largely constructed only after 1992, when Deng Xiaoping made his tour of southern China. Although, Wuhan was approved as one of the Chinese cities carrying out land use rights transfer in 1990, land reform policy was implemented in Wuhan only after 1992. Deng Xiaoping's policy of the "Three Alongs" (developing economic hubs along China's border, along the coast and along the Yangtze River) gave Wuhan its chance. Hence, Wuhan was able to speed up new development of the DNTDZ and the ZETDZ, and other infrastructure projects, which were becoming focal points of domestic and foreign investments.

Since then, Wuhan has become a huge construction site as all over the city new development and redevelopment have expanded. This leads to a completely new era for overall urban development. New infrastructure has been added: an international airport (Tianhe Airport), Hankou Railway Station, the harbour terminal, the Second Road Bridge over the Yangtze River, and the Fourth Bridge over the Han River (*yuehuqiao*). The Third Bridge over the Yangtze River (*Bashazhou daqiao*) was completed in 2000. These projects not only strengthen the role of Wuhan as the centre of transportation in central China but also improve its investment climate. In the economic sector, the ZETDZ car manufacturing base, the Yangluo Electric Power Plant, the Qingshan Trade Harbour and four new industrial parks in the DNTDZ gave a boost to both traditional and modern industries.

As shown in figure 3.5 (2000), four zones with various functions were located in three towns. Zone 3, which has the largest scale of leapfrog development, is the DNTDZ for car manufacturing. Zone 4, unplanned in the previous master plan (1996-2000), is another economic development zone for Taiwanese investment. The *Guandong* and *GuangNan* industrial parks, zone 1, are the research and production bases for the communication, software and electronics industries. The *Nanhu* and *Changhong* industrial parks, zone 2, are the centre for biological engineering, chemical engineering, new materials, electronics and aerospace engineering. This zone is a redevelopment project located on the site of the old airport. Zones 1 and 2 form the famous ZETDZ. Its site selection largely depends on its proximity to universities. Surrounding these zones are nearly 30 universities and colleges, and 0.3 million professional employees provide rich labour resources for these new industries. Zones 1, 2 and 4 are spatially adjacent to developed areas. These new zones have not only changed the industrial structure of Wuhan but are also the focus of foreign and domestic investments. Other new developments and re-developments close to or inside developed areas are dominated by small-scale real estate development. For example, in 1997 residential sites of 5 ha or larger numbered 120, with a total of 1,817 ha (WBRS, 1998).

In the 1990s, fast growth benefited from the improvement of the infrastructure (figure 3.4). The second highway bridge (upper reaches) over the Yangtze River was completed in 1994. This helped to create the first ring road of Wuhan, together with the first bridge. The ring remarkably improved overall accessibility by linking the three towns. Moreover, two more bridges over the Han River were planned before 1996 and completed in 2000. As a result, improved accessibility strongly reduced the traffic pressure between Hankou and Hanyang. The formation of the inner ring had a profound influence on real estate development. Although the third highway bridge over the Yangtze River was put into use in 2000, it was planned as early as 1988. The southward spread of new development after the 1980s was closely related to the bridge. Due to the bridge, zones 1, 2 and 3 are much more closely linked than before. In the future, the bridge, together with the fourth bridge will create the second ring.

In each town, two new major roads were also constructed (see figure 3.4). In Wuchang, a new road (*Cuxiong dadao*) is located between zones 1 and 2 to serve these areas of high population and employment density. In Hankou, an expressway was constructed for travelling to the new international airport. These new zones contributed to the emerging multi-centre structure of Wuhan. These centres are located near major roads and have integrated functions such as shops, new and high technology services, recreation, housing and other facilities.

3.4.3 Evaluation

For a comprehensive evaluation of temporal urban growth, an analytical perspective has to be chosen. This section compares the temporal growth of Wuhan in four periods (i.e.1949-1955, 1955-1965, 1965-1993 and 1993-2000), with respect to quantity, speed, morphology, land use structure, spatial pattern and master planning. Quantitative methods are used to perform the evaluation. The division of the four periods under study is based on data availability and the major policy changes as described in section 3.2.

(1) Urban growth rates

In 1949, Wuhan city had a population of 1.02 million (0.94 million in urban districts and 0.08 million in suburban districts) living in an urban area of over 303 km^2 (including 30 km^2 built-up areas) (ECWLR, 1996). Wuhan was directly administered by the central government until 1954, when it became the capital of Hubei province.

The administrative units in Chinese cities can be classified as municipality, urban district (suburban district and county), sub-district (town, township and farm) and neighbourhood (or residential committee). Since 1997, Wuhan municipality has consisted of two counties, nine urban districts (including 88 sub-districts and 1928 neighbourhoods) and two suburban districts. Its spatial hierarchy will be described in detail in chapter 4. The population of Wuhan municipality comprises agricultural and non-agricultural residents. The non-agricultural population is based on the *Hukou* system (to control the immigration from rural to urban areas) not on administrative divisions.

Figure 3.6 shows the population of Wuhan since 1949. It indicates a fast urbanisation process between 1949 and 1958 and then a slower growth rate until 1993; after 1993 growth rates increased again. Table 3.2 lists the calculated built-up areas for the four periods and the urban area of 1949, which is based on an official report (ECWLR, 1996), together with the population change. It can be seen that the city size in 2000 is nine times larger than that in 1949. Rapid urban growth occurred especially in the periods 1955-1965 and 1993-2000, with an annual growth rate of 13.4% and 4% respectively. Slow growth took place in the period 1986-1993, with an annual growth rate of 1.5%. From the table we can conclude that major development waves occurred in the periods 1955-1965 and 1993-2000. These waves are a result of major political events: industrialisation initiated in 1953 and land reform started in 1987 (which have been described in section 3.2).

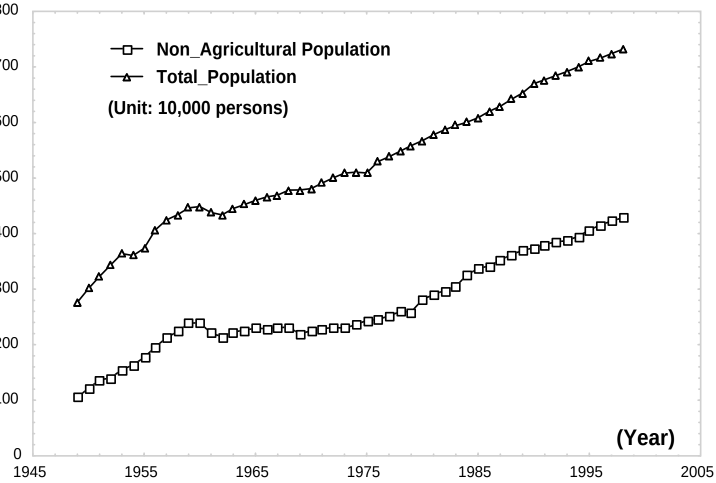

Figure 3.6 Population growth of Wuhan municipality from 1949 to 1999

Table 3.3 Urban temporal growth statistics

Year	1949	1955	1965	1986	1993	2000
Built-up (ha)	*3,000*	*5,503*	*12,870*	*19,315*	*21,414*	*27,515*
Annual growth (ha)	-	*417*	*737*	*586*	*300*	*872*
Annual growth rate		*14%*	*13.4%*	*2.4%*	*1.5%*	*4%*
Non-agri. population	*1,055*	*1,773*	*2,299*	*3,418*	*3,870*	*4,449*
Annual popu. growth	-	*9%*	*2.6%*	*1.9%*	*1.8%*	*1.9%*
Annual growth rate		*11.3%*	*3%*	*2.3%*	*1.9%*	*2.1%*
Gross popu. density (Persons/ha)	-	*322*	*179*	*177*	*181*	162

Population figures in thousands. Sources for urban areas in 1949 and population are from official statistical yearbook.

Generally, physical growth is consistent with population growth as a linear correlation is detected between the column "Built-up" and "Non-Agricultural Population", with a high correlation coefficient of 0.98. However, the annual growth rates are different. The most rapid annual population growth was in the period from 1949 to 1955. After 1955, the annual growth rate changed. This difference reflects population policies such as the migration of young people from urban to rural (*shang shan xia xiang*) and the natural disasters during 1958-1960. Population growth is strongly correlated with land use change and is a principal "driving force" of global land use change. Table 3.3 also shows that the gross population density was the highest in 1955 and then decreased sharply. We can conclude that the spatial patterns of urban growth have gradually shifted from compact to dispersed.

(2) Morphology analysis

Morphology analysis makes it possible to summarise the changes and trends of the urban spatial structure. The analysis provides a coarse comparison of temporal growth. The time series of urban expansion (figure 3.3) offers an intuitive hypothesis that the city gradually changed its development axes from rivers to major roads and also shifted from a monocentric to multi-nuclear spatial structure. GIS spatial analysis can assist us in testing this hypothesis.

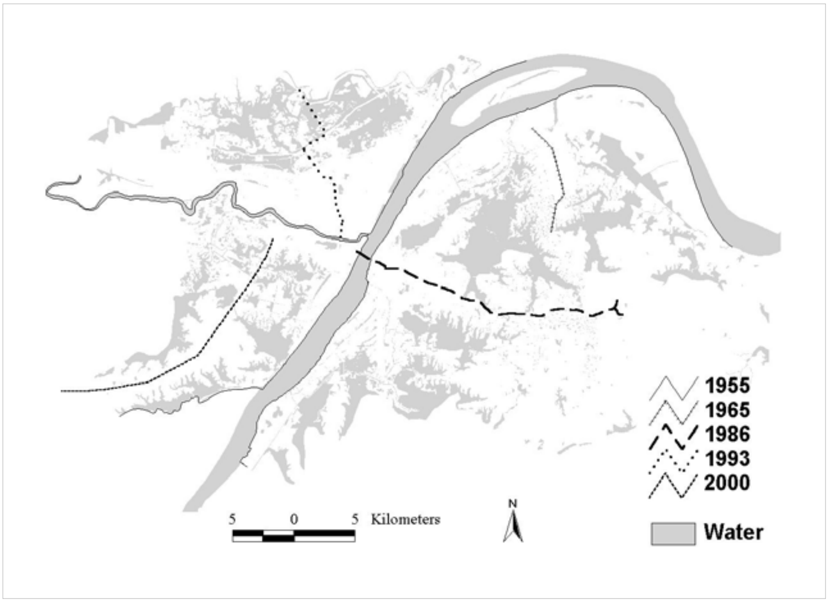

Figure 3.7 Development axes in five periods

The development axes can be rivers, railways, major roads and others. The proposed axes for Wuhan are shown in figure 3.7. The development axes before 1955 are the two rivers (Yangtze and Han), which are described in section 2.3. The main development axis in the period 1955-65 was a railway line. After 1965, development initiated on the major roads. The temporal relationships between the axes and urban growth are expressed in figure 3.8. The *X* axis indicates the percentage of developed areas, and the *Y* axis represents the distance of the developed areas to development axes.

Figure 3.8 indicates that 90% of the newly developed areas are within 3 km and approximately linear to the pre-selected axes. However the sharp and non-linear change of the remaining new development (10%) suggests sporadic and leapfrog development. The Pearson correlation coefficients *R* between the five *Y* variables (distance to each development axis) are all above 0.99. This means that the selection of the axes is confirmed and consistent between the five periods. The temporal change of the axes illustrates the trend and directions of urban growth. For instance, from 1955 to 1965, fast urban growth is related to a railway, which results in the large scale industrial area. Two main roads constructed between 1986/1993 and 1993/2000 lead to another urban growth trend for the 1986-1993 and 1993-2000 periods respectively. The direction of growth is outwards from the rivers. The difference is indicated by the speed and direction (both sides of rivers) of spread. For instance, the period 1955-65 was dominated by the fast spread on the right bank of the Yangtze River and slow growth in Wuchang.

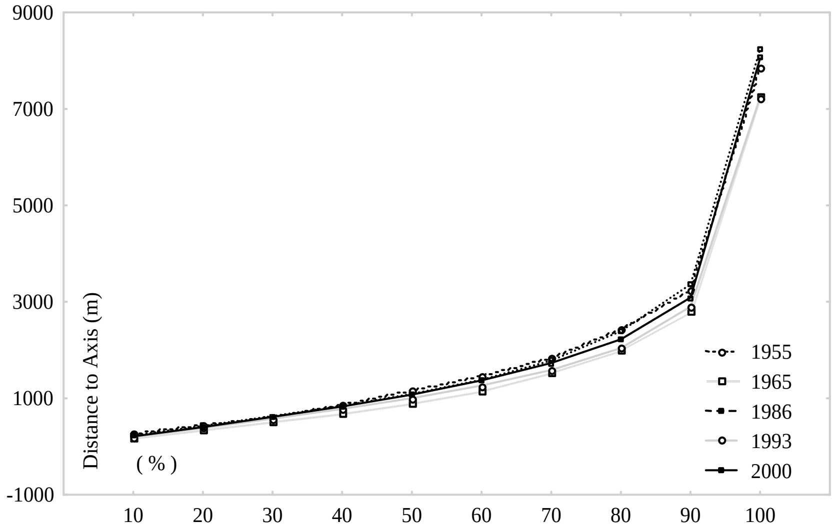

Figure 3.8 Urban growth and development axes in the five periods

This trend was shifted to slow spreading in Hankou for 1986-1993 and quick and parallel expansion to river for 1993-2000. From this, we are able to conclude that the new transport infrastructure was the key element in shaping the new urban morphology during the last five decades.

(3) Spatial pattern analysis

As the most frequently used algorithm, box-counting is able to quantify space-filling effects. The information dimension is more robust to data than the box-counting dimension in describing spatial distribution. The spread pattern analysis is implemented here for both temporal urban growth and road networks. For computation purposes, the same spatial extent is defined for all periods. This enables relevant comparisons. According to equation 2, the information dimension *D* can quantify the evenness degree of spatial distribution of the entities under study. Therefore, it can provide valuable information about the spread patterns of new development units. A greater value of the fractal dimension means that the new development is more evenly distributed. The spatial pattern of urban growth, including road networks, is impacted by natural constraints (e.g. topography) and socio-economic activities; the growth of the information dimension in various periods indicates the influences of physical and socio-economic processes on the spread pattern of urban growth. This is different from the box-counting dimension, which reflects the space-filling process.

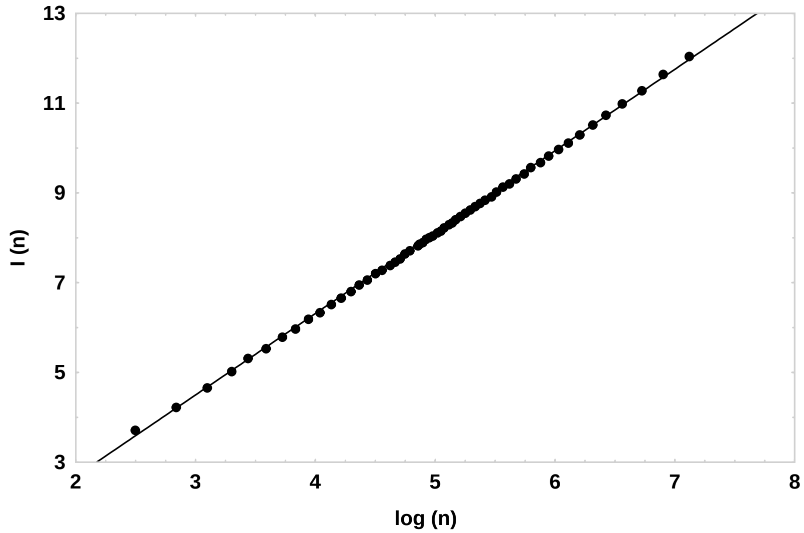

Figure 3.9 Plot of *I(n)* and *Log(n)* for the information dimension of the road network in 2000

In this research, the information dimension of road networks is calculated by using the MapBasic programming language based on the MapInfo GIS platform. The input and transfer of vector data from another GIS package such as ArcView are needed. In the case of urban growth, the information dimension is computed by a Visual Basic program. The raster layer of urban growth is exported into ASCII format, which is read by a module of the Visual Basic program for computing the information dimension.

Figure 3.9 shows the information dimension for the Wuhan road network in 2000. *I(n)* against *log(n)* in equation 2 (section 3.3) is plotted. It is a straight line with a slope of 1.492 and a correlation coefficient of 0.998. Table 3.4 shows all information dimensions of urban growth and road networks in five different periods. It indicates that the fractal dimension is increasing temporally in both urban expansion and road networks. However, the comparison of the fractal dimension is valid only for the same scale of development (Yeh and Li, 2001a), for example the same size of urban areas. Hence, the increase in the information dimension does not mean that the latter period is more balanced in spatial distribution than the former as the scale of the newly built-up areas is not the same. However, the annual growth rate of the fractal dimension (table 3.4) enables us to compare the change of spread patterns. As far as urban expansion is concerned, the annual growth rate is higher for the periods 1955-65 and 1993-2000 than for other periods. It indicates that urban expansion was spatially more even during the two waves of development. The first wave takes the highest value, meaning that the pattern of expansion was more limited by physical constraints and more influenced by social and economic activities.

This can be explained by two reasons. First, more developable land was available in 1955-1965 than in 1993-2000 as during the latter period water bodies also became part of urban development. Second, the free land transfer system introduced during the 1955-1965 period encouraged more spread urban expansion than did a paid transfer land market, where land value plays a crucial role in the site selection of projects. Interestingly, the growth of the road networks does not have concrete effects on expansion according to table 3.4. First, it shows that road infrastructure construction did not follow the same pattern as urban expansion over the past five decades. The information dimension (table 3.4) indicates a temporally increasing trend of homogeneity in the spread pattern. Second, large-scale construction of road infrastructure was initiated after 1993, and is visible in the high annual growth rates. In contrast to urban expansion, road network construction was less important than building railway lines in the 1955-1965 period, when major industrial centres were primarily linked by railway lines for goods transportation. The majority of new railway lines were constructed before 1986 (ECWLR, 1996).

Table 3.4 Information dimension *D* of temporal urban expansion and the road network

Information Dimension	1955	1965	1986	1993	2000
D value in urban growth	1.6703	1.7134	1.740	1.753	1.779
(Coefficients *R*)	(0.999)	(0.999)	(0.999)	(0.9998)	(0.9999)
Annual growth rate		0.26%	0.077%	0.11%	0.21%
D value in the road network	1.29	1.292	1.371	1.405	1.492
(Coefficients *R*)	(0.997)	(0.997)	(0.996)	(0.996)	(0.998)
Annual growth rate		0.02%	0.3%	0.354%	0.89%

(4) Urban land use structure change

Table 3.5 shows that the land use of 1955 was dominated by three classes; residential, public facility and industrial occupied 79% of the total land area of Wuhan. It should be noted that public facilities included institutions such as universities (totalling 14) and government offices, as well as the commercial sections. The "special uses" class is a military airport. In the case of major inter-city transportation, there were a couple of new railway lines added together with a new civil airport in Wuchang. The industrial and warehouse sections in total accounted for 18.2%, and were evenly distributed over the city. The main commercial activities were located in *Zhongshan* and *Jianghan* Avenue in Hankou and *Jiefang* Avenue in Wuchang, which formed a concentration area even before 1949. The new development exhibited a discontinuous and sporadic pattern in 1955 as most projects were still under construction.

Table 3.5 also indicates that the industrial, residential and public facilities accounted for 71% of the total land area in 1993. In particular, industry takes approximately the same percentage as residential, being equal to nearly 26%. Compared with 1955, the percentage of industry and warehouses increased by 13.4%; however, the residential section decreased by 15.5%. This indicates that the first wave of new growth before 1993 is dominated by secondary industry in Wuhan. The first column (from Yao (1998, p.73) shows the average land use structure of 15 super-mega-cities (population more than 1 million) of China in 1991. Apart from the major difference in the use covered by residential area, public facilities, industry and warehouse have the same proportion. This shows that the national policies of industrial structure were one of the major driving forces of urban development, in particular in super-cities, before 1993.

Table 3.5 Land use structure change (area: ha)

Classification	Chinese mega-cities (%)	Wuhan 1955 area & %		Wuhan 1993 area & %		Wuhan 1955/93
Residential	*33.62*	*1984*	***41.43***	*5609*	***25.82***	*-15%*
Industry	*24.92*	*659*	*13.78*	*5626*	***25.9***	*+12%*
Warehouse	*5.48*	*212*	*4.45*	*1249*	*5.75*	
Public Facility	*9.92*	*1185*	***24.75***	*4206*	***19.36***	*-5%*
Utility	*2.36*	*42*	*0.81*	*1159*	*5.33*	
Green	*4.62*	*216*	*4.52*	*1265*	*5.82*	
Transport uses	*11.31*	*425*	*8.88*	*1585*	*7.3*	
Special uses	*9.27*	*64*	*1.35*	*1026*	*4.72*	
Total	*100%*	*4787*	*100*	*21725*	*100*	

(Note: Chinese mega-cities in 1991: Shanghai, Beijing, Tianjin, Guangzhou, Shenzhen, Shenyang, Chongqing, Wuhan, Zhengzhou, Nanjing, Hangzhou, Kunming, Taiyuan, Xian, and Haerbin)

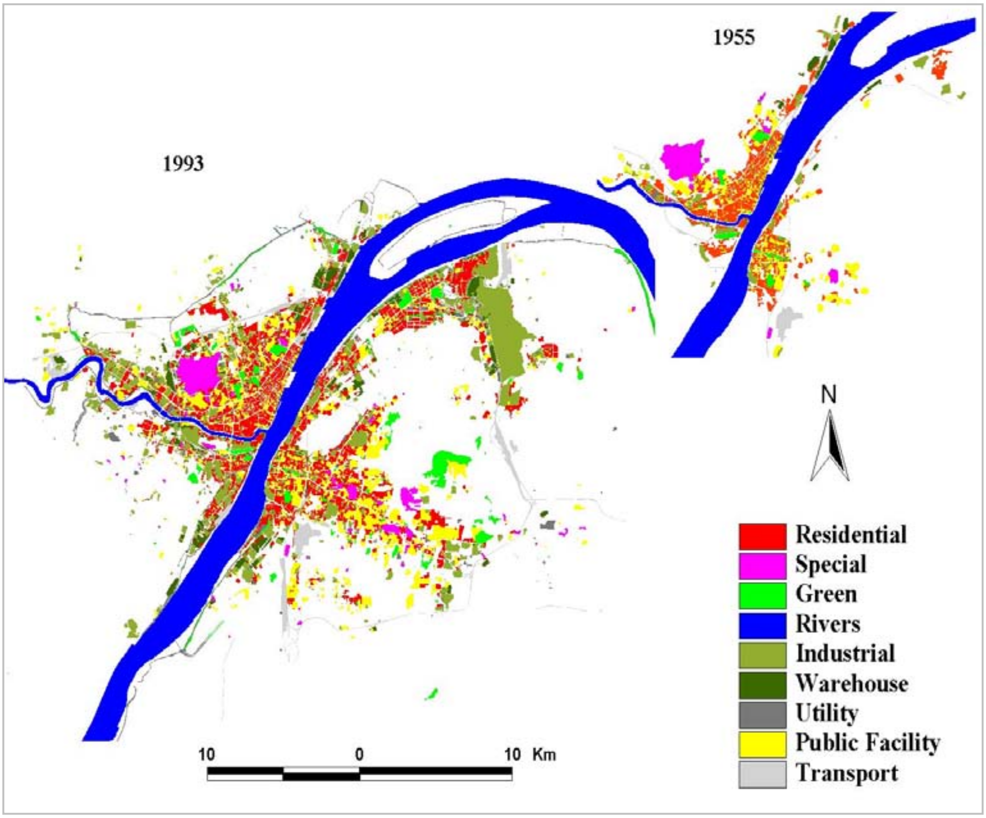

Figure 3.10 Urban land use in 1955 and 1993

Table 3.5 shows the major absolute changes of land use are dominated by three categories (industrial, residential and public facility). To further compare the changes in the spatial structure of the three categories, we introduce landscape metrics as quantitative measures of spatial patterns (from Patch-analyst Grid 2.1 in ArcView 3.20a extension). Here, seven indicators are calculated at the class level, each reflecting different structural content, nine at the landscape level (table 3.6). At the landscape level, SDI and SEI of 1993 show a 7% increase compared with the 1955 values (see table 3.1 in this chapter for the definition of these indicators). This reveals that social and economic activities during the 1955-1993 period were slightly diversified and evened in terms of spatial structure. This is reflected by the facts as shown in table 3.5, i.e. that many differences between residential and the other two in 1955 were reduced by 1993. Housing construction was replaced by more industrial projects.

Table 3.6 Landscape metrics of three land use in the two periods

Land use	MPS	PSCV	ED	MSI	AWMSI	MPFD	AWMPFD	SDI	SEI
I (1955)	*4.2*	*207*	*45*	*1.43*	*1.61*	*1.07*	*1.08*		
P (1955)	*3.27*	*235*	*85*	*1.60*	*2.03*	*1.09*	*1.11*		
R (1955)	*7.23*	*240*	*132*	*1.78*	*3.60*	*1.1*	*1.16*		
Landscape	*4.78*	*252*	*263*	*1.62*	*2.72*	*1.09*	*1.13*	*1.01*	*0.92*
I (1993)	*5.95*$^{+}$	*607* $^{+}$	*77* $^{+}$	*1.50* $^{+}$	*1.94* $^{+}$	*1.08*	*1.1*		
P (1993)	*2.47* $^{-}$	*320* $^{+}$	*72* $^{-}$	*1.48* $^{-}$	*1.82* $^{-}$	*1.08*	*1.1*		
R (1993)	*3.65* $^{-}$	*217* $^{+}$	*104* $^{-}$	*1.66* $^{-}$	*2.30* $^{-}$	*1.1*	*1.13*		
Landscape	*3.8* $^{-}$	*521*$^{+}$	*253* $^{-}$	*1.55* $^{-}$	*2.03* $^{-}$	*1.09*	*1.11*	*1.1* $^{+}$	*1.0* $^{+}$

I (Industrial / warehouse); P (Public facility); R (Residential); + : increase, - : decrease

Industrial development was the dominant landscape of Wuhan before 1993. MPS at landscape level shows a 20% decrease, globally indicating the diminishing of spatial agglomeration, from large-scale before 1955 to a smaller scale. This decrease is primarily indicated in residential and public facility land use, as shown in their MPS. PSCV at landscape level increased by 107%, indicating a significant increase difference in the variability of the size of units of land use. After 1955, small-scale development was mixed with larger. Change of PSCV at land use level is dominated by the 300% increase in industrial land use. This resulted from the in-fill land development pattern of small-scale industrial projects, particularly after 1965. ED, MSI and AWMSI show concrete results at both landscape and three land use levels, which are indicated by some decrease globally and only increase in industrial land use. This indicates a slightly decreasing heterogeneity globally and a slightly increasing heterogeneity in industrial projects development. A possible explanation is that new industrial projects were located close to old industrial centres. The fractal dimension is a measure of the fragmentation of functional units. MPFD and AWMPFD show a slight change at two levels in the two periods. This change focuses on little increase in industrial land use, implying a slow process of fragmentation in industrial project development. To sum up, the characteristics of urban land use dynamics in the period 1955-1993 can be threefold:

- Land development projects became more diverse and heterogeneous;
- The land development process was more fragmented and split;
- Industrial projects became spatially more clustered and smaller in size.

As described in section 2.2, during the period 1965-1992, large-scale industrial development was replaced by smaller-scale development and its spatial pattern was dominated by in-fill development inside urban districts. Housing and public facility development was weaken than before 1955. This can be explained by the focus of urban development strategy on industrial projects, particularly before 1992.

(5) Master plan matching

This section compares and evaluates the built-up areas between planned and actually developed urban land for the two periods 1954-1965 (master plan of 1954 and urban development in 1965) and 1988-2000 (master plan of 1988 and urban development in 2000). Both periods have a nearly equal time span, i.e. 11/12 years. Here, we use the Lee-Sallee Index (*LI*) for the quantitative measurement of the spatial match between planned and developed. Let *A* denote planned urban built-up areas and *B* developed areas. The *LI* index is defined as $A \cap B / A \cup B$. When omitting the built-up areas of the base year (1955 and 1986), varied *LI'* is recalculated.

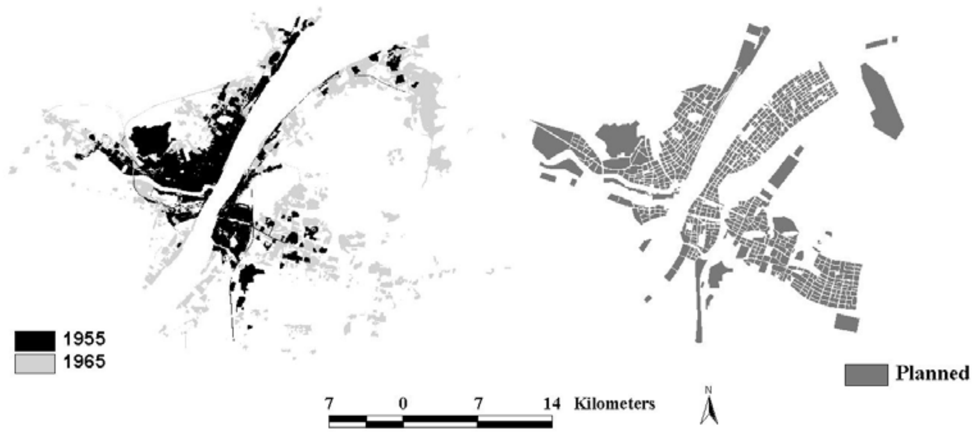

Figure 3.11 Master plan in 1954 and urban growth in 1955/1965

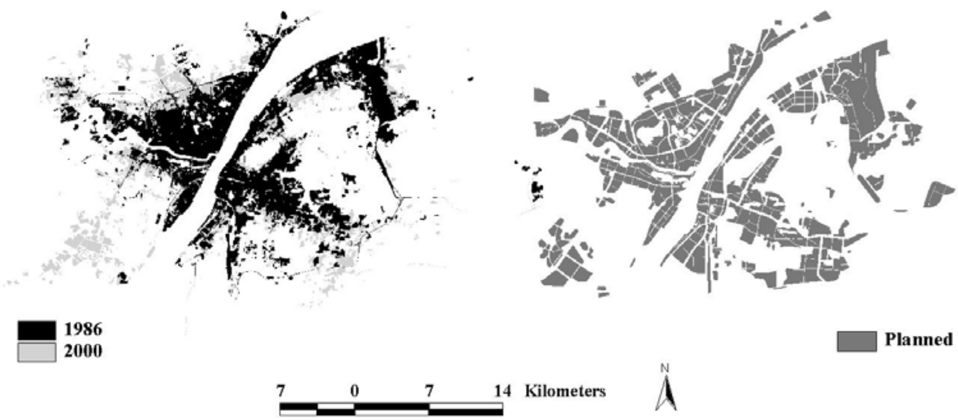

Figure 3.12 Master plan in 1988 and urban growth in 1993/2000

The results presented in table 3.7 generally imply that master planning under the two different political economic systems (command and market economy) did not play an important role in guiding urban expansion. However, influenced by the scale of existing urban development, *LI* is relatively less helpful in explaining the effects of master planning than *LI'*. The difference between the two values suggests that master planning under a market economy (1988-2000) exerted less control over urban expansion.

Table 3.7 The areas planned and developed (unit: ha)

Periods	$A \cap B$	$A \cup B$	*LI*	$A' \cap B'$	$A' \cup B'$	*LI'*
1954/1965	10,612	21,677	49%	2,561	10,496	24.4%
1988/2000	30,640	49,023	62.5%	3,642	21,878	16.6%

3.5 Discussion and Conclusions

3.5.1 Temporal urban growth

Wu (1998b) identified four development stages of spatial urban growth in Guangzhou city since 1952 (figure 3.13). The small industrial towns located in suburbs before 1960 dominated the first stage. Key projects formed the backbone of these towns but the factories themselves largely provided infrastructure. Low density was one of the main features of this period. The second stage focused on continuous developments surrounding the existing urban built-up areas and formed a belt of new extensions between 1960 and 1979. Insufficient infrastructure was the major physical constraint for large-scale development. The third stage was characterised by the emergence of sub-centres due to rapid spatial expansion spurred by economic growth between 1980 and 1987. The last stage featured both redevelopment in the inner city and urban sprawl after 1988. Urban sprawl was defined as a rapid expansion of the built-up area into suburbs in a discontinuous low-density form.

When applied to the temporal urban growth pattern of Wuhan, Wu's model needs the following adaptation. First, it should be noted that China’s development policies have a strong geo-political dimension, so that the coastal regions such as Guangzhou benefited from preferential policies for investment and resource allocation (Han, 2000) and were targeted with investment and reform programmes slightly earlier than non-coastal cities. For instance the commercialisation of housing was implemented in Guangzhou in 1984 and only four years later in Wuhan. The same happened with the land market, which was introduced in Guangzhou in 1988 and again four years later in Wuhan. Guangzhou had already become an open city in 1978 but Wuhan was declared an open city only in 1992. Therefore, the specific urban development stages vary among Chinese cities. In the case of Wuhan, a reasonable division into four stages is: 1952-1965, 1966-1983, 1984-1992 and after 1993. The relevant urban development policies and spatial processes determine this division.

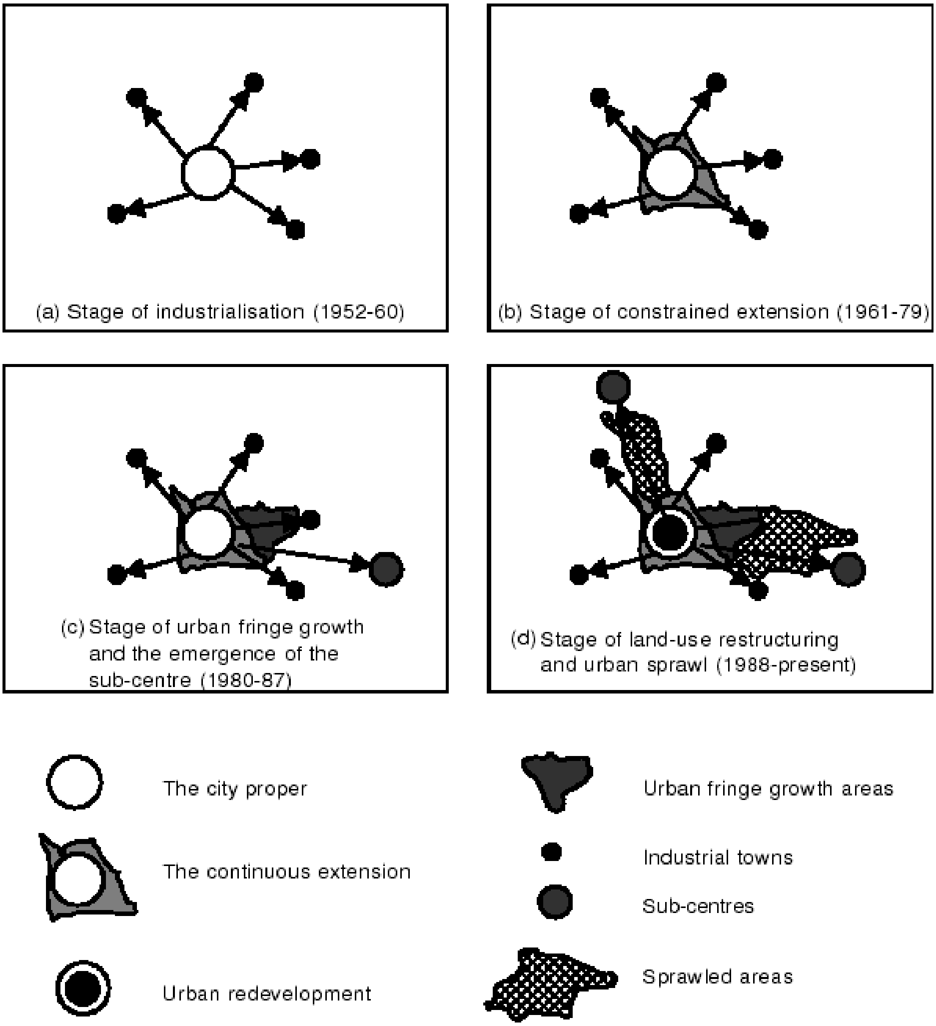

Figure 3.13 Temporal urban growth of Guangzhou (after Wu, 1998b)

Second, Wu's model, to some extent, does not fully reflect the spatial process of urban growth of Wuhan city. A major deviation is that the first stage (1952-65) was also characterised by the rapid urban sprawl of large-scale industrial areas in Wuhan. Multiple independent industrial centres started to appear. The growth rates of the information dimension *D* (urban expansion) in table 3.6 is relatively similar between the first (1955-1965) and the last period (1993-2000). Figure 3.3 shows a discontinuous pattern of urban expansion into rural areas before 1955 and 1965. Table 3.3 indicates a low-density spread, as gross population density drastically decreased from 312 to 179 persons/ha in this period.

Qualitatively, both the first and the last stage had a similar pattern of urban sprawl but with different economic components. During the first period, traditional manufacturing was dominant; during the last period modern manufacturing and tertiary activities were the prime driving force. The Chinese city of the 1949-1976 era sprawled outwards rather than upwards. The construction of large numbers of high-rise buildings in the 1980s and 1990s, particularly in the commercial sector, has come to symbolise the transformation of China's cities (Gaubatz, 1999).

Zhang (2000a) made a comparative study of urban sprawl between the USA and China and contended that the Chinese version after 1987 is characterised by a disproportionate expansion of the urbanised area and scattered development in the urban fringe. Unlike in the USA, low density and commercial strip developments are not characteristics of Chinese urban sprawl. Victor and Yang (1997) noted that the spatial pattern of urban growth in the Pearl River Delta, China, during 1979-1993 may be best described as "relatively concentrated dispersal". The determinants of such a spatial pattern are the preferential policies of local governments in the delta under the macro strategy of "Opening and Reform".

3.5.2 Data

Spatial and temporal urban growth requires multiple data sources with high spatial and temporal resolution. This research found that temporal resolution is a major issue in evaluating temporal urban growth. The data sources available are not consistent with the social and economic processes of urban growth. For example, the urbanisation stage in China is divided into 1949/60, 1961/77, 1978/1987 and 1988/present. However, spatial data sources at these specific watershed periods are non-existent. This seriously affects the linkage of spatial analysis of patterns and processes with policies and actors.

The primary data sources include remotely sensed imagery and traditional aerial photographs of different scales. This results in the requirement to integrate data of different resolutions, scales and themes. Data integration is the prerequisite to create spatial layers consistent in time, space and content. Apart from the necessary spatial and image processing, visual interpretation is very important to guarantee the accuracy and consistence of data by applying exact and identical technical specifications.

3.5.3 Structural and functional modelling

The findings of this chapter show that integration of multiple spatial indicators can improve the capacity of interpretation. The spatial indicators used here focus on structural and functional complexity, targeting quantification of the spatial distribution of land cover/uses, road networks, centres/sub-centres and master plans. Fractal modelling for calculating information dimension can reveal the spatial heterogeneity of urban growth and road networks. Landscape metrics can explain the fragmentation process and the diversity of urban land use. Morphology analysis based on development axes can compare the directional trend of temporal urban growth. The major characteristics found in this case study are fourfold. First, figure 3.4 implies that the morphology of Wuhan city has significantly shifted from multiple industrial concentrations to multiple sub-centres. This is a result of the spatial agglomeration of traditional industries and the modern new development zones respectively. The two waves of urban expansion were temporally influenced by national policies of urban development in those periods. Second, urban growth processes were dominated by the increase in small-scale industrial projects, and characterised by spatial fragmentation and diversification. Third, the physical factors shaping the temporal morphology are the rivers, railway lines and major roads taking temporally varied roles in affecting urban growth (figure 3.7). Construction of road infrastructure was enlarged in scale, with more homogeneous spatial distribution. Finally, the role of master planning in controlling urban expansion is diminishing.

However, urban growth is a dynamic process involving multiple actors and complex behaviour. This process is highly impacted by numerous clear and hidden factors related to political, economic and social activities. For example, the major policies during the last 50 years can be stratified into three levels. The transition from capitalism to socialism in 1949, the economic reform in 1978 and the land reform in 1987 are in the top level. The first brought about the rapid industrialisation stage that led the first development wave from 1953 to 1965. At this stage, central government was the major investor. The second spurred a new economic structure that allowed the coexistence of various types of economic entities. The third allowed the transfer of paid land use rights. The last two created new sources of investment, including foreign, domestic, central/local government and collective/individuals, which are the driving forces of the second development wave in Wuhan. These major political/economic reforms were followed by a series of changes in investment structure and industrial structure, which form the middle level. The change in investment structure influences the intensity and speed of urban development and determines the land demands of various social economic activities. These policies create the potentials and possibilities of urban development. The final level is housing, land use policy and master planning. This level transforms the possibilities and potentials for urban development stimulated by investment and industrial structure change into reality.

Driven by these macro policies, various actors changed their roles in impacting on the process of urban growth. For example, state and work units were the main urban developers before 1978 and urban planning principally contributed to the site selection of industrial projects. After 1987, the urban development process became much more complex, and is characterised by more actors, more types of behaviour, and a larger variety of actors.

As summarised in figure 2.2 of chapter 2, understanding the urban growth system involves five levels, from policies and actors to behaviour, pattern and process. The last three are the major concern of spatial and temporal modelling. The complexity in the spatial and temporal dimensions and the decision-making process requires a more systematic modelling method, which should integrate all significant factors into a model spatially and temporally. The quantitative methods proposed in this chapter helps to evaluate and compare the spatial indicators from different perspectives such as fractal and landscape metrics. They are the first step to systematically modelling dynamic processes, such as stimulating possible hypotheses. Here, temporally systematic modelling refers to integrating temporal urban growth into a unified framework, which is the purpose of chapter 4. Spatially systematic modelling includes understanding spatial and temporal patterns and processes, which are the major objectives of chapters 5 and 6.

Chapter 4*

Comparative Measurement of Temporal Urban Growth

Abstract

Urban growth has become a severe problem not only in the developing world but also in developed countries. Urban sprawl has been criticised for its inefficient use of land resources and energy and large-scale encroachment on agricultural land. With modern remote sensing techniques, extensive data sources of satellite imagery with various resolutions are becoming available and less expensive. This has greatly enhanced the possibilities for monitoring urban growth at various spatial and temporal scales. However, sustainable urban growth management and development planning need to take account of the dynamic process of temporal urban change. This results in a requirement for the comparative measurement of temporal urban growth. Dedicated measurement of urban form can provide a more systematic analysis of the relationships between urban form and process. This chapter presents an innovative method for such a measurement, which integrates the physical aspect of urban growth with the socio-economic information of built-up areas based on the concept of relative space. The method comprises temporal mapping, data dis-aggregation of socio-economic activities, integration of spatial gravity, and global evaluation. The method is tested in a case study of Wuhan city, P.R China, with the land use/cover series for the periods 1955-1965 and 1993-2000. High-resolution aerial photographs and SPOT images are the primary data sources for monitoring and mapping temporal urban sprawl.

Key words: urban growth, comparative measurement, relative space, aerial photographs and SPOT

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* Based on Cheng et al. (2002) and Cheng et al. (2003d).

4.1 Introduction

Urban sprawl has become a severe problem not only in the developing world but also in developed countries. Urban expansion is a current topic of debate among both academics and politicians. In the USA, urban sprawl is now at the top of the political agenda (Dieleman et al., 2002). Urban sprawl has been criticised for its inefficient use of land resources and energy and large-scale encroachment on agricultural land. These impacts threaten the principle of sustainable development. With modern remote sensing techniques, extensive data sources of satellite imagery with various resolutions are becoming available and less expensive (Masser, 2001). This has greatly enhanced the possibilities for monitoring urban growth at various spatial and temporal scales. However, sustainable urban growth management and development planning need to take account of the dynamic process of temporal urban change. This results in a further requirement for the comparative measurement of temporal urban growth. The measurement of urban form can provide a more systematic analysis of the relationships between urban form and process (Yeh and Li, 2001b).

Fractal-based models (Batty and Longley, 1994; Makse et al., 1998; Frankhauser, 2000; Shen, 2002a) describe, measure and analyse spatial phenomena and structures characterised by irregularity, scale-independence and self-similarity and provide us with a very different perspective on urban spatial patterns. Batty and Longley (1994) first systematically explain how the structure of cities evolves in ways which at first sight may appear irregular, but when understood in terms of fractals reveal a complex and diverse underlying order. However, it should be noted that fractal measures of spatial complexity still lack the interpretative capability because the same value of a fractal dimension may represent different forms or structures. Comparisons of the fractal dimension are valid only for the same scale of development; for example the same size of urban areas (Yeh and Li, 2001a). They do not offer any capacity for identifying and comparing the relative degree of temporal urban growth.

I-Shian (1998) measures the degree of sprawl based on the physical aspects of residential development patterns, which is represented as a function of residential development density, residential lot size, the scattering of residential development, residential land use composition, and residential land use configuration. This research applies cluster, factor and regression analysis based on parcel-level data. It identifies three types of sprawl: low density, scattered and leapfrog.

Shou (2000) defines urban sprawl as the spatial discontinuity in urban land use. According to this definition, he develops two sets of new urban sprawl statistics: the primitive and the normalised statistics. These new measures take the shape, size, boundaries and intensity effects of urban land use patches into account.

The entropy method developed by Yeh and Li (2001b) is based on the direct measurement of the land development density of buffer zones in relation to geographical features such as city centres or road networks. The method is effective for the comparison of various types of urban sprawl in the same period. However, this measurement can not be used to analyse temporal urban growth as the absolute space concept may lose its comparative effect when applied for a longer period, e.g. 50 years.

Torrens and Alberti (2000) explore several approaches to measuring sprawl in an empirical manner, which use surfaces, gradients, fractal measurements, architectural primitives, image processing, geometrical measurements, ecological approaches and accessibility calculations. These measurements share a common drawback: the pure geometry perspective, which separates new growth from existing urban built-up areas and also ignores the linkages with social and economic activities.

Galston et al. (2001, p.681) devise a measure of sprawl that is based on “eight distinct dimensions of land use patterns: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity.” They apply this method to 13 metropolitan areas and find New York to be the most sprawling and Atlanta the least sprawling metropolis.

In summary, previous studies regarding the measurement of urban growth only took physical aspects into account. They ignored the fact that the urban system is a complex mixture of physical, social and economic systems. Absolute distance-based measurement cannot accurately interpret the social and economic implication of various types of urban growth. In particular, it will become less effective when the temporal dimension is incorporated. Given these considerations, this chapter proposes a new method for the comparative measurement of temporal urban growth, based on the integration of remotely sensed imagery and socio-economic data. Following the introduction, section 2 presents the method, which principally comprises four steps: temporal mapping, data disaggregation, activities integration and global evaluation. Section 3 will test this method by a case study, the city of Wuhan, P.R. China, in the periods 1993-2000 and 1955-1965. Section 4 ends with further discussion and conclusions.

4.2 Methodology

4.2.1 Urban growth

Urban growth is a broad and vague concept that can be subdivided into various types such as sprawling or compact, dispersed (scattered) or clustered, continuous or leapfrog, spontaneous or self-organising, planned or organic. It may comprise physical growth, population growth, economic growth and environmental change (decline), although there is often a focus on the physical aspect in the domains of remote sensing and GIS. These different classification systems vary according to the demands of applications and evoke numerous debates not only in academic circles but also in the urban planning profession.

Wu (2000c) identifies two classes of urban growth: spontaneous and self-organising. The former is characterised by small-scale and scattered development and contains random components. The latter is dominated by large-scale and high-density development, which can be easily simulated by bottom-up models such as cellular automata. The appearance of a circular configuration is actually a phenomenon of self-organisation (Benati, 1997). This classification is based on the pattern, particularly the spatial agglomeration of new development units.

In Batty and Longley (1994), urban growth is generally classified as organic (or natural) or planned (or artificial) growth. The distinction between the two is multifold and often blurred. Basically, planned growth appears to be more man-made, in that the patterns produced are more regular, reflecting more control over the building process. Most cities and towns provide a blend of both, usually containing elements of the planned against a backcloth of organic growth. The irregularity and fill-in effects of new urban growth can be quantified through fractal geometry.

Clarke and Gaydos (1998) classify urban growth pattern into five types: spontaneous, organic, spread, road-influenced and diffusive. This can be simulated and controlled by five coefficients (diffusion, breed, spread, slope and roads) in a cellular automata environment. One of the major deficiencies of this approach lies in the fact that there is not a sharp boundary between them, or rather they spatially overlap to some extent.

The classifications mentioned above primarily focus on the spatial patterns (form, density and distribution) of physical growth and the spatial impacts (planned or self-organised) of human activities. In some sense, they are interrelated. For example, planned and self-organised patterns are quite similar to clustered growth. Spontaneous and dispersed patterns are more or less the same as organic growth. The advantage of these classification systems is the close linkage with spatial patterns, which is one of the major concerns of GIS and modern urban modelling approaches such as fractal and cellular automata. However, their deficiency is the ignorance of the interactions between the new development units and the urban social and economic activities that derive urban growth. Due to their weak explanatory power, they can only provide partial information for decision-making in the context of urban growth management.

The classification of compact development or sprawl will be more attractive and useful to urban activists, planners and politicians as the impacts of sprawl or compact development can be evaluated from social, economic and environmental perspectives. However, what is urban sprawl? What is the explicit distinction between compact development and a pattern of sprawl? Urban planners and other academic researchers have attempted to define urban sprawl, but few of the definitions have gained general acceptance as they all have a different focus, depending on the interests of user groups.

Describing and explaining urban sprawl has proved difficult for two reasons. First, we have no consistent definition of what counts as sprawl as urban spatial change is a phenomenon with significant temporal and regional variations (Ottens, 2002). Second, sprawl is both a macro- and micro-spatial phenomenon. At the macro level, sprawl may reflect growing population, interregional migration, increasing income, and changes in transportation technology that facilitate extensive commuting. At the more micro level, differences in climate, geography, actor behaviour and local public policy may all impact on the way in which expanding cities develop. Thus, to properly study sprawl we need, on the one hand, data where sprawl is clearly and measurably defined and, on the other hand, data that provide sufficiently detailed information to capture the micro-spatial determinants of sprawl. Moreover, these data should have exhaustive coverage to also allow the study of macro-spatial determinants.

Urban economists usually link urban sprawl with decentralisation and evaluate its effects from the perspectives of costs and benefits, in particular in North America (Ewing, 1997; Gordon and Richardson, 1997). Consumer and business location preferences and economic efficiency are given prime attention (Ottens, 2002). This approach leads to a negative assessment of current urban sprawl as it is much more costly than compact development. From the perspective of geography, this definition lacks effective spatial measures as cost and benefit indicators need a large quantity of social and economic data on micro scale.

Ewing (1994, 1997), an urban planner, takes a very deliberate approach to conceptualising urban sprawl. He surveyed 15 academic articles on the subject, written between 1957 and 1992, and found that the terms low-density, strip or ribbon, scattered, or leapfrog development are often used to characterise urban sprawl. In particular, urban activists have labelled urban sprawl as decentralised, low-density, non-clustered housing, leapfrog, too much strip, and the separation of uses. This definition is fuzzy as "low" density, "too much" and "non-clustered" are difficult to operationalise in quantitative terms.

To summarise the commonality of various definitions, the key phenomena defining urban sprawl are the spatial distribution of new units, the intensity of social and economic activities such as population and employment, and the spatial relationship between the new units and existing urban built-up areas. An analysis of spatial relationships is able to judge continuous or leapfrog development patterns. An analysis of the spatial agglomeration of new units is able to identify clustered or scattered patterns. Measuring the intensity of social and economic activities enables the density of new growth to be quantified. Hereby, to some extent, the concept "sprawl" is the mixture of various classifications.

4.2.2 Relative space

The measurement of geographical phenomena involves two perspectives of space: absolute and relative. The absolute representation of space dominated the scientific world until the beginning of this century when the theory of relativity was formulated in Einstein's work (Marceau, 1999). The relative view of space focuses on objects as the subject matter, and space is measured as relationships between objects. In this view, the impact of space is perceptible in the location strategies of activities seeking sites that are accessible from everywhere within the metropolitan region. Sprawl is associated with a decline in the importance of absolute space. We argue that urban sprawl should be measured in relative space, i.e. the spatial relationship between new growth and urban socio-economic activities. This relationship represents the global and local spatial impacts of socio-economic activities.

The simplest measure of sprawl, and one used many times by urban economists and others, is the average density of the metropolitan area. Measures of population density capture the low-density aspect of sprawl pattern, but fail to account for the leapfrogging and non-contiguous development that may be associated with sprawl.

The gradient of density is frequently utilised for quantifying the urban growth in various periods (Torrens and Alberti, 2000). It is based on concentric rings around the urban central business district (CBD). This method has been shown to be highly sensitive to the arbitrary choice of ring width (Muth, 1969) and the location of the city centre. Consequently, when the physical size of a city is quite different between points in time (as shown in figure 4.1), the number of zones for calculating the gradient of density will vary temporally. This may result in the incomparability of the density gradient values computed. Moreover, in most large cities, the centre structure underwent a certain degree of change and a shift from mono-centre to multi-centre.

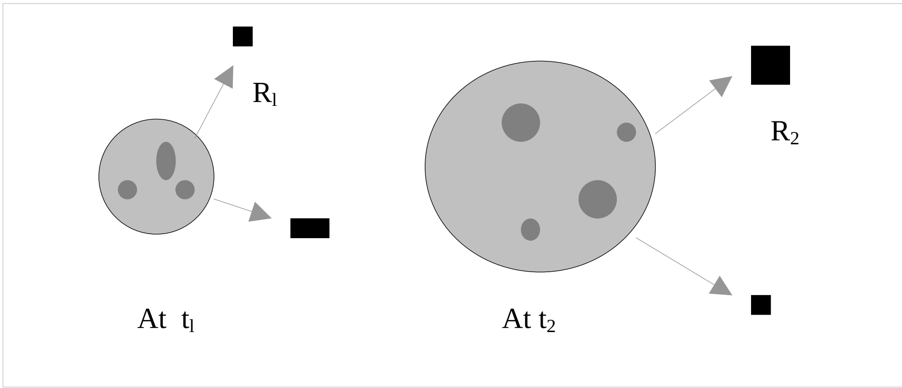

Figure 4.1 Illustration of relative space in temporal urban growth

As illustrated in figure 4.1, the extent of the urban built-up area at time t_l and t_2 ($t_2 > t_l$) is significantly different. In this case, absolute distance cannot solely represent the relative pattern of urban sprawl as the same distance may represent a different interpretation of the social-economic situation, particularly when the period to be modelled is very long. For example, the urban built-up area of Wuhan city in 2000 was five times larger than that in 1955 (chapter 3). So the 500 m sprawl in 1955-1965 cannot be compared with the 500 m sprawl (may be 2000 m) in 1993-2000. Meanwhile, its urban structure has changed dramatically from a monocentric to a multi-nuclear city region. As a consequence, absolute space is not adequate for temporal measurement.

A major barrier to implementing an urban sprawl definition in practice is the difficulty of quantifying it. The quantification should be comparable in both the spatial and temporal dimensions. As an antonym of sprawl, compactness is also not easy to define. One city's sprawl may be another city's compact development, under different social and economic circumstances. One period's sprawl may be another period's compact development. As a consequence, we need to set up referencing points in the spatial and/or temporal dimensions; in this way, quantification can be based on the measurements relative to these referencing points. Sprawl is just a matter of degree, not an absolute phenomenon. Given this consideration, the measurement of relative sprawl should integrate the distance, the spatial distribution and the density. Form and density aspects of urban de-concentration are at the heart of urban consumption (Ottens, 2002). How to quantify relative sprawl will be elaborated next.

Obviously, the relative intensity of growth is equivalent to gravity in physics, which depends on the scale of urban social-economic activities and the distance between both. This idea results in a new methodology for comparatively measuring temporal urban sprawl, as displayed in figure 4.2. This methodology primarily comprises temporal mapping, dis-aggregation to pixel level, integration with urban activities and global evaluation. Socio-economic processes are the primary drivers for land use and land cover change, which in turn determines the structure, function and dynamics of most landscapes. The pattern and intensity of urban growth are essentially influenced and determined by human activities. Measuring urban sprawl, towards understanding the complex system, should be integrated with socio-economic activities.

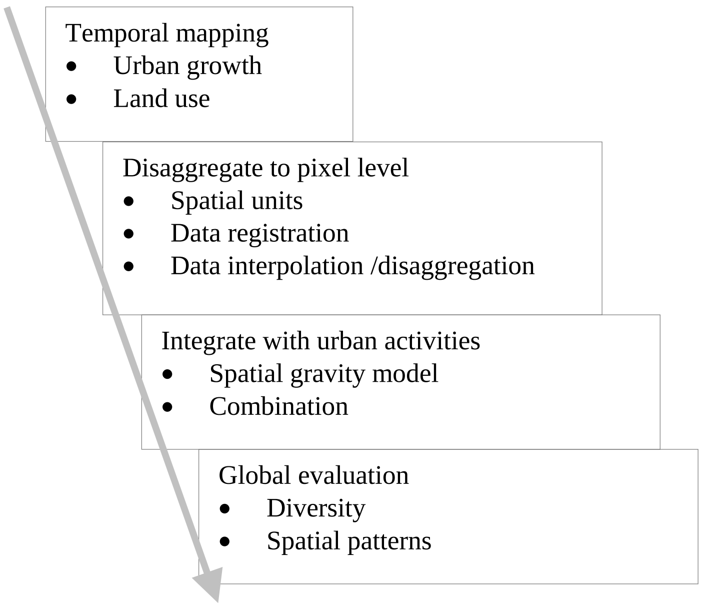

Figure 4.2 Flowchart of the methodology

4.2.3 Temporal mapping

Temporal mapping here includes time series urban sprawl and land use. SPOT PAN/XS data are an ideal source to produce land cover maps at the urban-rural fringe (Jensen, 1996). However, the use of aerial photographs for land use survey and urban analysis has been well established since the 1940s (Kivell, 1993). Conventional aerial photographs are likely to remain the primary source of remotely sensed information for the foreseeable future at the land parcel level (i.e. 1:2500–1:500 scales), which is the basic building block of the databases used by those involved in urban planning and land administration (Masser, 2001).

Many researchers have initiated automatic solutions for land use classification based on digital imagery, but there are many aspects that remain unsolved, such as image understanding and pattern recognition. Therefore visual interpretation is still a reliable solution and is applied in this study for the creation of land use/cover maps, especially when aerial photographs and images are used together for temporal change detection.

4.2.4 Disaggregating to pixel level

The spatial heterogeneity inherent in urban social and economic activities requires a more detailed analysis on a micro scale. Zone-based spatial models do not take account of topological relationships and ignore the fact that socio-economic activities and their environmental impacts are continuous in space (Wegener, 2001). This step is to disaggregate or spatially interpolate zonal data (e.g. population and employment) registered for spatial statistical units (e.g. census tract, block) to pixel level. The spatial disaggregation of zonal data consists of two steps: the generation of a raster representation of land use, and the allocation of the data to raster cells (Wegener, 2001). Various weight values are assigned to each land use. According to the principles of spatial statistics/econometrics, the weight parameters should be varied locally (Fotheringham and Rogerson, 1994). We suppose that m denotes the number of urban land use classes, n denotes the number of homogeneous spatial units, w_{ij} means the weight value of urban land use i in unit j, and n_{ij} the number of pixels of land use i ($1 \le i \le m$) in unit j ($1 \le j \le n$). Then, based on the population census, we are able to compute the population value of each pixel, which varies with j and i (see equation 1). Assuming that the total population in spatial unit j is TP_j, the population value of the pixel with land use i and in unit j can be computed as P_{ij} (equation 1).

$$P_{ij} = w_{ij} * TP_j / \Sigma w_{ij} * n_{ij} \tag{1}$$

When spatial statistical units are not clearly defined or census data are not available, we can make approximate estimations according to a gradient of density such as a negative exponential function (or an inverse power function) (Clark, 1951; Wang, 2001; Wu and Yeh, 1997). For example, employment data are not available at the lower level of spatial units in most cities of China. Under this condition, the distance-decay of variable y (population or employment) can be expressed as follows (equation 2).

$$Y_j = a_0 * \exp(-\lambda * r_j) = w_{ij} * TP_j / \Sigma w_{ij} * n_{ij} \tag{2}$$

where λ is the gradient of density and r_j is the distance in relation to dominant geographical features such as centres and major road networks, and Y_j the population in buffering zone j between r_j and r_{j+1}. w_{ij} refers to the weight value of urban land use i in buffering zone j, n_{ij} the number of pixels. In contrast to equation 1, equation 2 is computed based on theoretical assumption, and not on observational data. The selection of a_0 and λ should have sufficient evidence from other cities with similar social and economic backgrounds.

4.2.5 Integrating urban activities

We argue that the index of spatial gravity between urban activities and new development units can better represent the relative impacts of urban activities on sprawl than absolute distance. The concept of interaction is referred to as isolation or exposure. Generally speaking, the interactions can be integrated as follows (equation 3):

$$Z_{ij} = \Sigma w_k * l_{ki} / d_{ij}^{\alpha} \tag{3}$$

Where Z_{ij} indicates the spatial gravity of pixel j (urban sprawl from time t_l to t_0) from pixel i (in urban built-up area at time t_0). d_{ij} is the Euclidean distance between pixel i and j. In practice, a threshold value φ needs to be set, when $d_{ij} > \varphi$, pixel i is not calculated. α indicates the intensity of interaction or the relative importance of distance, α=2 corresponds to the normal gravity model. w_k is the weight value of urban activity k, which is illustrated by population, employment or economic output. l_{ki} is the standardised value of pixel i in relation to activity k.

$$T_j = \Sigma Z_{ij} \tag{4}$$

T_j is the integrated impacts of urban activities on pixel j. We argue that the spatial pattern and intensity of T_j can better define and compare urban sprawl. The greater T_j is, the more centripetal pixel j is. In contrast to absolute distance measurement, T_j integrates physical and socio-economic information. However, T_j does not contain information on the density of urban growth. This will be implemented by global evaluation of its pattern. The relative degree of sprawl is based on the statistic of T_j .

4.2.6 Global evaluation

As described before, the measurement of urban sprawl may have a varied focus. It results in a demand for multiple indicators for different perspectives.

(1) Diversity

Shannon's entropy (H_n) can be used to measure the degree of spatial concentration or dispersion of a geographical variable (T_j in equation 4) among n zones. Its formula is defined as follows (equation 5)

$$H_n = \Sigma\, p_j \log(1/p_j)/\log(n) \qquad (5)$$

Here, n is the number of classes designed by user. When used for temporal comparison, classification should be uniform for all periods. p_j $(= T_j / \Sigma T_j)$ is the proportion of pixels in class j of the total. Principally, entropy represents the diversity of the phenomena to be modelled, not exactly the degree of spatial cluster (Yeh and Li, 2001b). As real urban sprawl is the mixture of multiple types, the entropy value can quantify the degree of the mixture. Entropy provides an index for measuring land use heterogeneity and quantifying the degree of mixing across land use categories.

(2) Spatial pattern

The most common interpretation of spatial auto-correlation is in terms of trends, gradients or patterns across a map. Moran's *I* statistic is one of the most common and powerful (equation 6). Here, T_i , T_j indicates the integrated value (from equation 4) at locations i and j respectively. u is the average of all n pixels. W is the spatial weights matrix; its element w_{ij} indicates the potential spatial interaction between locations i and j. W_{ij} is defined as binary (0/1) by using critical distance thresholds. Any two pixels are considered as neighbours and assigned value 1 in W if the distance separating them is smaller than the selected thresholds. The influences of W can be graphically displayed by the Moran'*I* correlogram, a function relating the spatial auto-correlation *I* with distance. The correlogram is calculated with various lags, normally specified as equal distance bands.

$$I = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(T_i - u)(T_j - u)}{\sum_{i=1}^{n} (T_i - u)^2} \qquad (6)$$

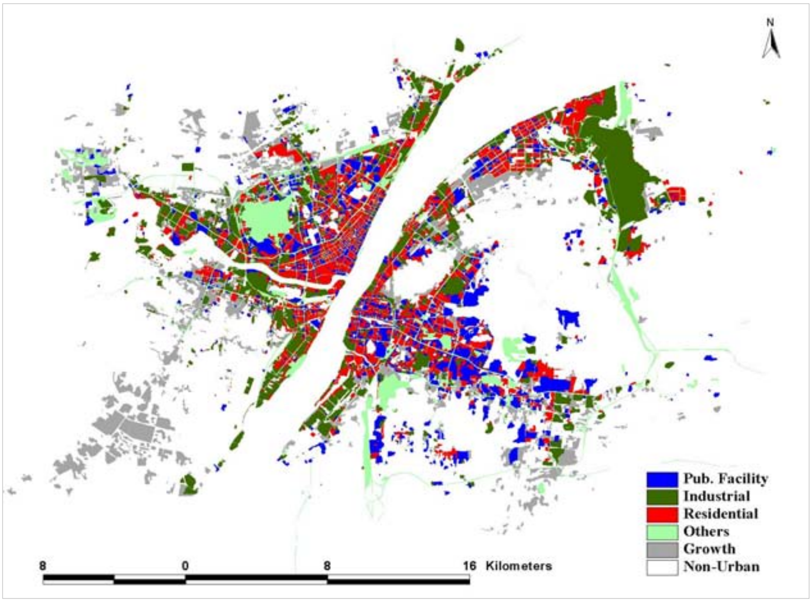

Figure 4.3 Urban growth (1993-2000) and land use (1993)

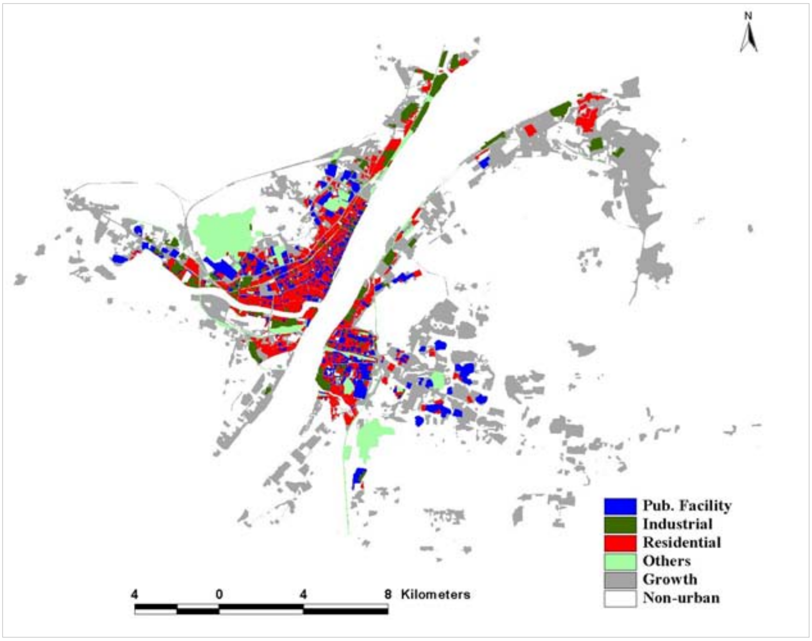

Figure 4.4 Urban growth (1955-1965) and land use (1955)

4.3 Case Study

During the last five decades, Wuhan underwent rapid urban growth, from 3,000 ha of built-up area in 1949 to 27,515 ha in 2000, in two waves of development: 1955-1965 and 1993-2000 (table 3.3 in chapter 3). Qualitatively, these two waves had a similar pattern of urban sprawl but with different economic components (section 3.5.1 in chapter 3). Therefore, we need to quantitatively compare the relative degree of urban sprawl in the two periods.

4.3.1 Temporal mapping

The imagery employed here includes SPOT PAN/XS of 2000 (November) and aerial photographs of 1955 (B/W, scale 1:25,000) and 1965 (B/W, scale 1:8000). The image processing was implemented using the ERDAS IMAGINE 8.4 package (section 3.4.2 in chapter 3). Here, land cover is classified as urban built-up, agricultural, water body and protected area (green, sands, special uses), which are principally extracted for 1965 and 2000. The land use map of 1993 is available directly in digital format from the local planning organisation. Its major urban land use classes include Residential, Industrial, Warehouse and Public Facility (commercial, institutional etc.). This classification is also utilised for the visual interpretation of land use of 1955 from aerial photographs. As interpretation of either image or photo is subjective, the whole operation was carried out by one person to guarantee temporal comparability. Urban sprawl and land use in 1993-2000 and 1955-1965 are displayed in figures 4.3 and 4.4 respectively.

4.3.2 Spatial statistical units

The design of spatial statistical units is the prerequisite for socio-economic data integration and spatial structure analysis. For example, in the USA the hierarchy of statistical units is census blocks, block groups, tracts, city boundaries, and county boundaries. Various socio-economic data such as employment, tax and population are spatially organised into a standard data format, based on these units. The TIGER format is supported by GIS software packages such as ArcView and is free to access (Census TIGER Data published on ArcData Online at http://www.esri.com/). However, in China the issue of spatial statistical units has not been fully recognised to date. Most socio-economic data are not available at the detailed levels (e.g. block) crucial for urban planning. The most usable items come from the population census, which is carried out nearly every 10 years (1954, 1963, 1982, 1990 and 2000). The present units are only based on limited levels of administrative boundary (Cheng and Turkstra, 1997). The administrative units for survey are stratified as municipality, district, sub-district and neighbourhood. Their administrative relationships are represented as figure 4.5.

Here, the urban area *(shi qu)* is not a real administrative unit, but it is the watershed of urban and rural population. The sub-district, organised by a street committee, has much denser population and more urban activities. The town is a settlement meeting a minimum non-agricultural population, employment, industry output values and other criteria. These are subject to changes due to rapid urbanisation. A township is a smaller settlement with fewer urban components than a town. When a township develops up to a certain level, it can be approved and upgraded to a town. A farm is an a-typical unit that originated from the large-scale agricultural production in the period of the Great Leap Forward (1953-1957). Farms are located in the rural areas but form an urban population according to the *Hukou* system (to control the immigration from rural to urban areas). The neighbourhood administered by a residential committee (*ju wei hui*) is the lowest spatial unit for registration.

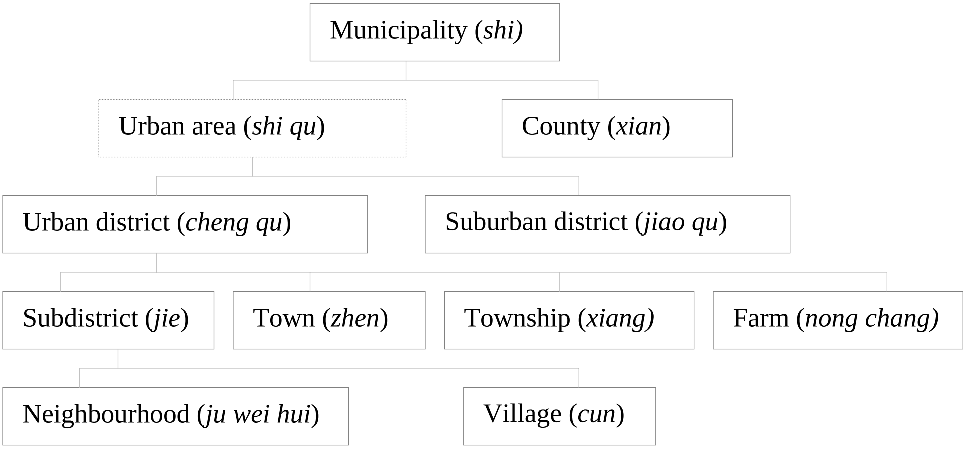

Figure 4.5 Administrative structure of Wuhan municipality

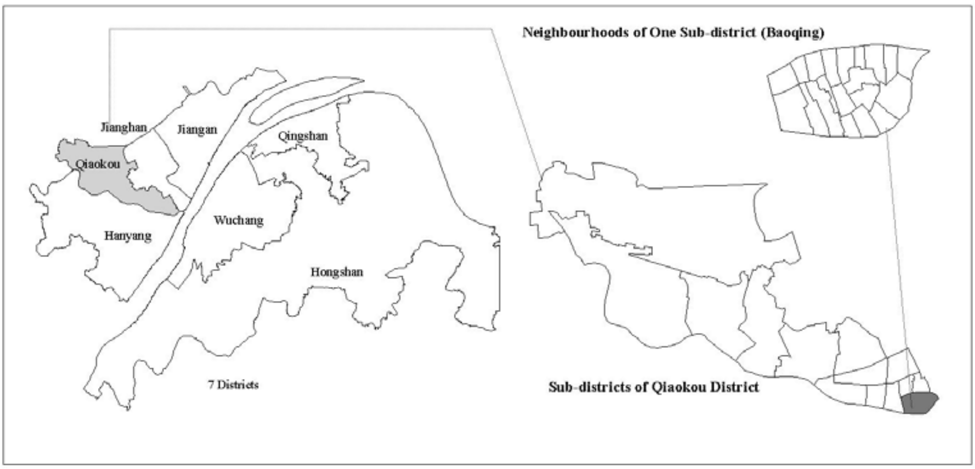

Figure 4.6 Illustration of spatial statistical units

One example showing the spatial hierarchy between district, sub-district and neighbourhood can be seen in figure 4.6, which corresponds to Wuhan city in 1993. Its urban area then included seven urban districts (*Qiaokou, Jianhan, Jiangan, Hanyang, Wuchang, Hongshan* and *Qiangshan*). The district *Qiaokou* comprised 13 sub-districts and one township (figure 4.6). Their size varies with the distance to the city centre. The maximum is 1,723 ha for the furthest township and the minimum is 25 ha.

Of the 13 sub-districts, *Baoqing* contains 19 neighbourhoods of varying size (figure 4.6). A 1: m relationship between these three units provides a simple spatial framework for data aggregation and disaggregation. For example, census data can be disaggregated from district to sub-district level in this research. It should be noted that these units were subject to partial changes of spatial extent in the past five decades, such as splits, merges and the removal of sub-districts or neighbourhoods. For instance, Wuhan municipality comprised five urban districts and four suburban districts in 1952. A series of expansion, re-merging and re-splitting continuously occurred in 1955, 1956, 1957, 1958, 1959, 1964, 1976, 1983 and 1986 respectively (ECWLR, 1996). It comprised seven urban districts, two suburban districts and two counties in 2002. This often creates problems. The most obvious is that it prevents long-term comparisons. A less well documented but equally important problem is that it prevents many earlier censuses being accurately mapped as the boundaries of the units used to publish them are not available. The traditional response to both of these problems has been to aggregate the data into larger units with stable boundaries. This strategy not only sacrifices spatial detail to increase temporal extent but also increases the problems associated with MAUP (modifiable areal unit problem) to such an extent that many forms of analysis must be considered suspect (Gregory, 2002).

4.3.3 Registration of socio-economic data

The registration of socio-economic data is divided into two types: a census survey every 10 years and a yearly statistical report based on a 1% sampling. The neighbourhood is the basic unit for the population census. The census database is developed in the local municipal bureau of statistics for official uses, and the public publication of the population census is aggregated to the sub-district level. In contrast, the population yearbook, which is published once a year, is only at district level. The former undoubtedly has more detailed information and a much higher resolution than the latter. The number of census items is also increasing gradually in response to the changing demands of social and economic statistical analysis. The census survey of 2000 started to include tax, ownership of buildings, and many other items. The item "total population" is split into agricultural and non-agricultural sections, which are affected by the specific *Hukou* system. The non-agricultural section should be the major representative of urban social and economic activities, which is the main item of this research. Although the neighbourhood (even sub-neighbourhood) is the lowest statistical unit for census registration, it is not a practical one for data disaggregation as the boundary of neighbourhoods covering whole urban districts is subject to change and is difficult to map. Hence the sub-district units (including town, township and farm) are frequently utilised for data disaggregation from the district. A uniform formula can be defined to integrate both census and yearly statistical data (equation 7) when a linear trend (interpolation) is assumed.

$$P_{ij}(t) = P_i(t) * P_{ij}(t_0) / P_i(t_0) \qquad (7)$$

Where t is the year for data disaggregation and t_0 is the nearest base year of the census survey. $P_{ij}(t)$ is the non-agricultural population at sub-district j of district i in year t, $P_{ij}(t_0)$ in base year t_0. $P_i(t)$ is the non-agricultural population in district i in year t, $P_i(t_0)$ in base year t_0. For instance, in this research, when t =1993, t_0 = 1990. In 1990, Wuhan had seven urban districts with 78 sub-districts, 2 towns, 13 townships and one farm in the study area. They are the best possible statistical units for the disaggregation of population data as the boundary map of neighbourhoods is not available. The same procedure can be applied for the disaggregation of other census items.

4.3.4 Disaggregation to pixel level

(1) 1993

For urban sprawl in 1993-2000, the spatial statistical units selected are the urban district and sub-district. The census data in 1990 were disaggregated from district to sub-district level in 1993. Major land use classes include residential area (*R*), industrial area (*I*) and public facility (*P*). Here, the "public facility" includes institutional, commercial, and other public uses. This classification is related to the data source of 1:10,000 topographic maps of 1993. It is also the footprint of the social command system during that period in China as work units were also undertaking house construction for their employees (Wang and Murie, 1999; Wu, 1996, 2001; Zhang, 2000b).

After statistical tests, we can determine the weight values of two land uses (residential and public facility) evidentially: W_R=3 and W_P=1.Therefore, the population of each pixel can be computed according to equation 8, where $P_{R,j}$, $P_{P,j}$ mean the population value of a pixel with land use R or P respectively in sub-district j; TP_j represents the total population in unit j (from equation 1); and $n_{R,j}$ and $n_{P,j}$ represent the number of pixels with land use I or P in unit j. The ArcView package is used for implementing the computational procedures above. The results are displayed in figure 4.7.

$$P_{R,j} = 3 * TP_j / (n_{R,j} + n_{P,j}), \quad P_{P,j} = TP_j / (n_{R,j} + n_{P,j}) \qquad (8)$$

(2) 1955

With regard to urban sprawl in 1955-1965, as the census data and the map of sub-district boundaries are not available for this period, a theoretical assumption (negative exponential gradient of population density) is adopted here for approximate disaggregation to pixel level. Local planners argue that the urban development of Wuhan was dominated by outward expansion along the two rivers (the Yangtze and Han rivers) before 1955 (see chapter 3). From this, we can suppose that the urban built-up area in 1955 followed a negative exponential growth in relation to these rivers. From the statistical report (WBUPLA, 1995) of Wuhan municipality, the total non-agricultural population was 1,594,000 residents in 1955. In equation 2, the parameters a_0 and λ need comparative evidence to quantify. Here, we subjectively define three weight values (W_i) as equation 9 for different ranges of buffering zones (x_i) according to the principle of density gradient.

$$\begin{cases} x_i < 1000 \text{ m}, & W_i = 10 \\ 1000 <= x_i <= 2000 \text{ m}, & W_i = 3 \\ x_i >= 2000 \text{ m}, & W_i = 1 \end{cases} \tag{9}$$

With the same value as the former period (W_R=3 and W_P=1), we are able to disaggregate the total population to pixel level ($P_{i,j}$) in terms of equation 10, where $j=R$ or P, and i refers to the three zones defined above. $n_{i,j}$ represents the total number of pixels in zones i and with land use j. The result of disaggregation is displayed in figure 4.8.

$$P_{i,j} = W_{i,j} * 1594000 / \Sigma\, \Sigma\, W_{i,j} * n_{i,j} \tag{10}$$

4.3.5 Spatial gravity model

The spatial gravity model is based on the extensive computation of pair-pixels between urban land use and urban growth, as indicated in equations 3 and 4. This is very time consuming when pixel size is very small or the spatial resolution is high.

In this research, the disaggregation of population data is based on a 10 × 10 m^2 pixel size, but interaction computation is based on a 50 × 50 m^2 pixel size, which results in a 1220 × 800 grid. Here, the threshold value φ is set as 5 km and α=2 (equation 3). The results of spatial interaction between urban growth (1993-2000) and urban land use (residential and public facility in 1993) is displayed in figure 4.7, where colours indicate the relative compactness of urban growth, and the grey-scale the disaggregated population value at the pixel level. The classification is based on an equal interval. The same procedure is applied for the period 1955-1965, as shown in figure 4.8.The greater the interaction, the more compact the urban growth; conversely, the greater the sprawl. Compared with absolute space-based measurement, this methodology offers a comparative perspective. If we classify the interactions into five classes and compare the relative degree of urban sprawl in the two periods as listed in table 4.1, we can conclude that urban growth in 1993-2000 exhibited a more compact and less scattered pattern than that of 1955-1965, as the latter is stronger in the first three classes and weaker in the last two classes.

This difference can be easily explained by both the availability of developable land and the land lease system initiated in 1987. In the period 1955-1965, large-scale developable land

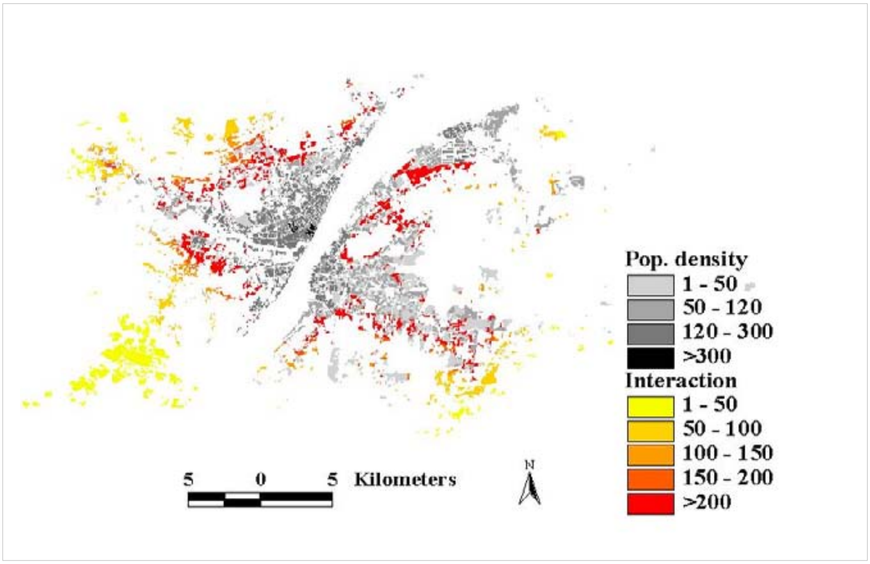

Figure 4.7 Disaggregation and integration for 1993-2000

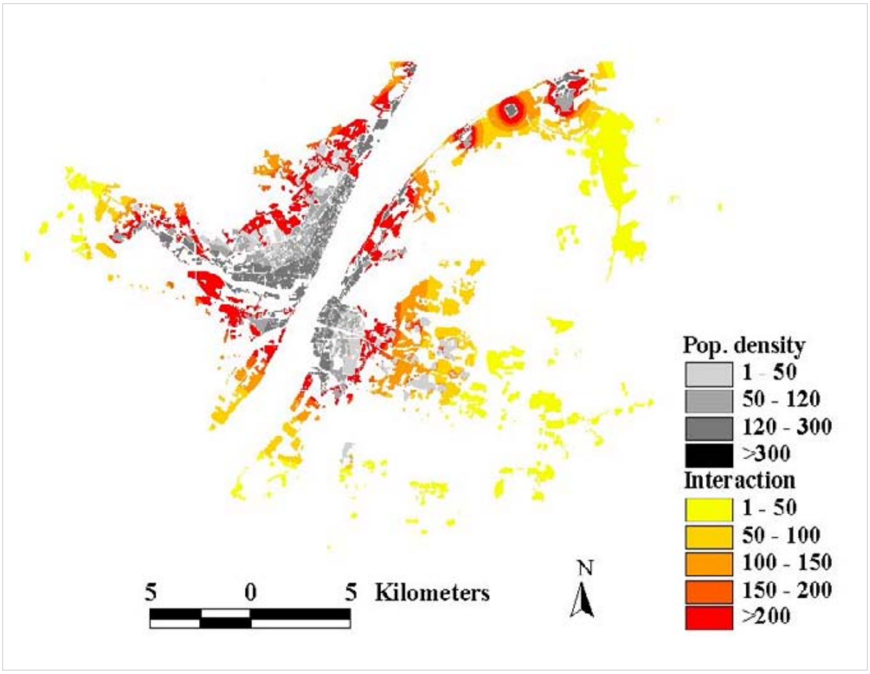

Figure 4.8 Disaggregation and integration for 1955-1965

was available without any charge. However, after 1987, constrained by poor physical topography such as water bodies, large-scale developable land was very scarce and costly.

Table 4.1 Statistics for the two periods

Interaction	1955-1965 (%) (a)	1993-2000 (%) (b)	Difference (b-a)
< 50	30.8	26.6	-
50-100	20.1	18.9	-
100-150	14.8	8.5	-
150-200	6.8	8	+
> 200	27.6	30	+
Total	100	100	
Pixels	31,682	24,402	

4.3.6 Global evaluation

(1) Diversity

According to the statistical distributions of interaction values, here we make 15 classes with equal interval values (=40), i.e. class 1=[1~40]. The entropy value of urban sprawl is 0.868 for 1993-2000 and 0.798 for 1955-1965 in terms of equation 5. This indicates that the urban growth in the later period exhibits a mixture of more diverse growth.

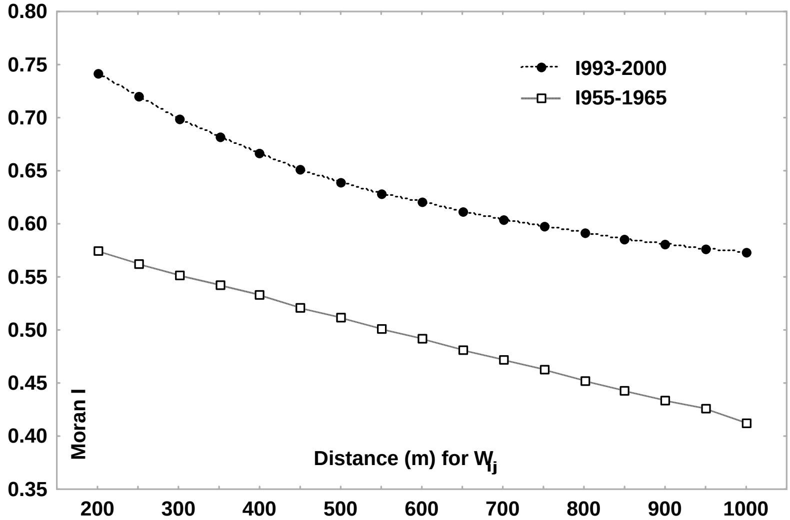

Figure 4.9 Correlograms of urban sprawl in 1993-2000 and 1955-1965

(2) Spatial patterns

The Moran 'I index reflects the relative degree of spatial agglomeration of the phenomena to be studied. In this case, the Moran 'I index can quantify the relative roles of spatial interactions on a clustered pattern. A positive coefficient means that the spatial cluster results from the spatial interactions. Thus, in a relative sense, it reveals a more reasonable and compact development pattern. Our experimental study shows that urban sprawl is more clustered in 1993-2000 than in 1955-1965 as the Moran 'I index of the former (0.75~0.57 when W: 200m~1000m) is much higher than that of the latter (0.57~0.41 when W: 200m~1000m) (see figure 4.9).

4.4 Discussion and Conclusions

This chapter provides preliminary results to illustrate a methodology based on the concept of relative space. It consists of several steps involving data, spatial analysis and understanding. In the progress towards any successful applications, there is still a need to discuss some practical issues and GIS analytical techniques.

4.4.1 The spatial interaction model

The methodology proposed is advantageous in integrating physical and social-economic data. As an example, this chapter only employs population data as it is, constrained by the availability of other census data. Temporal urban sprawl is interpreted from the perspective of population density. In principle, other variables such as employment and industrial output, which can be spatially linked with public facility (P) and industry (I) and can represent more urban activities, should be incorporated in the spatial interaction model (equation 3). This could offer the methodology stronger interpretative capacities. We can explain the relative degree of sprawl from the perspectives of population, employment and economic output value.

To some extent, the weight values of various activities (W_k in equation 3) could be utilised for simulating the scenarios of urban development planning. For instance, adjustable and subjective weight values based on AHP (analytical hierarchy process) (Wu and Webster, 1998) are an ideal instrument to test both the intentions of local planners and the impacts of urban sprawl. This direction should be explored in the future.

As with traditional spatial interaction models, the validation of parameters such as the distance function (inverse power or negative exponential function), density gradient and weight value is still a bottleneck. If the same set of parameters are used for the two periods, the final results should be concrete. Here we test this sensitivity to parameters by assigning α=1 (linear distance); its corresponding outcome is listed in table 4.2. Compared with table 4.1, this table shows the differences between the two periods, which are indicated by "--" and "++". As such, a decrease of α would improve the discriminative capacity of the difference. As shown by the entropy value, there is no significant change in the evaluation of two spatial patterns of urban sprawl.

Table 4.2 Sensitivity analysis to parameters of interaction model (α=1)

Classification	1955-1965 (%) (a)	1993-2000 (%) (b)	Difference (b-a)
3,500 - 7,000	26.8	0.6	- -
7,000-10,500	31.2	23	-
10,500-14,000	18	21	+
14,000-17,500	10.2	13.5	+
17,500-50,000	13.8	41.8	+ +
Total	100%	100%	
Total (pixels)	31,682	24,402	
Entropy	0.81	0.862	

The d_{ij} in equation 3 is the absolute distance between two pixels. In reality, some decisions involved in urban growth is conducted completely according to relative distance, such as the shortest path in network analysis or the structural distance in space syntax (Jiang et al., 1999), which are measured by the perception of the human being or measured in a systematic way. However, numerous empirical studies have shown that relative distance can better quantify spatial structure and that absolute distance can better represent spatial morphology. Urban sprawl is more related to the latter and urban real estate development could be more relevant to the former. Spatial morphology should be measured by proximity rather than accessibility, which is a major spatial indicator of spatial structure. Physical distance or its economic surrogates still provides the basic logic for locating some activities in time and space. The intuitive spatial decision-making is generally based on the understanding of the direct spatial relationships among spatial entities, such as the distance between city centre and residential location.

4.4.2 Data disaggregation

Data aggregation and disaggregation have been attracting attention in the fields of GIS and relevant social and economic applications. The methodology developed in Wegener (2001) is suitable for raster-based modelling; however, no further research is reported regarding the way of determining the weight values of various urban land uses. Martin (Martin, 1996, 1998; Martin and Bracken, 1991) developed surface modelling techniques in the area of census geography based on British practices. His approach is limited to point events, which need rich data sources. No matter what approach can be applied, the crucial point is the spatial and temporal resolution of statistical units, as urban activities are characterised by remarkable spatial and temporal heterogeneity. Spatial resolution is defined by the size and standard deviation among the selected level of spatial statistical units. Temporal resolution is determined by the temporal interval of two consecutive census surveys. In the case of China, it is nearly 10 years, which is too coarse for population data interpolation as in equation 11. The higher the resolution is, the higher the accuracy of the disaggregation is.

In this research, among 78 sub-districts the maximum size of a sub-district is 3406 ha, the minimum size is 9.65 ha and the average size is 374 ha. At the level of the neighbourhood, taking *Baoqing* sub-district as an example (figure 4.6), the maximum size is 5.1 ha, the minimum size is 0.9 ha and the average size is 2.37 ha among 19 neighbourhoods. As a consequence, the method for locating census survey on more detailed scales needs further study.

Given recent developments that make spatially and/or temporally referenced data more available at the individual level, the spatial analysis of human behaviour at the individual level will become more possible in the near future (Kwan, 2000). The parcel will be the most ideal unit to register social and economic activities with higher spatial and temporal resolutions.

However, data disaggregation involves complex spatial processes that are impacted by heterogeneous social and economic activities, which are represented by land uses. These spatial processes vary locally beyond the boundaries of statistical units, as determined by numerous factors such as the distance to city centre, distance to road networks, and land development intensity. This spatial locality is indicated by localised weight values, which are spatially effective in a varying size of neighbourhood. How to accurately determine these weight values becomes the key issue for data disaggregation. It involves a complex process of modelling beyond currently available GIS techniques, which should be the subject of more research in the future, such as Monte Carlo micro simulation. This chapter skips this complex procedure where weight values are treated as uniform in whole space.

4.4.3 Data completeness and consistency

The methodology in this chapter is based on the spatial integration of socio-economic and physical data on a micro scale. Social and economic data are needed for a starting year, such as 1955 or 1993. Land use data are needed for the starting year and urban sprawl data for the change period to be modelled. Remotely sensed imagery has proved an ideal source for land use and land cover change detection. Social and economic data have proved to be a barrier to GIS applications in social sciences such as urban planning and management. This phenomenon is even worse in the developing world as data collection is usually very costly. Consequently, the implementation of this methodology needs the adequate institutional support in the favour of a local information infrastructure, such as a census surveys on more detailed scales. In this research, the local spatial information infrastructure is not consistent with the census surveys. Population registration can be detailed to a neighbourhood level; however, the spatial data framework is not available at neighbourhood level. Geo-referencing various social and economic activities relevant to urban sprawl should be a topic for further research.

In temporal sprawl measurement, adequate attention should also be paid to the completeness and consistency of data, which may influence the accuracy of measurement. Completeness includes a diversity of social and economic activities involved in impacts on urban growth, spatial extent covered, and the availability of multi-resolution temporal data. In this research, the census data around 1955 are not available, which results in a lower accuracy for data disaggregation for this period. The map of sub-district boundaries in 1993 does not cover the entire study area. Consistency refers to spatial resolution, spatial statistical units, data registration, and the terms used. The administrative structure of Wuhan municipality underwent major changes in the period modelled. The same district may have different boundaries in any two periods. Hence, the population data of this district are not compatible in the two periods. The concept "non-agricultural population" has a different meaning in the past five decades as urban development policies underwent major modification.

4.4.4 Temporal complexity in urban growth

Temporal complexity in this chapter results from the incomparable measurement of a series of urban sprawl patterns. Temporal comparability is actually a subjective theme. In urban growth, the evaluation of urban growth depends on the purpose of the analysis. For example, each country or city has its own economic, cultural, ecological or even political situation. By using the concept of relative space, the temporal complexity can be transformed into spatial complexity, which is indicated by the complex spatial interactions between urban sprawl and urban social and economic systems. The methodology proposed attempts to interpret the macro patterns of urban sprawl from micro urban activities, as the global pattern originates from the self-organising processes of local activities. Relatively, activities can be more comparable and interpretative than spatial patterns as activities are directly linked with actors and their behaviour. As a result, this research shows that pattern, process and behaviour must be integrated into a whole towards understanding the complexity in urban growth.

Chapter 5*

Modelling Urban Growth Patterns

Abstract

Urban development is a complex dynamic process involving various actors with different patterns of behaviour. Modelling urban development patterns is a prerequisite to understanding the process. This chapter presents a preliminary multi-scale perspective for such modelling based on spatial hierarchical theory and uses it for the analysis of a rapidly developing city. This framework starts with a conceptual model, which aims at linking planning hierarchy, analysis hierarchy and data hierarchy. Analysis hierarchy is the focus of this chapter. It is divided into three scales: probability of change (macro), density of change (meso) and intensity of change (micro). The multi-scale analysis seeks to distinguish spatial determinants at each of the three scales, which are able to provide deeper insights into urban growth patterns shaped by spontaneous and self-organised spatial processes. A methodology is also presented to implement the framework, based on exploratory data analysis and spatial logistic regression. The combination of both is proved to have a strong capacity for interpretation. This framework is tested by a case study of Wuhan city, P.R. China. The scale-dependent and scale-independent determinants are found significantly at two scales.

Key words: pattern, hierarchy, multi-scale, exploratory data analysis, spatial logistic regression

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* Based on (Cheng and Masser, 2003c) and (Cheng and Masser, 2003a)

5.1 Introduction

During the last five decades, a series of political events has occurred in China (such as the establishment of a new government in 1949, economic reform in 1978 and land reform in 1987). These have brought about unparalleled changes in the urban development of Chinese cities. The outcome of these changes resulted in a rapid urban growth during the period of industrialisation before 1978 and large-scale urban new development and redevelopment under the market economy, especially after 1987 (Gaubatz, 1999; Wu, 1998b). The exploration of an urban development process that spans so long a period is crucial to decision-making for sustainable land management and future urban developmental planning. Previous studies of Chinese urbanisation have paid less attention to spatial and temporal dimensions due to the lack of available data. Presently, however, new opportunities are emerging with the development of new technologies.

As a result of the rapid development of remote sensing (RS) and geographical information sciences (GIS) and techniques, increasingly large-scale studies of urban development have been facilitated (Masser, 2001). Modern satellite imagery, together with traditional aerial photographs, provides rich multiple resolution and scales of data sources for monitoring urban development processes. By using GIS, it is technically possible to integrate large quantities of data for further spatial analysis related to urban development. However, it has become common knowledge that urban development is a complex dynamic process, which involves various physical, social and economic factors. The complexity arises from the unknown number of factors, multi-scale and cross-scale interactions among factors, and their unpredictable dynamics. Pattern and process are reciprocally related like "chicken and egg", and both they and their relationships are also scale-dependent. The identification of determinant factors on varied scales is the first step to understanding the dynamic process.

Facing the challenges, we need to develop innovative methodological frameworks for understanding the interaction between spatial patterns and processes. Urban development is divided into urban growth and redevelopment, which are typically projected on to different scales of land cover and land use change respectively (Stanilov, 1998). Spatially explicit modelling of land use changes is an important way of describing processes of change in quantitative terms and of testing our understanding of these processes. Consequently, the modelling of land cover and land use change is increasingly applied in the areas of agricultural, environmental and ecological systems (Schneider and Gil Pontius, 2001; Walsh and Crawford, 2001). It is also crucial to understand the importance of the urban development process. Initially it was assumed that the patterns of urban growth have distinct degrees of spatial and temporal heterogeneity across varied scales. This means that spatial and temporal patterns are determined by various locational and socio-economic factors.

Urban growth can be divided into spontaneous and self-organisational processes (Wu, 2000c). The former results in a spatially homogeneous and sparse pattern, which contains more random components, whereas the latter results in spatial agglomeration, which is impacted by more self-organised socio-economic activities. To understand spatial processes and patterns, we must take both types into account.

Wu and Yeh (1997) applied logistic regression methods for modelling land development patterns in two periods (1979-1987 and 1987-1992), based on parcel data extracted from aerial photographs. They found that the major determinants of land development have changed: from distance to the city centre to closeness to the city centre; from proximity to inter-city highways to proximity to city streets; and from more related to less related to the physical condition of the sites. To some extent, this is an example of spatial pattern modelling on various temporal scales. It shows that various factors are changing their roles in the process of land development. However, it only takes development probability or stochastic processes into account. It does not accommodate the details of spatial pattern such as density and intensity that represent the self-organising process of urban growth.

With these considerations in mind, this chapter puts forward a new spatial analysis perspective for modelling urban growth patterns, which is centred on seeking the varied determinants on various scales. Following the introduction, section 2 presents a hierarchical multi-scale framework, which is distinct from traditional multi-scale and multi-level methods. Section 3 describes the methodology for testing the proposed framework, which includes both exploratory and confirmatory data analysis approaches. A case study is introduced; next, a relevant database is developed based on remotely sensed data sources and GIS. The fourth section analyses some findings. This chapter ends with further discussion of relevant issues and possible directions for future research.

5.2 A Conceptual Model

5.2.1 Hierarchy theory and the scale issue

Complexity frequently takes the form of hierarchy (Kronert et al., 2001). Hierarchy theory was developed by general systems theorists, notably Koestler and Simon, to deal with complex and multi-scaled systems (O'Neill, 1988). Hierarchy theory applies hierarchy to organise concepts and interpret various complexities. In essence, a hierarchy is an ordered ranking, which is a basic property of any system from the angle of general systems theory. A hierarchy is often called a multi-level system, i.e. *A* contains *B* and *B* contains *C*. A fundamental point is that a component in a larger system (higher level) is also a system. Higher levels set constraints or boundary conditions for lower levels. Larger scales operate much too rapidly to be of interest and can be ignored (O'Neill, 1988). The theory examines closely the issues of scale, levels of organisation, levels of observation, and levels of explanation in a complex system characterised by hierarchical structures and interactions across levels.

The key to understanding hierarchical structure is scale. Scale is a form of hierarchy. The importance of scale has been recognised in the sciences concerned with the spatial organisation of human activities and physical processes on the Earth's surface for more than four decades (Marceau, 1999). It can function as a sort of container in space or time for heterogeneous phenomena and processes that have form and dynamics. Much of the difficulty in the treatment of "scale" is the great variability in the interpretation and meaning of "scale" (Withers and Meentemeyer, 1999), such as absolute size, relative size, resolution, granularity, extent and detail. Cartographic scales represent the ratio of a distance on a map to the corresponding distance on the ground. This usage is often qualified as "metric scale". In spatial analysis, the scope of scale can be threefold: spatial, temporal and decision-making.

Spatial scale is linked with the terms “resolution” and “extent”. Resolution is the precision of measurement, usually defined by specifying the grain size, which determines the lowest or smallest visible level in a hierarchy or minimum sampling unit. In the case of raster or image data, resolution is the size of a rectangular pixel. Extent represents the boundary of the study area under consideration, and appears unambiguous. Extent and resolution define the upper and lower limits of resolution of a study. Pereira (2002) argued that the definitions of both resolution and extent become complementary rather than contradictory.

Temporal scale is related to the terms “time step” and “duration”. The time step is the smallest temporal unit of analysis in a model, while duration refers to the length of time that the model is applied.

Decision-making scale can be described in similar terms: “agent” and “domain”. Agent refers to the human actor or actors in the model who are making decisions. The individual human is the smallest single decision-making agent; other agents can include a household, neighbourhood, county, state, province or nation. Domain, on the other hand, refers to the broadest social organisation incorporated in the model. While the agent captures the concept of who makes decisions, the domain describes the specific institutional and geographical context in which the agent acts. Institutionally, agents may overlap spatially.

The multi-scale issue has received considerable attention in the spatial analysis of various fields, including the ecological fallacy (Robinson, 1950) and the MAUP (modifiable areal unit problem) (Openshaw, 1977, 1984). Numerous empirical studies have shown the significant effects of scale on statistical inferences and models. The first step in the analysis of the scale problem was the development of appropriate quantitative methods for detecting scales or discrete levels at which regular and irregular patterns occur in the landscape (Marceau, 1999).

5.2.2 Multi-scale in urban growth

Scale issues are inherent in studies examining the physical and human forces driving land use and land cover changes (Currit, 2000). The multi-scale issue in urban growth has distinguishing spatial, temporal and decision-making dimensions. As remotely sensed imagery is a primary data source for monitoring urban growth, its temporal dimension is impacted by the requirements of temporal pattern analysis and the availability of time-series imagery. For example, Wu's models of land development patterns (Wu and Yeh,

1997) for two different periods (1979-1987 and 1987-1992) indicate a varied temporal scale.

Spatial patterns of urban growth first can be differentiated with varied spatial resolutions. This multi-resolution analysis principally explores the details of information extracted, which is utilised to test the sensitivity or stability of the models. Numerous experimental studies in various areas such as the agricultural, ecological and environmental sciences have reached consensus that resolution is an influential factor (Kok and Veldkamp, 2001; Page et al., 2001; Stein et al., 2001; Walsh and Crawford, 2001). Data collected at a gross scale (coarser resolution) are considered less reliable in aiding the interpretation of events operating at fine scales (finer resolution) (Goodchild, 2000). However, multi-resolution analysis is implemented under a definite spatial extent as the latter largely affects the availability of data sources. For instance, 1 m resolution IKONOS images are too costly to cover a whole mega-city, especially in developing countries, but they are reasonable sources for one district.

The second multi-scale pattern analysis is from the perspective of spatial extent. Relatively, not enough attention has been paid to this analysis. A question is coming up: How can spatial extent be effectively defined, in particular for the purpose of interpreting corresponding spatial processes? In most studies, spatial extent is limited to the hierarchy of administrative boundaries from the national to the regional to municipal levels. Such definitions based on administrative boundaries are consistent with land administration; moreover, more socio-economic information such as census data can be integrated into modelling. Hence, the model can be closely linked with the socio-economic and political processes of urban growth. For instance, Kok and Veldkamp(2001) modelled land use change based on six Central American countries. They found that the effect of changing the spatial extent on the set of land use determining factors is substantial, with a strong increase in explanatory power when reducing the extent from regional to national. This implies that urban growth pattern analysis should be based at its highest level, such as the municipal level.

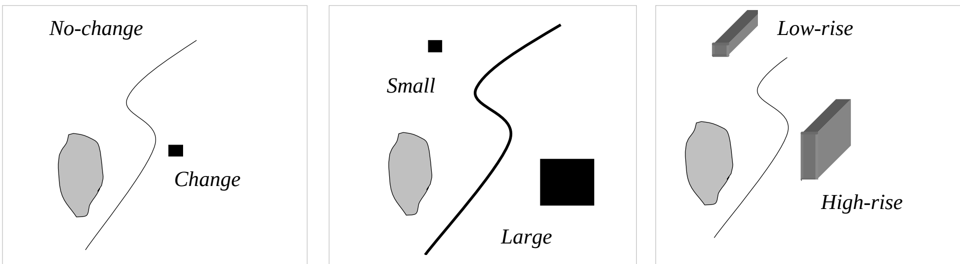
If focusing on the spatial process, however, urban growth is not physically inhibited by administrative boundaries, in particular at the lower level, as these boundaries are expanding and changing, especially over a long development period such as 10 years in fast developing countries such as China. Moreover, urban growth frequently occurred before the formation of a new urban administration unit as it was located in the fringe. For instance, in China, a new administration unit is transformed from rural to urban (e.g. from a rural village to an urban sub-district) only when new development in this area reaches a certain scale. From the perspective of the spatial process, such hierarchies can only represent the discrete process rather than the continuous process. They can less effectively reflect spatial heterogeneity of urban growth.

Therefore, we argue that a relative spatial hierarchy can be defined to satisfy the specific purposes of spatial analysis, e.g. for explaining spatial processes. In this context, the term "relative" means subjective instead of objective boundaries. To some extent, this definition is more ambiguous than the former but it can better represent continuous spatial processes, as they are natural not artificial classifications and in essence are continuous not discrete, fuzzy not crisp. In a later section, a new relative spatial hierarchy will be described in detail towards linking with the decision-making scale.

At the decision-making scale, it is supposed that urban growth is strictly controlled (or highly impacted) by urban development planning; the hierarchy (or details) of urban growth management and planning indicates the scale of decision-making. In the case of Chinese cities, the urban development planning system ranges from general land use planning or strategic planning, to master planning or structural district planning, down to detailed zone planning. Each level has its own specific objective, information requirements and institutional organisation, which will be explained in the next section. The higher level spatially and conceptually defines constraints for the lower level. When projected on to the land system, each level of planning needs specific information support on certain spatial and temporal scales. In this sense, the decision-making scale is conceptually the highest, which determines the required spatial and temporal scales. For example, from general land use planning down to zone planning, their spatial extent is decreasing and their temporal resolution is increasing significantly. General land use planning covers the whole municipality and can be valid for 20 years or longer. Conversely, zone planning focuses on a much smaller area and suffers from more frequent revision in response to the dynamic environment.

From the perspective of planning, what are the information requirements at various decision-making scales that might be provided by the domain of geographical (spatial) information science? A fundamental research question is: What should be modelled in spatial patterns of urban growth? This chapter conceptualises three points, as illustrated in figure 5.1. The question can be divided into three sub-questions:

- Where should change take place?
- How much should the change be?
- How strong should the change be?



a) Where to change? (Probability of change) **b)** How much change? (Density of change) **c)** How strong change? (Intensity of change)

Figure 5.1 Research questions for urban growth patterns

From the perspective of modelling, they can be conceptually transferred to the probability of change, the density of change and the intensity of change respectively, which are defined as follows:

- "Probability" is defined as the possibility of land cover transited from non-urban area to urban use in any pixel;
- "Density" is defined as the possibility of land cover change agglomerated in any pixel;
- "Intensity" is defined as the possibility of high-density land cover change intensified in any pixel.

Obviously, the three concepts represent three different probabilistic events, which are becoming the main concerns of urban development planning systems. The detailed calculation procedures can be seen in a later section.

For example, in the case of Chinese cities, general land use planning needs information support regarding the major determinants of change probability patterns, which can be utilised for guiding sustainable land management. Master or structural planning needs information such as the principal determinants influencing change density and change type and different scale constructions, which can facilitate the decision-making in site selection for major projects. The lowest level of control planning needs more detailed information of the spatial factors affecting the intensity of change, which is indicated by different floors of high-rise buildings. These can be utilised for the control of plot ratio etc.

The next question is: How are the three concepts spatially defined? According to their definitions, they can be definitely stratified as follows:

- The probability of change is spatially defined in the whole study area;
- The density of change is only defined in the extent of land cover change from non-urban to urban;
- The intensity of change is spatially limited to the extent with higher density of change.

The definition exactly determines a relative hierarchy of spatial extent. Here, the probability of change defines a binary spatial system A (A_1: change, A_0: non-change). Its component A_1 (spatial extent of change density) also defines another binary system B (B_1: high density, B_0: low density). Again system B's component B_1 (spatial extent of change intensity) defines a third binary system C (C_1: high intensity, C_0: low intensity). "Relative" is indicated by the spatial definition of the change density and intensity, which aims to identify the relative degree of development density and intensity. As a consequence, the urban growth pattern can be analysed from a simple three-level hierarchy, which defines a three-scale spatial extent.

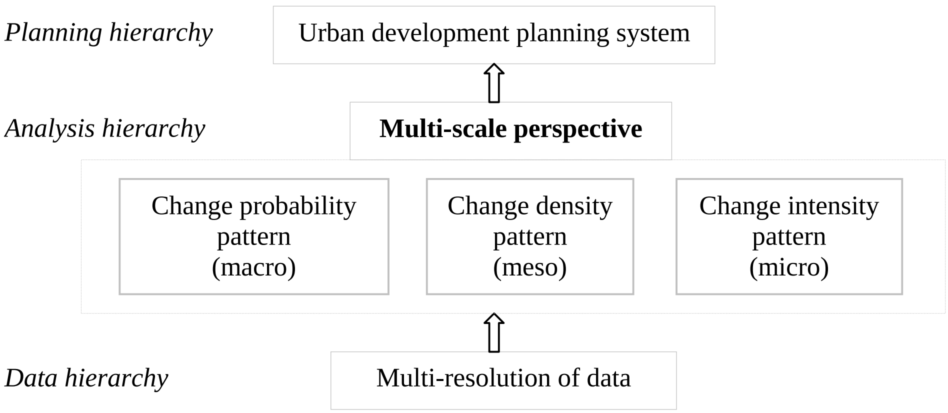


Figure 5.2 A relative spatial hierarchy for a new multi-scale perspective

Summing up, urban growth patterns involve three interrelated hierarchies (figure 5.2) through the concepts or planning, analysis and data hierarchies. Being planning-oriented, the conceptual hierarchy determines the decision-making scales and information requirements for the analysis hierarchy. The data hierarchy not only provides required resolutions (spatial and temporal) as input into the analysis hierarchy but also seriously affects its results. For example, the probability of change needs a sample of land cover pixels with and without change, which can be directly extracted from SPOT images. The density of change needs another sample of land cover change with high and low density. The intensity of change further needs three-dimensional data, i.e. floor number in high-density change area., This chapter focuses on the analysis hierarchy, the core of the three hierarchies that bridges the conceptual and data hierarchies. This hierarchy defines a new multi-scale spatial extent: macro (probability of change), meso (density of change) and micro (intensity of change). The division from macro to micro is consistent with corresponding levels of development planning but not identical to the hierarchy of administrative boundary.

This new multi-scale perspective links up with decision-making scales and also explicit spatial processes. The scale of change probability principally reflects more stochastic processes, change density for more self-organised processes, and change intensity for more spatial behaviour, as more actors are involved in the decision-making of development intensity. This chapter will focus on testing their effects on urban growth patterns, an area that has not received much attention. As limited by data availability, the test is implemented on only two scales: probability of change and density of change.

5.3 Methodology and Data

Multi-level modelling has recently started to receive attention (Jones and Bullen, 1993; Jones and Duncan, 1996; Huang and Clark, 2002) as a cross-scale statistical analysis approach due to its advantages in dealing with a number of issues such as heterogeneity, intra-unit correlation, the small-number problem, the MAUP, aggregation bias, and the ecological and atomistic fallacies (Jones and Duncan, 1996). However, the application of multi-level modelling relies on a priori definition of a discrete set of spatial units at each level of the hierarchy. Imposing a discrete set of boundaries on most spatial processes is unrealistic (Fotheringham et al., 2000). Published applications mostly focus on social and economic processes rather than on spatial processes. Due to the current lack of cross-scale methods, scale-specific methods should be preferred (Kronert et al., 2001), in particular for spatial pattern and process modelling.

When focused on spatial processes and patterns, the main objective is to seek and compare determinants of urban growth patterns on multi-scales; hence the causal-effect interpretation capacity of modelling techniques is of vital importance. The major methodology developed here consists of exploratory and confirmatory data analysis.

5.3.1 Exploratory data analysis

The real power of GIS resides in their display facilities but they still lack the facility to visually explore relationships between multivariate data. Graphical representation of spatial relationships is generally more easily interpreted than numerical output. Towards this direction, exploratory spatial data analysis (ESDA) techniques are used to detect spatial patterns in data**,** and to suggest hypotheses, which may be tested in a later confirmatory stage (pre-modelling exploration). In modelling patterns, ESDA is receiving more and more attention (Bell et al., 2000; Brunsdon, 2001; Goodchild, 2000).

In urban theories, a widely accepted assumption is the negative exponential decrease in density of development units such as buildings, people and resources, illustrated in equation 1, where *x* is the radial distance from the central business district (CBD) situated at the core, and λ is the density gradient.

$$f(x)=\beta\, e^{-\lambda x} \tag{1}$$

The density gradient quantifies the extent of the urban spread around the central core. Urban models based on economic theory (Muth, 1969), discrete choice theory (Anas, 1982) and other approaches such as entropy maximisation (Wilson, 1970) have made widespread use of the negative exponential function. Here, we extend the CBD to other development factors such as major roads, minor roads and developed areas, and also extend density to both the probability of change and the density of change. We assume here that the probability and density of change are characterised with exponential increase or decrease in relation to each development factor. In two cases, function *f(x)* could be transferred to *p(x)* (probability) and *d(x)* (density) respectively through discretisation (equations 2 and 3).

$$f(x) = \lim_{\Delta x \to 0} \frac{\Delta p}{\Delta x} \approx \Delta p = \frac{ch_{\Delta x}}{ch_{\Delta x} + nch_{\Delta x}} = \beta_1 e^{\lambda_1 x} = p(x) \tag{2}$$

$$f(x) = \lim_{\Delta x \to 0} \frac{\Delta d}{\Delta x} \approx \Delta d = \frac{ch_{\Delta x}}{\sum ch_{\Delta x}} = \beta_2 e^{\lambda_2 x} = d(x) \tag{3}$$

Where *p(x)* is the change probability function and *d(x)* the change density function. Δp indicates the probability of change in the scope (x, $x+\Delta x$), Δd for the density of change in (x, $x+\Delta x$). When Δx is very small, *p(x)* and *d(x)* could be approximately equal to Δp and Δd respectively. Δx is a radial distance interval, which should be as small as possible. The $ch_{\Delta x}$ counts the total amount of land cover change located in the scope (x, $x+\Delta x$), $\Sigma\, ch_{\Delta x}$ is the total land cover change in the whole study area. $nch_{\Delta x}$ means the total amount of developable land in the scope (x, $x+\Delta x$). Δx is the actual buffering distance interval. After a logarithmic transformation, we can calculate the density gradient λ_1 and λ_2 (equations 4 and 5) respectively, which exhibit the spatial influence of each factor on growth.

$$Log\ (\Delta p) = log\ (\beta_1) + \lambda_1 x \tag{4}$$

$$Log\ (\Delta d) = log\ (\beta_2) + \lambda_2 x \tag{5}$$

The slopes λ_1 and λ_2 indicate the degree of spatial influences; $\lambda>0$ (λ_1, λ_2) means a positive influence; $\lambda<0$ indicates a negative effect. The correlation coefficient R indicates its accuracy or reliability.

From the standpoint of probability theory, Δp and Δd represent two types of probability value respectively, which are limited in the same scope Δx. Let A denote the event of land cover change, and B/A the event of high-density change when A occurs (conditional probability), theoretically, $\Delta p = p(A)$, $\Delta d = p(B/A)$. Hence, $p(AB)=p(A)*p(B/A)=\Delta p * \Delta d$ (*AB* means the event of high-density change). Based on the two formulas (equations 4 and 5), we are able to calculate the probability value (i.e. $\Delta p * \Delta d$) of high-density change.

The distance-decay effect of each factor can be visualised for pattern detection and hypothesis formation by displaying the scatter plots ($log(\Delta p)$ & $log(\Delta d)$, x). Spatial outliers can be detected for detailed data checking. When a curve has multiple peaks, it may result from an unreasonable definition of the spatial indicator. In this case, the indicator should be split or merged (see a later section). Slopes λ_1 and λ_2 indicate the growth patterns in relation to its development factor at two levels. A steeper slope may imply a more compact pattern, otherwise a more dispersed or scattered pattern. Intercept b represents the initial value of probability. Systematic comparisons of λ_1, λ_2 and b_1, b_2 can offer deep insights into the spatial influences. The key feature of multi-scale models is that they specify the potentially different intercepts and slopes for each space as coming from a distribution at a high level.

5.3.2 Spatial logistic regression

Traditional statistical analysis techniques such as multiple regression and logistic regression are still widely used in pattern modelling. For example, Lopez et al. (2001) employed linear regression for exploring the relationship between urban growth and population growth. Wu and Yeh (1997) and Wu (2000b) applied logistic regression methods for explaining land development pattern and industrial firm location respectively. The techniques have proved effective in seeking some determining variables for the occurrence of certain spatial phenomena like urban development.

Table 5.1 Comparison of multi-regression, log-linear and logistic regression

Type of regression	Dependent variable	Independent variable	Computation method	Normality assumption	Relationship
Multivariate regression	Continuous	Only continuous	OLS	Yes	Linear
Log-linear regression	Categorical	Only categorical	GLS	No	Non-linear
Logistic regression	Binary Categorical	Mixture	GLS	No	Non-linear

(GLS: Generalised Least Square, OLS: Ordinary Least Square)

Compared with multiple regression and log-linear regression (see Table 5.1), logistic regression is advantageous in its dependent variable, explanatory variable and normality assumption. As a complex socio-economic system, the urban growth phenomenon does not usually follow normal assumptions. Its influential factors are mostly a mixture of continuous and categorical variables.

The general form of logistic regression is described as follows:

$$y = a + b_1 x_1 + b_2 x_2 + \ldots + b_m x_m \tag{6}$$

$$y = \log_e\left(\frac{p}{1-p}\right) = logit(p) \tag{7}$$

$$p = \frac{e^y}{1+e^y} \tag{8}$$

Where $x_1, x_2, x_3,..., x_m$ are explanatory variables. y is a linear combination function of the explanatory variables representing a linear relationship (equation 6). The parameters b_1, $b_2,..., b_m$ are the regression coefficients to be estimated. The p means the probability of occurrence of a new unit, i.e. the transition from rural to urban. Function y is represented as logit(p), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable is 1 (equation 7). In logistic regression, the probability value can be a non-linear function of the explanatory variables (equation 8). This is a strictly increasing function; the probability p will increase with value y. The regression coefficients $b_1, b_2,..., b_m$ imply the contribution of each explanatory variable in probability value p. A positive sign means that the explanatory variable will help to increase the probability of change and a negative sign means the opposite effect. The statistical technique is a multivariate estimation method in examining the relative strength and significance of the factors (explanatory variables).

However, as the primary data sources regarding urban growth come from remotely sensed imagery, spatial heterogeneity is the main concern. Logistic regression has to consider spatial statistics such as spatial dependence and spatial sampling. Ignoring these issues will lead to unreliable parameter estimation or inefficient estimates and false conclusions regarding hypothesis tests (Irwin and Geoghegan, 2001; Pa´ez et al., 2001). This chapter will design a spatial sampling scheme to reduce spatial dependence phenomena on two scales.

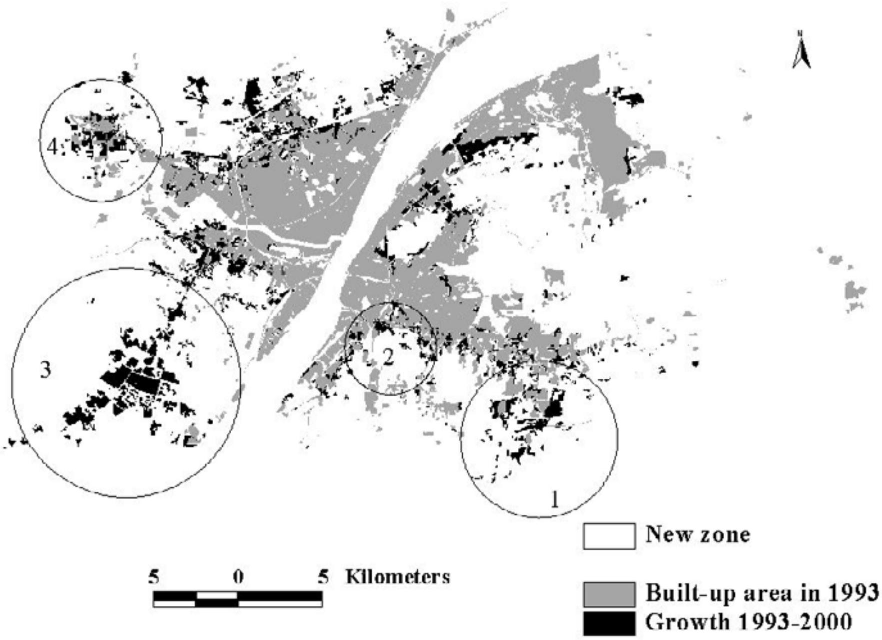


Figure 5.3 Urban growth from 1993 to 2000

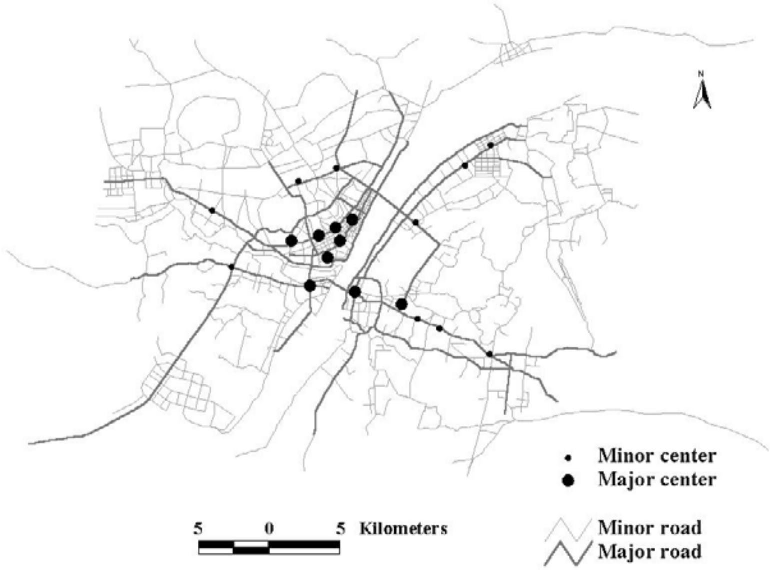


Figure 5.4 Spatial distribution of road networks and centres

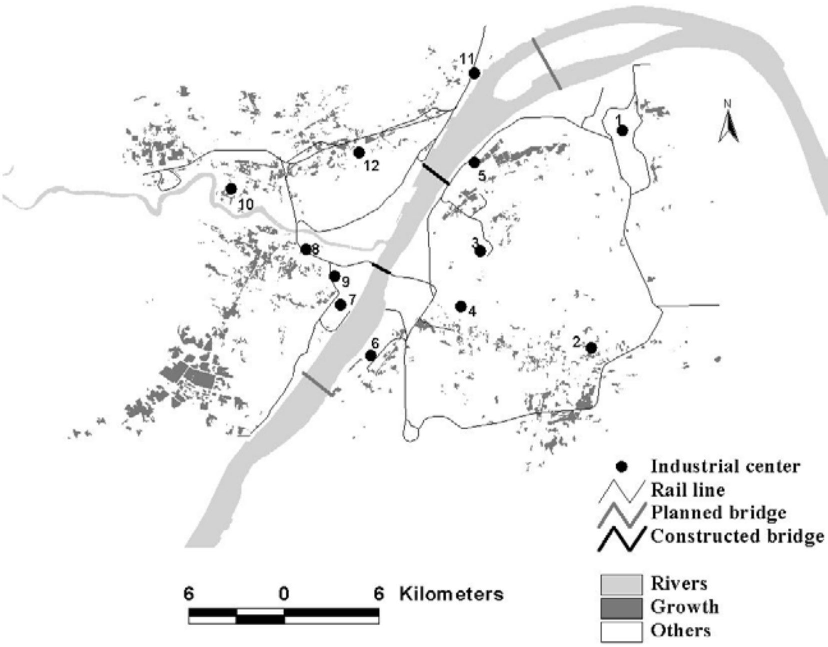


Figure 5.5 Spatial distribution of railway lines, bridges and industrial centres

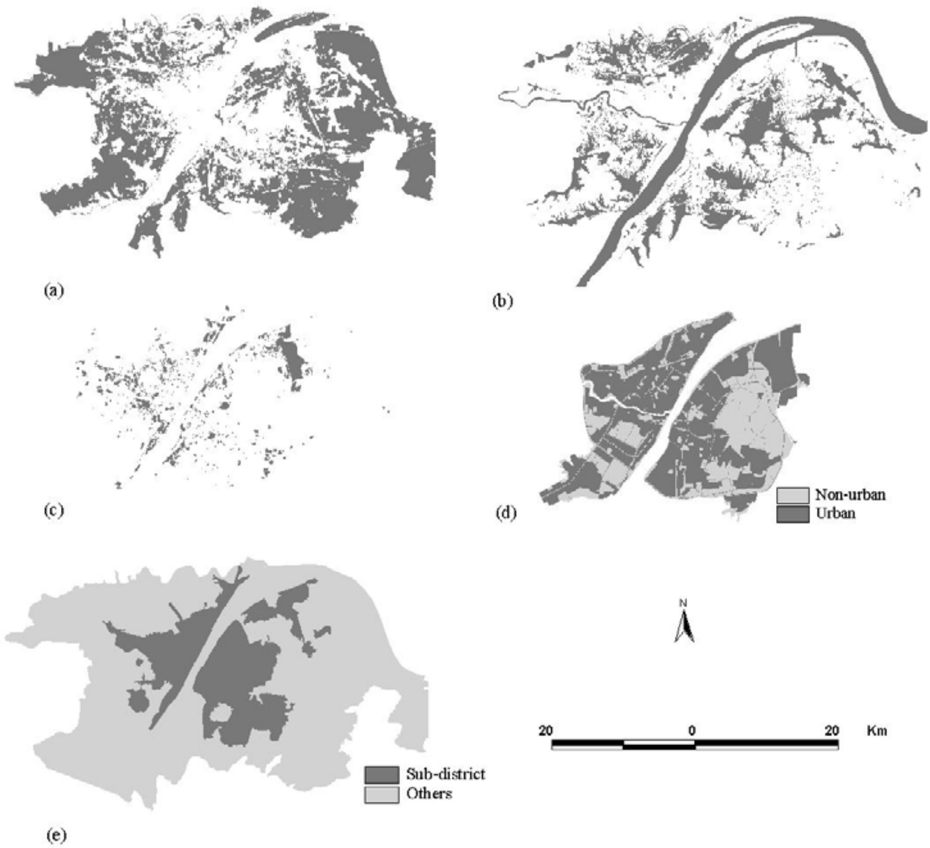


Figure 5.6 Spatial distribution of other explanatory variables (a): Agricultural land; (b): Water bodies; (c): Industrial sites; (d): Master plan; (e): Administration

5.3.3 Variables and GIS data analysis

In this research, Wuhan is taken as a case study (section 3.4.1 in chapter 3) for testing this methodology. The main information requirements available for the model comprise land cover in 1993, land cover change 1993-2000 (figure 5.3), physical factors (road network, railway network, city centres/sub-centres, industrial centres, bridges, rivers) (figures 5.4 and 5.6), physical constraints (water bodies and protected areas) and institutional factors (administration, master planning) (figure 5.7), which are extracted and processed from primary and secondary sources (see section 3.4.2 in chapter 3). Land cover is here classified as water body, agricultural, urban built-up area and protected area (including green and sands). In this research, in order to reduce the uncertainty in classification, only two classes (major and minor) are used to identify their impacts on urban development. It is the same for the definition of city centres/sub-centres. The determination of major roads and major city centres are principally based on the local knowledge available from master and transportation planning schemes and tourist maps. Some interviews with local planners are also necessary for further confirmation.

Table 5.2 Varibles and descriptions

Variables	Descriptive
Dependent Variable	
CHANGE	Binary variable, 1-change from non-urban to urban; 0-no-change.
CH_DENSITY	Binary variable, 1- high density; 0 – low density.
Proximity Variable	
DIST_RAIL	Countinuous variable, distance to railway lines;
DIST_INDUC	Countinuous variable, distance to industrial centers;
DIST_CENT	Countinuous variable, distance to city center/sub-centers;
DIST_MCEN	Countinuous variable, distance to major centers;
DIST_OCEN	Countinuous variable, distance to minor centers;
DIST_MRD	Countinuous variable, distance to major roads;
DIST_ORD	Countinuous variable, distance to minor roads;
DIST_RIVER	Countinuous variable, distance to the Yangtze/Han rivers;
DIST_YZ	Countinuous variable, distance to the Yangtze river;
DIST_HAN	Countinuous variable, distance to the Han river;
DIST_PBRID	Countinuous variable, distance to planned bridges;
DIST_CBRID	Countinuous variable, distance to constructed bridges.
DIST_CBRI1	Countinuous variable, distance to the No:1 bridge;.
DIST_CBRI2	Countinuous variable, distance to the No:2 bridge.
Neighbourhood Variable	
DENS_WATER	Countinuous variable, density of neighbouring waters;
DENS_DEVE	Countinuous variable, density of neighbouring areas developed;
DENS_INDU	Countinuous variable, density of neighbouring industrial areas;
DENS_AVAIL	Countinuous variable, density of neighbouring developable areas;
Categorical Variable	
PLAN_NO	Binary variable, 1-planned as built-up area; 0-not;
STREET_NO	Binary variable, 1-sub-district; 0-not (town, township and farm);

From the viewpoint of the temporal dimension, a few layers have a certain degree of fuzziness in their definitions, especially when the study area is large and the period is long. For instance, the construction of roads may occur in a different phase of the period to be modelled. Their construction time should be taken into account. In this research, a major road (linking with the Third Bridge over the Yangtze River) was completed in early 2000. It can be clearly seen in the SPOT images of 2000. This major road should not be included in the Major Road layer as it did not create any practical impact on urban development in the period 1993-2000. This judgement is also confirmed by very sparse land cover change surrounding the road. Other layers are spatially defined by following a similar regulation. This treatment is able to maintain the temporal consistence within each layer.

Wuhan city can be treated as flat landscape, except for a few hills of higher elevation. Hence, slope is not an influential factor. Physical constraints principally comprise water bodies, which will be analysed in the next section. The master planning scheme was approved by the central government in 1996 and will be valid till 2020. This scheme map includes detailed land use classification.

Being focused on methodology, this chapter only describes the spatial indicators that can be measured from available data. All the variables are listed in table 5.2. They are created via the spatial analyst module in Arcview 3.2a and based on a 10×10 m^2 pixel size, which results in a 6100×4000 grid for data analysis.

Dependent variables: on the macro scale, the dependent variable CHANGE is binary. The value “1” represents land cover change from non-urban to urban, whereas the value “0” remains non-urban. Theoretically, water bodies should be completely excluded from land cover change. However, in this special case study (*Jiang cheng*), 18% of the land cover change in the period 1993-2000 comes from water bodies, which include ponds and lakes. They are mostly small-scale water bodies or on the fringe of large lakes. A general procedure can be designed for defining this specific layer:

- Extracting water body layer from land cover layer;
- Neighbourhood statistics (based on a circular neighbourhood with a 200 m radius);
- Selecting sum > 800 (if totally neighbouring 800 cells are also water).

The layer created is named "excluded", which is utilised as a physical constraint from the water bodies. Another physical constraint comprises protected areas, which include green space, sands and riverbanks from the topographic maps of 1993.

On the meso scale, the dependent variable CH_DENSITY measures the spatial agglomeration of new urban development; the value “1” represents high density of change, whereas the value “0” indicates a low density of change. Figure 5.3 shows that the urban growth in 1993-2000 was characterised by a large scale of spatial agglomeration. There are four new development zones (see Figure 5.3. 1: *Guandong* and *Guannan* industrial parks; 2: *Nanhu* and *Changhong* industrial parks; 3: *Zuankou* Car Manufacturing Base; 4: Taiwanese Economic Development Zones). The calculation of change density is completed using the neighbourhood statistics method. A circular neighbourhood with a 500 m radius is defined to summarise the quantity of land cover change surrounding each pixel (based on SUM neighbourhood statistics). With this neighbourhood, we are able to gain a normal distribution for CH_DENSITY. A median value is utilised to identify high and low density. Here when SUM > 3000, it is classified as high density, otherwise low density.

Explanatory variables: First, proximity is a prime cause of urban expansion; transport and communication changes represent a major explanatory variable in helping to account for the continuing demand for urban land (Kivell, 1993). As the focus is on land use change modelling, physical variables such as road networks are considered exogenous in this chapter because the construction of roads is part of the urban growth process. Here, the proximity variables measure the direct access to city centres/sub-centres (DIST_CENT, DIST_MCEN, DIST_OCEN), industrial centres (DIST_INDUC), major roads (DIST_MRD), minor roads (DIST_ORD), railway lines (DIST_RAIL), the Yangtze/Han rivers (DIST_RIVER, DIST_YZ, DIST_HAN), constructed bridges over the Yangtze River (DIST_CBRID) and planned bridges on the Yangtze River (DIST_PBRID) respectively. The constructed bridges are No:1 (in 1957) (DIST_CBR1) and No:2 (in 1994) bridge (DIST_CBR2) over the Yangtze River. The planned ones are *Baishazhou* (lower reach) and *Tianxinzhou* (upper reach). The spatial distribution of the explanatory variables can be seen from figures 5.4 and 5.5. The physical indicators equip any site with necessary development potential. Its spatial analysis is implemented through the "Find Distance" sub-menu in ArcView 3.2a.

Second, urban growth patterns, for instance, are largely a function of the availability of usable sites. The likelihood that a specific site will be developed varies according to its own availability for development, but also according to the availability of other sites located at different distances from various activity centres or generators of demand for development. A neighbourhood variable quantifies the spatial effect of neighbouring cells. From the aspect of urban development, the spatial influence (promotion or constraint) principally comes from the spatial agglomeration of the developed areas (DENS_DEVE), industrial sites (DENS_INDU), agricultural land (DENS_AVAIL), and water constraints (DENS_WATER). They are density-oriented/based indicators. Its spatial measure is based on the neighbourhood statistics technique. The type and size of selected window (neighbourhood) reflect the distance-decaying mechanism of various factors. A circular neighbourhood with a 500 m radius is chosen to calculate the density value towards a normal distribution.

Third, the social and economic activities are the main driving forces of urban development. These indicators include land value, employment opportunity, population pressure etc. However, they are not the major concern of this chapter as they are limited by poor data infrastructure in Chinese cities.

Finally, urban development is under the control of the master planning and municipal administration management, which are generalised as macro policy variables. Whether a site is planned as built-up (1) or non-urban area (0) (PLAN_NO) will essentially decide its change possibility. Whether a site is within the administrative boundary of a sub-district or others such as town, township and farms (STREET_NO) will also influence its development scale and speed in a specific period. The spatial distribution of two variables (STREET_NO, PLAN_NO) can be seen from figure 5.6.

5.4 Findings

5.4.1 Exploratory data analysis

In equations 2 and 3, $ch_{\Delta x}$ and $nch_{\Delta x}$ in each Δx are processed by using "Tabulate areas" between the layers (land cover change and buffering theme) in the ArcView package. Here $\Delta x = 100\ m$ is defined for proximity variables and Δx = 2% for neighbourhood variables. The table file created is exported into the software STATISTICA for calculating Δp and Δd from equations 4 and 5 in section 5.3.1. The scatter plots ($log(\Delta p)$ & $log(\Delta d), x$) explore in detail the spatial influences of each variable on two scales (see figure 5.7). The significance of slope λ, intercept B and correlation coefficients R are shown in table 5.3. L will be explained in section 5.5.

Table 5.3 Exploratory data analysis on two scales

Variables	Probability of Change				Density of Change			
	λ_1	b_1	R_1	P_1	λ_2	b_2	R_2	P_2
DIST_RAIL	-0.00027	*-1.57*	*-0.84*	*-0.73*	*-0.00046*	-2.98	-0.92	-0.77
DIST_INDUC	-0.00013	*-1.56*	*-0.65*	*-0.78*	*-0.00016*	-4.22	-0.69	-0.42
DIST_CENT	-0.000272	*-0.61*	*-0.85*	*-0.79*	*-0.00027*	-3.53	-0.80	-0.57
DIST_OCEN	-0.000275	*-0.57*	*-0.85*	*-0.78*	*-0.00027*	-3.53	-0.80	-0.57
DIST_MCEN	-0.000225	*-0.17*	*-0.85*	*-0.69*	*-0.00009*	-4.8	-0.37	*
DIST_MRD	-0.00076	*-1.05*	*-0.96*	*-0.9*	*-0.00086*	-2.59	-0.76	-0.91
DIST_ORD	-0.0012	*-2.06*	*-0.83*	*-0.84*	*-0.00175*	-2.71	-0.87	-0.92
DIST_RIVER	-0.00003	*-2.43*	*-0.19*	*	*-0.00018*	-4.26	-0.65	-0.44
DIST_HAN	-0.00009	*-1.42*	*-0.55*	*-0.21*	*-0.00008*	-4.7	-0.54	-0.18
DIST_YZ	-0.00005	*-2.14*	*-0.31*	*	*-0.00011*	-4.5	-0.59	-0.23
DIST_PBRID			*	*			*	*
DIST_CBRID	-0.000178	*-0.35*	*-0.84*	*-0.75*	*-0.00003*	-5.29	*	*
DIST_CBRI1	-0.00019	*0.01*	*-0.86*	*-0.74*	*-0.00004*	-5.5	-0.21	*
DIST_CBRI2	-0.00013	*-0.48*	*-0.93*	*-0.86*	*-0.00001*	-5.7	*	0.2
DENS_WATER	1.46	*-2.84*	*0.77*	*0.54*	*-4.11*	-2.59	-0.97	-0.92
DENS_DEVE	0.465	*1.01*	*0.88*	*0.97*	*-0.182*	-0.37	-0.91	-0.8
DENS_INDU			*	*	*-10.2*	-1.73	-0.96	-0.86
DENS_AVAIL	-1.1	*-1.51*	*-0.74*	*-0.52*	*3.19*	-6.0	0.85	0.96

*: not significant (p>0.01); R: correlation coefficients; λ: slope; B: intercept; P: inverse power function

From figure 5.7 and table 5.3, it can clearly be seen that most variables have a statistically significant linear trend (negative exponential function), except for five variables ("#" in R_1 and R_2 in table 5.3) on two scales. In particular, the distance to major roads and to the second bridge over the Yangtze river show over 90% accuracy on the scale of change probability, together with the distance to rail lines and the density of neighbouring water bodies, developed areas and industrial areas on the scale of change density. Spatial outliers exist in some variables but they are not removable because urban growth itself is so complex, inevitably creating a certain degree of stochasticity. Not only R but also the slope

λ and intercept B show much spatial variation among variables. However, in this chapter, the difference of intercept B is meaningless for comparing the probability and density of change due to incomparable formulas. Slope is a major indicator for exploring varied probability and density on two scales. A steeper slope indicates more compact urban expansion in relation to the physical factor considered. Also, the variable DIST_RIVER has two peaks, which results in a lower R. It indicates that two rivers may have a different distance range of spatial influence. So it needs to be divided into two variables, each with one river.

Surely two variables, DIST_YZ and DIST_HAN, especially the latter, exhibit a better trend. Following this principle, we create DIST_MCEN, DIST_OCEN from DIST_CENT, and DIST_CBRI1, DIST_CBRI2 from DIST_CBRID. Such division is able to seek more accurate spatial determinants. For instance (in terms of slope), we are able to make the following conclusions for proximity variables:

- Minor road networks, major road networks, minor city centres, rail line networks, the No:1 bridge, industrial centres and rivers show a ranked order from high to low value in negatively affecting the probability of change (the nearer, the clearer);
- In the density of change, the slope of some variables (minor and major road networks, railways, industrial centres, rivers) show a certain degree of increase, others (minor centres, constructed bridges) a degree of decrease, compared with the probability of change.

For the neighbourhood variables, the findings are as follows:

- Density of neighbouring water bodies and developed areas shows statistically significant positive impacts on the probability of change (the greater, the clearer);
- In the density of change, only the density of available land is statistically highly positive.

These results clearly show some significant differences on two scales, which enable us to make a hypothesis that road infrastructure is still playing a crucial role in urban growth but the relative importance of these variables is undergoing some change. A major difference is also indicated in neighbourhood variables.

The other two categorical variables (STREET_NO, PLAN_NO) are further confirmed by using a T-test (continuous type) and Chi-square test (categorical). STREET_NO is statistically significant in change density and PLAN_NO for change probability.

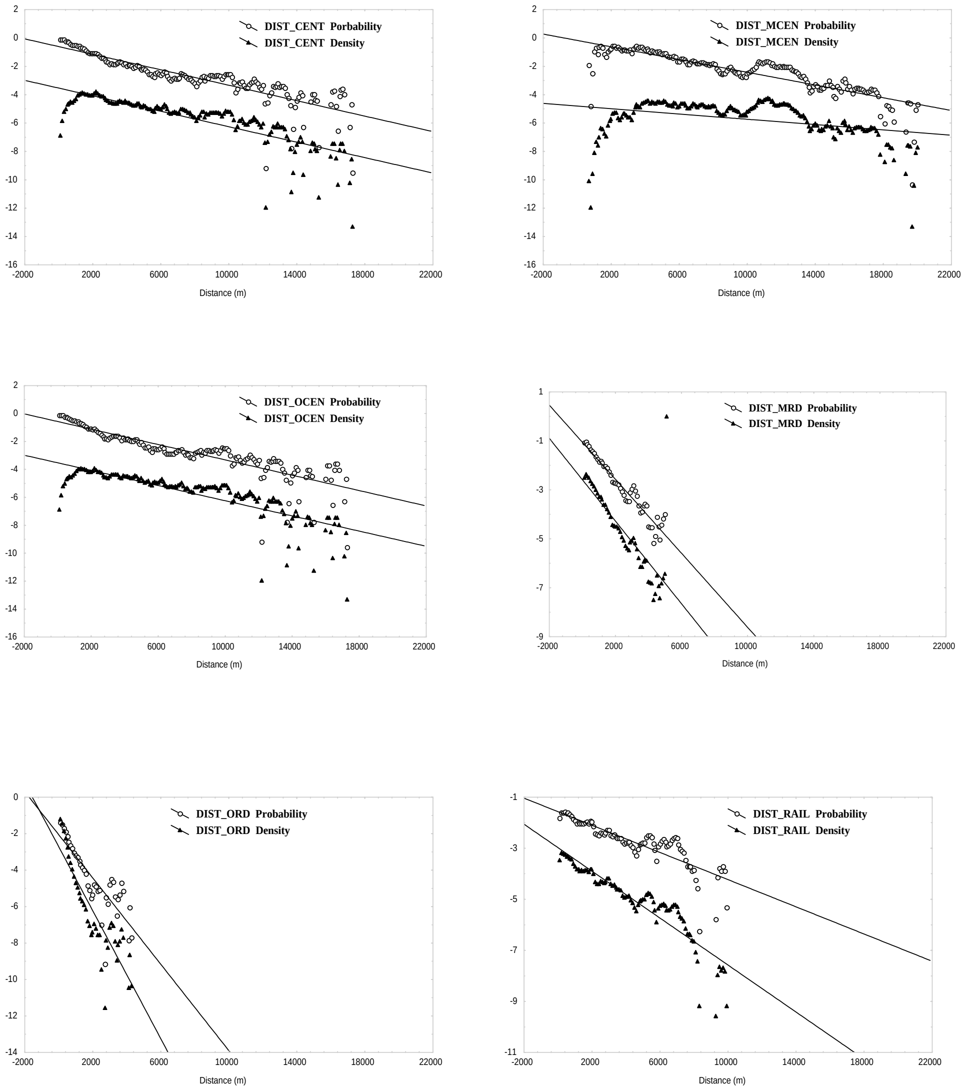


Figure 5.7 Scatter plot of spatial influences from explanatory variables

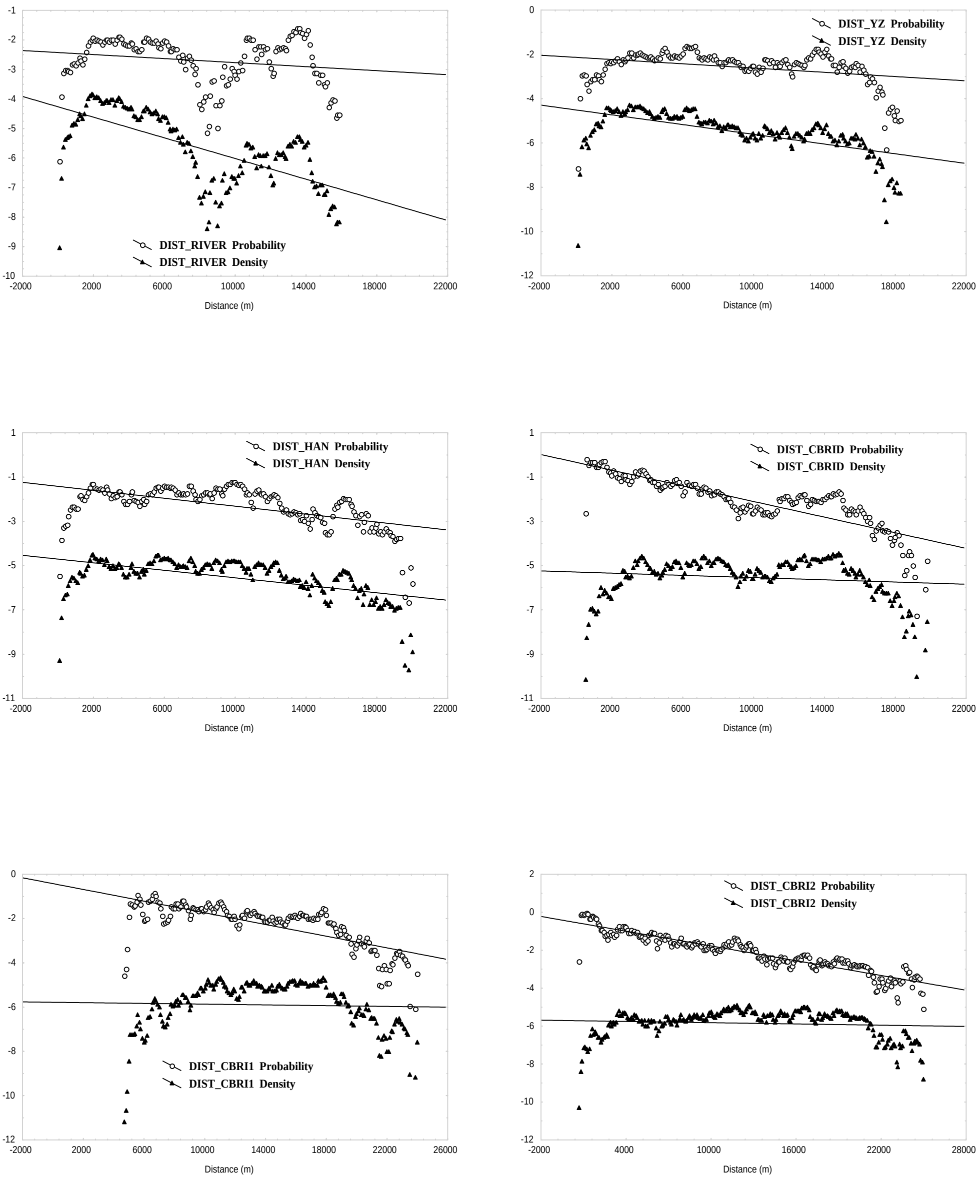


Figure 5.7 Continued

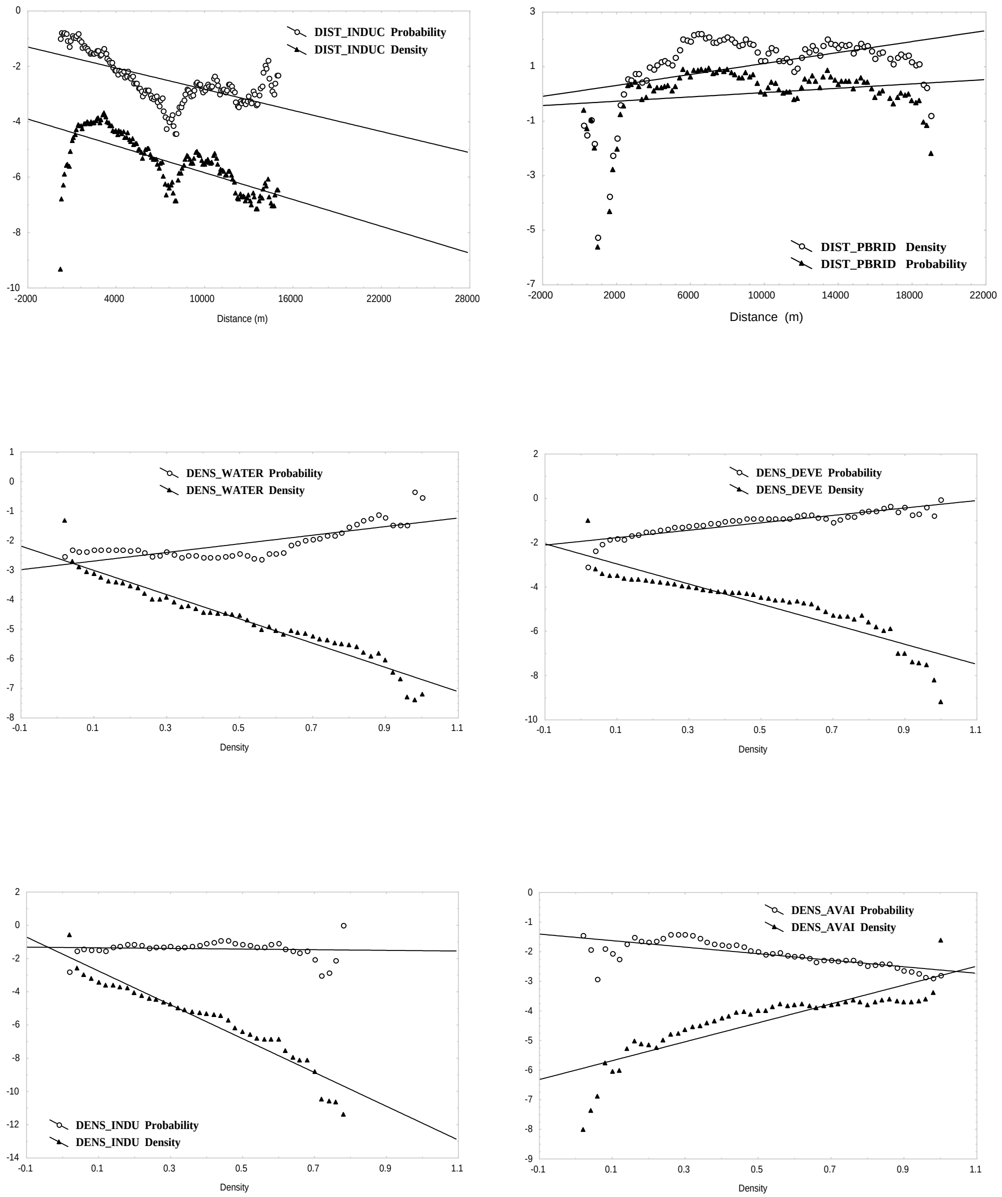


Figure 5.7 Continued

5.4.2 Logistic regression modelling

Traditional logistic regression does not take spatial dependence into account (see e.g. Tang and Choy, 2000; Wu, 2000b; Wu and Yeh, 1997). There are few selective alternatives to considering spatial dependence. One is to build a more complex model incorporating an autogressive structure (Gumpertz et al., 2000). Another is to design a spatial sampling scheme to expand the distance interval between the sampled sites. The latter results in a much smaller size of sample, which will lose certain information. However, the maximum likelihood method, upon which logistic regression is based, relies on a large sample of asymptotic normality, which means that the result may not be reliable when the sample size is small. Consequently, a conflict occurs in applying logistic regression: the removal of spatial dependence and the large size of the sample. A reasonable design of a spatial sampling scheme is becoming a crucial point of spatial statistics. This has attracted more and more researchers in various areas (Stehman and Overton, 1996). Frequently adopted schemes in logistic regression modelling are either stratified random sampling (Atkinson and Massari, 1998; Dhakal et al., 2000; Gobin et al., 2001) or systematic sampling (Sikder, 2000). Their advantages and drawbacks were reviewed and compared by Stehman and Overton (1996).

Unlike the spatial prediction purpose in the area of geo-statistics, the population studied here is completely known. Spatial sampling aims to reduce the size of samples (here the study area has around 6100 × 4000 pixels, which is beyond the capacity of most statistical software) and remove spatial auto-correlation. Systematic sampling is effective to reduce spatial dependence but may lose some important information, such as relatively isolated sites, when population is spatially not homogeneous. In particular, its ability to represent the population may decrease when the distance interval increases significantly. Conversely, random sampling is efficient in representing population but less so in reducing spatial dependence, especially local spatial dependence. Following this idea, we argue that the integration of both systematic and random sampling is better able to balance sample size and spatial dependence.

On the scale of change probability, first a systematic sampling scheme is implemented for the whole population. When a 20th order lag (20 pixels or 200 m in east-west and north-south directions) is reached, Moran’s I index (to quantify the degree of linear spatial association between observed locations and a weighted average of the corresponding neighbouring sites) is significantly reduced for all continuous variables. After the systematic sampling, the ratio between the size of samples with values 1 and 0 becomes 1:11. To gain unbiased parameter estimation, we continue to randomly select another 10% from sample 0. This random sampling creates nearly a 1:1 ratio for the final sample. Its total size is 3002 pixels. Systematic and random sampling is implemented under the spatial module of ArcInfo 8.0.

On the scale of change density, we first implement a fourth-order (40 m) systematic sampling for value 0, and a 10th order (100 m) systematic sampling for value 1, which results in a reduced size of samples; next, we apply a 7% random sampling for both 0 and 1. This random sampling creates nearly a 1:1 ratio for the final sample. Its total size is

2945. After sampling, Moran's I index significantly decreases for all continuous independent variables.

Regarding multi-collinearity, of all pairs of variables with a correlation over 0.80, one variable is omitted. Of all pairs of variables with a correlation over 0.50, only one variable is allowed to enter a regression equation (Kok and Veldkamp, 2001). The use of a stepwise regression procedure solves the remaining multi-collinearity problems. A forward stepwise variable selection is employed via the SPSS 10.0 package. After steps 8 and 10, the results were calculated separately, as listed in table 5.4.

Table 5.4 Logistic regression modelling on the two scales

Variables	Probability of Change			Density of Change		
Steps of regression	8			10		
Sample size	3,002			2,945		
Co-efficients	*B*	*SE*	*Wald*	*B*	*SE*	*Wald*
DIST_RAIL	-[b]			-1.34	0.42	10.3
DIST_INDUC	2.71	0.5	29.6	-[b]		
DIST_CENT	-[b]			6.977	2.95	5.6
DIST_OCEN	-6.75	0.79	72.1	-10.4	2.87	10.1
DIST_MCEN	**			**		
DIST_MRD	-7.2	0.51	203	-4.31	0.4	113.6
DIST_ORD	-49.8	4.0	155	-2.92	0.32	83.3
DIST_RIVER	-[b]			**		
DIST_HAN	2.425	0.6	16.1	**		
DIST_YZ	**			-2.1	0.32	44.6
DIST_PBRID	-[b]			-[b]		
DIST_CBRID	-[b]			-[b]		
DIST_CBRI1	-2.84	0.58	23.8	-[b]		
DIST_CBRI2	-[b]			-[b]		
DENS_WATER	-0.85	0.29	8.9	1.133	0.31	13.4
DENS_DEVE	**			2.52	0.58	18.8
DENS_INDU	-[b]			-[b]		
DENS_AVAIL	**			8.56	0.55	239
STREET_NO (1)	**			0.67	0.14	22.3
PLAN_NO (1)	-0.85	0.12	54.1	**		
CONSTANT	12.4	0.55	510	2.55	0.77	10.9
Tests						
-2 LL	2362			2923		
Cox & Snell R^2	0.451			0.325		
Nagelkerke R^2	0.601			0.434		
PCP (%)	83.2			75.6		

**: Non-statistically significant (p>0.01), -[b]: Not selected , -2LL refers to the 2 times log likelihood.
PCP: percentage correctly predicted, S.E.: Standard Error

5.4.3 Interpretation of the multi-scale issue

The logistic regression model is estimated by the maximum likelihood algorithm. There are various ways to assess the goodness-of-fit of logistic regression. One way is to cross-tabulate prediction with observation and to calculate the percentage of correctly predicted (PCP). Table 5.4 shows the estimated logistic regression models. The two models are significant at the 1% level. The overall percentage of correctness is about 83% for the probability of change and 76% for the density of change. The lower accuracy of the latter might be related to reduced spatial extent.

On the scale of the change probability: in order, the major determinants (with strong negative effect) are the distance to minor road, the distance to major road, distance to minor centre, the distance to No:2 bridge (the nearer, the clearer). There are no statistically and practically significant determinants with strong positive effects. Some factors are statistically significant but practically not significant (e.g. master planning, the distance to the Han River, distance to industrial centres and density of neighbouring water body).

On the scale of the change density: in order, the major determinants (with strong negative effect) are distance to minor centre, distance to major road, distance to minor road, distance to the Yangtze River and distance to the railway line (the nearer, the clearer). The major determinants with strong positive effects are, in order, the density of agricultural land areas, developed areas and water bodies (the greater the density value is, the greater the probability value is), and sub-district administration. The others are either not statistically significant or practically not significant.

Comparing the spatial determinants on two scales, major differences are indicated in four aspects. The first difference is the statistical significance of neighbourhood variables, which are dominated by the density of agricultural land, developed urban area and water body. The variables are only influential for change density. This strongly shows that large-scale new developments are either very close to the urban built-up area or far away in the rural area and some were converted from water bodies. The second is the significance of sub-district administration, which only exerted certain influences on the density of change. The third is the differences of few proximity variables. The distance to railway and the distance to the Yangtze River are only effective for density of change. Finally, the three key proximity variables (distance to minor and major roads and to minor centres) are all influential on two scales but their relative importance values vary with scale. In particular, the minor road networks are the most influential factor for the probability of change, and density of change is mostly dependent on minor sub-centres and the major road networks.

The comparison made above implies that relatively speaking, proximity variables are more scale-independent than neighbourhood variables and others. Urban infrastructure is the crucial factor impacting on the occurrence of urban growth and also on the spatial agglomeration of social and economic activities. However, old city centres have become less important than suburban centres in attracting large-scale development. This indicates a changing urban spatial structure.

From the perspective of the spatial process, the probability and density of change may represent the spontaneous and self-organisational processes of urban growth respectively. When urban growth is solely a spontaneous process, only the probability of change is able to explore its spatial pattern, or we can say all determinants might be scale-independent on the two scales. However, when urban growth is the mixture of spontaneous and self-organisation processes, the probability of change is not sufficient in itself to explore its spatial pattern, or we can say some determinants could be scale-dependent on the two scales. The number of scale-dependent determinants may be affected by the degree of self-organisation process. Hereby, the multi-scale method is able to compare and uncover the processes through analysing their spatial patterns.

The multi-scale of the pattern is also able to explain the temporal process of urban development planning. For example, the temporal process at least includes two stages: site selection and local growth (details see chapter 6). At the stage of site selection, change density is the major concern for locating various scales of land development project, when the distance to sub-centres, the distance to major road networks, and the density of agricultural land are the principal criteria. However, at the next stage of local growth, change probability is becoming the major concern when local factors such as the distance to minor road networks takes the dominant role.

In terms of Harken's theory of synergetics, the order parameter of a self-organising system is principally controlled by slow variables rather than by quick variables (Haken, 1993). In this sense, we can infer that the determinants on the scale of change density represent slow variables, and the determinants on the scale of change probability represent quick variables. Slow variables mainly include minor centres, major roads, agricultural land and developed areas. Quick variables are dominated by minor roads. In reality, slow variables are actually working on the macro scale and have longer-term and broader-scope spatial influence than quick ones on the meso scale. For example minor centres and major roads, as the order parameter of self-organising urban growth may determine the spatial morphology of a city. Conversely, minor roads only affect local growth. As a consequence, such multi-scale analysis is helpful in understanding the complex patterns of spatial systems.

5.5 Discussion and Conclusions

This chapter has shown that hierarchical theory can provide a conceptual and logical framework for the spatial analysis of complex spatial patterns of urban growth. The partial results on only two scales have shown that a scale-dependent property exists in urban growth patterns, although quite a number of other explanatory variables are not yet included in the model due to limited data availability. This multi-scale property theoretically is able to strengthen deeper insights into urban development processes and guide urban planning.

To complete the proposed multi-scale framework, we still need to explore another micro scale – intensity of change. Intensity of change has distinct spatial, temporal and decision-making dimensions. In the spatial dimension, it requires more disaggregated data as detailed as parcel and building level, which are able to provide such information as floor number, ownership, land value, and even actors. In the temporal dimension, it undergoes relatively quicker change or it is more unpredictable. In decision-making, more actors are involved. For example in China, local government, work units (employers), investors, real estate developers and households have different roles in locational decision-making. It involves a more complex social, economic and even political processes. As a result, this scale will exhibit more complex spatial patterns, which should be based on a new data framework. The data framework should be able to incorporate more spatial behaviour of actors and socio-economic factors into pattern modelling. At present, it is theoretically promising but practically lacks a rich data infrastructure, in particular in the developing world.

From the angle of remote sensing, SPOT imagery is not an appropriate source to satisfy the information requirement on the micro scale. However, with the 1 m resolution of IKONOS satellite images, we are able to identify high-rise and low-rise buildings for defining the binary variable (1: high intensity; 0: low intensity), which will be input into a pattern model like the logistic regression equation. The outcome on this scale can be utilised for systematic comparisons with the others. Such comparisons can uncover the complex spatial processes of urban growth on various scales, which can assist in decision-making at each level of urban development planning. In the future, the multi-scale framework is expected to link with multi-scale process modelling, such as cellular automata (CA), multi-agent (MA) and random utility models for exploring the interaction between pattern and process.

To implement the multi-scale framework, logistic regression is not the only method of spatial pattern analysis. As a focus on the capacity for interpretation, simple exploratory data analysis and spatial logistic regression is an effective means to distinguish the determinants on two scales. However, the methodology itself still has some issues which need further research in the future. The measurement of neighbourhood variables like DENS_DEVE largely depends on the type and especially the size of the neighbourhood chosen. Over- or under-defined neighbourhoods will lead to a highly skewed histogram, which makes the results unreliable. As a simpler way, a number of tests with different choices have to be made for comparison, but it is very time-consuming and laborious. In consequence, it is necessary to develop an algorithm for automatically seeking an optimal neighbourhood, which is able to create approximately normal distribution.

The spatial analysis of this research is based on the 10×10 m^2 pixel size. The selection corresponds to the resolution of SPOT PAN images and also has more powerful interpretation. However, other resolutions from 20×20 to 100×100 m^2 need to be comparatively checked for the sensitivity analysis of logistic regression modelling results. The exploratory data analysis is based on the radial distance interval of 100 m; tests with 200 m and 300 m further confirm the stability of the analysis, especially that the slope of each variable remains the same. This research is actually based on the minimum spatial resolution (10 m from SPOT PAN) and maximum spatial extent (municipal level). From published literature, such a strategy can provide more convincing results.

Unlike natural science, urban development like other social sciences is in essence not a completely random or stochastic process. The proximity and neighbourhood variables are created according to spatial dependence or we can say that spatial proximity is one form of spatial dependence. Consequently, the complete removal of spatial dependence is impossible. As Jacquez (1999) argued, spatial auto-correlation is almost always present and its strength varies considerably from one kind of variable to another. A feasible way is to compare various sampling schemes for a compromise alternative according to current development and techniques of spatial statistics. Apparently, the scale of change density has a stronger spatial dependence as its spatial extent shrinks. It results in a decrease of logistic regression modelling (table 5.4). A new approach based on a polygon format such as parcel is also worth exploring in the future.

In urban theories, the inverse power function, is also frequently applied for density gradient modelling (Makse et al., 1998). When compared with the negative exponential function, equations 1 and 4 are correspondingly modified as follows (equations 9 and 10):

$$f(x)=\beta x^{-\lambda} \tag{9}$$

$$Log\ (\Delta p)=log\ (\beta_1) + \lambda_1\ log(x) \tag{10}$$

The linear correlation coefficients P of both the proximity and neighbourhood variables are also computed and listed in table 5.3. They clearly indicate that generally the negative exponential function has a higher accuracy than the inverse power function. As a consequence, this research suggests that urban growth obeys the law of negative exponential function in terms of the probability and density of change.

The results from logistic regression modelling are basically consistent with those of the exploratory data analysis (see table 5.2). However, the latter to some extent confirms the accuracy or reliability of the former and is also able to model the relative importance of each independent variable in a systematic way.

This research also found that logistic regression analysis is very sensitive in multi-stages such as data transformation and spatial sampling. The logarithmic data transformation Ln($y+\beta$) (β is to be determined by experiments) and various combinations of sampling type and size may significantly influence parameter estimation and model accuracy. Here, the proximity-based variables sampled are transformed by using Ln(y+1). Then, all continuous variables are standardised according to the formula: (y-min)/(max-min). So all the independent variables are universally transformed into the range from 0 to 1 for further logistic regression modelling. The selection or design of reasonable data transformation and spatial sampling schemes still needs further systematic research for spatial logistic regression. Spatial exploratory data analysis, like the simple approach proposed in this chapter, can facilitate testing the detected patterns with the outcome of logistic regression. Exploratory spatial data analysis is able to discover the influence of each continuous variable but does not provide a systematic ranking. Logistic regression is efficient in systematically evaluating their relative contribution. Consequently, the integration of both is a feasible way for hypothesis formation, and the test of model accuracy.

Chapter 6*

Understanding Spatial and Temporal Processes of Urban Growth

Abstract

Understanding the dynamic process of urban growth is a prerequisite to the prediction of land cover change and the support of urban development planning and sustainable growth management. The spatial and temporal complexity inherent in urban growth requires the development of a new simulation approach, which should be process-oriented and have stronger capacities for interpretation. This chapter presents an innovative methodology for understanding spatial processes and their temporal dynamics on two interrelated scales (municipality and project), by means of a multi-stage framework and a dynamic weighting concept. The multi-stage framework aims to model local spatial processes and global temporal dynamics by incorporating explicit decision-making processes. It is divided into four stages: project planning, site selection, local growth and temporal control. These four steps represent the interactions between the top-down and bottom-up decision-making involved in land development for large-scale projects. Project-based cellular automata modelling is developed for interpreting the spatial and temporal logic between various projects forming the whole urban growth. Dynamic weighting attempts to model local temporal dynamics at the project level as an extension of the local growth stage. As a non-linear function of temporal land development, dynamic weighting is able to link spatial processes and temporal patterns. The methodology is tested with reference to the urban growth of a fast growing city, Wuhan in the P.R.China from 1993 to 2000. The findings from this research suggest that this methodology can interpret and visualise the dynamic process of urban growth more temporally and transparently, globally and locally.

Key words: urban growth, spatial and temporal processes, cellular automata, multi-stage, dynamic weighting.

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* Based on (Cheng and Masser, 2002) and (Cheng and Masser, 2003b)

6.1 Introduction

Understanding the urban development processes is highly crucial in urban development planning and sustainable growth management. The urban development process involves multi-actors, multi-behaviours and various policies, which results in its spatial and temporal complexity. The non-linear dynamics inherent in these growth processes opens up the possibility for emergencies (sudden changes) that are difficult or impossible to predict. Due to the hidden complexity of reality, our science has become less orientated to prediction but more an aid to understanding and structuring debate (Batty and Torrens, 2001). Orjan (1999) argued that without a proper understanding of the recent past we are in no position to comprehend – let alone predict – emerging patterns and processes. Couclelis (1997) first put forward the idea of a spatial understanding support system (SUSS). Horita (2000) reported a new SUSS for representing community disputes. Limited by existing sciences and techniques, understanding-oriented modelling is oriented to more practicability than to prediction, or, rather, a proper understanding of the complex system is the prerequisite to its prediction. Towards reasonable understanding, we need reliable information sources and models. Successful models should have a strong capacity for interpretation and an interactive environment to simulate 'what-if' scenarios. Consequently, an innovative simulation approach is required. The first step to aid such decision-making is to identify the process of decision-making. This is the same as the area of information management, where we need to recognise the data flow chart and data model before establishing any operational information system.

Remote sensing and geographical information science (GIS) have proved an effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Masser, 2001). However, they are still not adequate for process-oriented modelling as they lack social and economic attributes, in particular at detailed scale. In developing countries, socio-economic data acquisition and integration still have a long way to go. On this occasion, local knowledge (expert opinions, historical documents), albeit only qualitative or semi-quantitative, can be very valuable in assisting process understanding such as urban growth patterns, driving forces and the major actors involved. Hence, local knowledge should be incorporated into simulation modelling at certain stages and in certain ways.

Cellular automata (CA), a technique developed recently, has been receiving more and more attention in urban and GIS modelling due to its simplicity, transparency, strong capacities for dynamic spatial simulation, and innovative bottom-up approach. When applied to real urban systems, CA models have to be modified by including multi-states of cell, relaxing the size of neighbourhood with distance-decay effects, probabilistic rules, and link with complexity theory. In fact, many – if not all – urban CA bear little resemblance to the formal CA model (Torrens and O'Sullivan, 2001). Considerable literature in the field of urban CA modelling includes at least two classes of successful applications on various spatial and temporal scales. One concentrates on artificial cities to test the theories of complexity and urban studies (Couclelis, 1997; Benati, 1997; Batty, 1998; Wu, 1998a). The other is focused on real cities to aid decision support of urban planning at the regional, municipal and town levels (Besussi et al., 1998; Clarke and Gaydos, 1998; Ward et al., 2000a; White and Engelen, 2000; Yeh and Li, 2001a; Silva and Clarke, 2002; Wu, 2002). These studies have revealed that urban CA-like models are effective in simulating the complexity of urban systems and their sub systems from emergence, feedback and self-organisation. Nevertheless, the interpretation of transition rules, which is highly important for urban planners, still receives little attention in urban CA modelling, particularly in linking to the process of urban planning.

Most previous studies of urban CA models ignore the fact that urban growth is a dynamic process rather than a static pattern. For example, the urban growth model of Clarke and Gaydos (1998) has attracted a lot of attention in urban growth prediction (e.g. Silva and Clarke, 2002). Their CA model controls the evolution of city growth by five coefficients (diffusion, breed, spread, slope and roads). The diffusion factor determines the overall outward dispersive nature of the distribution. The breed coefficient specifies how likely a newly generated detached settlement is to begin its own growth cycle. The spread coefficient controls how much diffusion expansion occurs from existing settlements. The slope resistance factor influences the likelihood of settlement extending up steeper slopes. The road gravity factor attracts new settlements towards and along roads. This is a successful simulation model of patterns, which principally focuses on spontaneous, organic, spread, road-influenced and diffusive patterns. It still lacks the capacity to interpret causal factors in a complete process model, because similar patterns from the final outputs of CA simulation do not indicate similar processes. Thus, the transition rules validated are not evidential to explain the complex spatial behaviours behind the process. Therefore, process-oriented rather than pattern-oriented simulation should be the main concern of urban growth CA modelling. This point has been supported and recognised recently in some journals (Torrens and O'Sullivan, 2001). Dragicevic et al. (2001) apply fuzzy spatio-temporal interpolation to simulate changes that occurred between snapshots registered in a GIS database. The main advantage of this research lies in its flexibility to create various temporal scenarios of urbanisation processes and to choose the desired temporal resolution. The authors also declared that the approach does not explicitly provide causal factors; thus it is not an explanatory model.

Wu (1998c) developed an AHP-driven CA model to simulate the spatial decision-making process of land conversion. AHP refers to the analytical hierarchy process originated by Saaty (1980). The AHP uses pair-wise comparisons to reveal the preferences of decision makers. The AHP is an ideal means for calculating weight values from the qualitative knowledge of local experts. This CA model is in essence a dynamic multi-criteria evaluation (MCE) as a dynamic neighbourhood (updated during model runs) is treated as an independent variable. This model is successful in linking explicit decision-making processes with CA. The adjustment of factor weights is able to generate distinctive scenarios. Hence, this model has a stronger capacity for interpretation. However, the AHP-driven decision-making process is not spatially and temporally explicit as the weight values are fixed for the whole study area and for the whole period of modelling. They are not able to model processes, especially temporal dynamics. The incorporation of spatially and temporally explicit decision-making processes into a CA model has not been reported so far.

With this in mind, we need to develop a new methodology based on present urban CA, which is able to model and interpret spatial process and temporal dynamics, and also incorporates local knowledge for interpreting these processes. With this in mind, this chapter is organised into four sections. Following the introduction, the next section introduces the concepts regarding urban growth understanding: process, dynamics, global and local; and the second discusses in detail a proposed methodology, which mainly comprises a multi-stage framework and dynamic weighting concept. The former incorporates explicit decision-making processes into the modelling of local spatial processes and global temporal dynamics. The latter continues to model local temporal dynamics by representing the dynamic interaction between pattern and process at a lower level. CA-based simulation is developed to support and implement each method. Their mathematical foundations are described step by step. Section three focuses on the implementation of the methodology in a case study of Wuhan City, P.R China. Section four ends with some further discussion and conclusions.

6.2 Methodology

6.2.1 Complex processes and dynamics

Urban growth can be defined as a system resulting from the complex interactions between urban social and economic activities, physical ecological units in regional areas and future urban development plans. This interaction is an open, non-linear, dynamic and local process, which leads to the emergence of global growth patterns. The urban growth process is a self-organised system (Allen, 1997b).

Process generally refers to the sequence of changes in space and time; the former is called a spatial process, the latter a temporal process. It should be noted that strictly speaking the spatial and temporal processes cannot be precisely separated, as any geographical phenomena are bound to have a spatial and a temporal dimension. Understanding change through both time and space should, theoretically, lead to an improved understanding of change and of the processes driving change (Gregory, 2002). However, the spatial process is much more than a sequence of changes. It implies a logical sequence of changes being carried on in some definite manner, which lead to a recognisable result (Getis and Boots, 1978). Summing up, the key components of process are change and logical sequence. The former is defined by a series of patterns and the latter implies an understanding of process. In contrast to pattern, process contains a dynamic component.

An urban growth system consists of a large number of new projects on varied scales. Large-scale projects are characterised by dominant functions, heavy investment, long-term construction and numerous actors involved. Examples include airports, industrial parks, and universities. In contrast, small-scale projects are characterised by a single function, rapid construction, light investment and few actors. Examples can be a private house and a small shop. The project, as the basic unit of urban development, is the physical carrier of complex social and economic activities. The spatial and temporal heterogeneity of social and economic activities creates massive flows of matter, people, energy and information between new projects and also between the projects and the other systems (developable, developed and planned). They are the sources of the complex interactions inherent in urban growth. As such, the urban growth process is the spatial and temporal logic between varied scales of land development projects. The spatial and temporal organisation of projects is the key to understanding these processes and dynamics. This understanding can be based on two scales: municipality (global) and project (local). For instance, on the global scale, in space, projects can be organised into clustered or dispersed patterns; the former implies a self-organised process, the latter a stochastic process. In time, projects can be organised into quick or slow patterns. The local process refers to spatial growth at the project level. Global dynamics means the temporal logic between the projects forming the whole urban growth, local dynamics only the temporal logic between the spatial factors or elements within a project. This research has two specific objectives towards systematically understanding the spatial and temporal process of urban growth:

- To understand the local spatial process at the project level and the global temporal dynamics, based on a multi-stage framework;
- To understand local temporal dynamics at the project level, based on the dynamic weighting concept.

6.2.2 A conceptual model for global dynamics

The complexity of the urban growth process can be intuitively projected onto decision-making processes, and their spatial/temporal dimensions. The former involves multiple actors and behaviours. The latter involves various spatial and temporal heterogeneities. Or we can say, the former is a cause, the latter the effect and projection. In consequence, we must start with the decision-making process in order to understand the spatial and temporal processes of urban growth.

Decision-making in urban growth is related to plans, policies and projects. Projects are special land use or development proposals initiated usually by various types of actors such as investors, planners, developers, land owners and work units. They evolve in the context of various levels of policy and plans. The project development process is a dynamic spatially nested hierarchy of multiple decision-making procedures, from the municipal to the building level and vice versa. The global dynamics of urban growth results from the interactions between the top-down and bottom-up processes of decision-making. Top-down decision-making includes financial resources allocation, master planning and the time schedule of projects; bottom-up decision-making contains building style, building density and plot ratio.

Global patterns can be described as a cumulative and aggregate order that results from numerous locally made decisions involving a large number of intelligent and adaptive agents. At the municipal scale, its decision-making process can fall into four stages: project planning, site selection, local growth and temporal control (as illustrated in figure 6.1).

The first stage (project planning) answers the questions: How many large-scale projects were planned in the past periods? and how much area was constructed in each project? This stage is a typical top-down decision-making process based on the systematic consideration of physical and socio-economic systems. Municipalities need to plan land consumption according to their social-economic development demand. When land consumption is projected onto the physical land cover system, it results in different scales of new projects. Land development projects can be divided into spontaneous and self-organisational types (Wu, 2000c). The former corresponds to small-scale or sparse development, which may contain more stochastic disturbance and involve lower-level actors such as individuals or organisations. The latter represents larger-scale projects with a dominant land use and a higher level of actors. They are the main concern of this project planning stage. The project here can be called an 'agent', which is a spatial entity linking with distinct actors and spatial and temporal behaviours. In this sense, the project-based approach proposed here is also a kind of agent-like modelling.

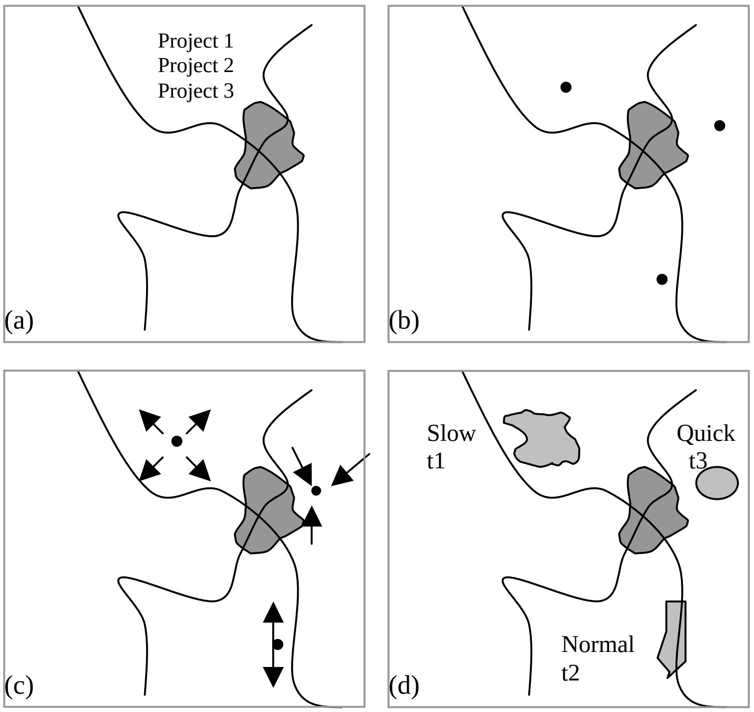

Figure 6.1 A conceptual model of the decision-making process: (a) project planning; (b) site selection; (c) local growth and (d) temporal control

The first stage belongs to non-spatial modelling, resulting in proposals for development projects. These new developments will be projected in their spatial and temporal dimensions. Spatial complexity can be considered from two aspects: the location of the site and the spatial interactions among sites. The former is the issue of spatial site selection or location, which becomes the second stage. The latter is the issue of local growth or the control of development density and pattern, the third stage of the framework. Temporal complexity, which is typically indicated by temporal heterogeneity or the timing of local growth, will be described in the fourth stage.

The second stage (site selection) deals with the question: Where were the various scales of projects located? This stage is a typical spatial decision process involving municipal decision-makers. This aims to systematically optimise and balance the spatial distributions of socio-economic activities as each project has specific socio-economic functions planned. This stage is the static projection of the projects planned at the first stage. The rules of site selection are represented by multiple physical, socio-economic and institutional factors, incorporating various global and local constraints. Rules are differentiated between planned projects in terms of influential factors, weights and constraints. To some extent, the stage provides growth boundaries and seeds for the next stage (local growth). This site selection stage results in a number of potential spatial sub-systems through the top-down process.

The third stage (local growth) copes with the question: How did each project grow locally? This question includes development density, intensity and the spatial organisation of development units. After its spatial location was agreed, each project was developed based on more local decision-making from land owners, investors and individuals. This results in different spatial processes. The outcomes of these local growth processes can be concentric, diffusive, road-influenced and leapfrog. They are affected by numerous factors, which change their influential roles spatially and temporally. Spatial heterogeneity (heterogeneity in a spatial context means that the parameters describing the data vary from place to place) suggests that spatial processes are locally varied. In spatial statistics, global analysis is being complemented by local area analysis such as local indicators of spatial association (LISA) (Anselin, 1995) and geographically weighted regression (GWR) (Fotheringham and Rogerson, 1994). As for understanding local urban growth, its spatial process mostly depends on the local conditions such as physical constraints and the socio-economic circumstances. Based on CA, we are able to explore the dominant causal factors locally. The stage is dominated by the bottom-up approach.

The last stage (temporal control) answers the question: How fast did each project grow temporally? This stage shifts to manage the local growth speed from a global perspective. The image of the whole urban growth process comprises the temporal sequences of all projects. For example, we can define such patterns as quick, basic or normal, and slow local growth, representing three identifiable timing modes. The rate of local growth is governed by numerous factors resulting from top-down and bottom-up decision-making. For example, the former includes financial resources allocation from higher-level organisations and master and land use planning control. The latter include man-power allocation and facility supply. The temporal land demand amount decided at this stage should be input as a guide or constraint to the local growth stage. Hence, the stage is primarily a top-town procedure for controlling local temporal patterns and conditioned by a bottom-up one.

It should be noted that each stage described above involves the interactions between top-down and bottom-up decision-making. For example, although the land demand of each project is planned by municipal organisations, actual consumption is influenced by a number of local constraints. The whole process of urban growth should contain numerous feedback loops between both on various spatial and temporal scales. To provide a focus, top-down socio-economic modelling at certain stages is treated as exogenous variables in this research.

This framework is primarily designed for understanding the dynamic processes of urban growth. When used for planning support, the first question will become: "how many large-scale projects will be planned in the coming years ?" The socio-economic model for determining land consumption of projects should be included at this stage in this case. The other questions at various stages will follow similar modification. Such a multi-stage framework can offer a transparent and friendly environment for constructing various scenarios of plans.

6.2.3 Land transition models

The multi-stage framework discussed above has conceptually transformed the global dynamics of the whole urban growth process into the local land conversion processes of large-scale projects. These local processes have complex spatial and temporal interactions, which can be simulated by the urban CA approach. The identification of large-scale projects and their functions is of importance for understanding the spatial behaviour of relevant actors. 'Large-scale' has two meanings, from the spatial and socio-economic perspectives respectively. One refers to a certain scale of spatial clustering new development units. A project defined in this way may have no definite socio-economic implications as it was not planned as a complete spatial entity. This is a relative spatial division. Another refers to larger-area land development with special socio-economic functions such as a car manufacturing centre. A project defined in this way may have no ideal spatial agglomeration as it may be low in building density. To focus on interpretation, the latter is highlighted in this research as it is linked to the underlying socio-economic activities. However, it should be noted that the former is also significant and necessary in some spatial process modelling. Small-scale projects with mixed functions are conceptually merged into one class. Historical documents and interviews with local planning organisations are a necessary means for identifying large-scale projects. As the process of CA modelling is identical for each project, as an example, we only refer to project *d* in the following description; the other projects follow the same procedures.

(1) Project planning

$$L(t)|_{t=n} = L_d \tag{1}$$

Here, L_d is the actual (or planned) area of land development project d (from stage 1) in the whole period [$t=1\sim n$]. L_d in principle should result from traditional top-down socio-economic models (e.g. White and Engelen, 2000). Here it is assumed to be an exogenous variable (known value from the urban growth analysis of past years); for example, a shopping centre occupied 5 ha from 1993 to 2000, i.e. $L_d=5$ (ha). $L(t)$ is the simulated area of land development project d till time t; $L(1996)$ means the simulated land transition amount from 1993 to 1996. $L(t)$ will be calculated from the section (4).

(2) Constraint-based site selection model

$$Sites = Neighbourhood * Center(x,y), \quad Center(x,y) = \prod_{i=1}^{m} Cons_i \tag{2}$$

Here, the site selection of projects includes a central point and its surrounding area or neighbourhood. The location of the centre is determined by various critical constraints. Like other research (Ward et al., 2000a; Yeh and Li, 2001a), constraints operate at the local, regional and global levels. Global constraints taking account of the whole study area include physical (e.g. ecological protection zone, accessibility to transport infrastructure and city centres/sub-centres), the economic (e.g. investment, land value), social (population density) and the institutional (master planning) aspects. Regional constraints are defined by the availability of developable or developed land and its density in a neighbourhood. It should be noted that the regional level has a varied spatial extent as the size of neighbourhood varies from project to project. In some cases, we have to define multi-level regions (e.g. Batty et al., 1999b). Local constraints refer to the physical conditions of a site or pixel such as slope, soil quality and geological condition. All the criteria at the three levels vary from project to project, and from case to case, as they should be able to interpret the specific spatial behaviours of the actors involved in each project. For example, slope does not take effect in a flat city. Equation 2 is based on the assumption that site selection depends on a limited number of equally weighting constraints as in practice the decision-making process is primarily qualitative and simple among decision-makers. This stage is implemented by GIS analysis based on spatial operation (e.g. 'find distance', 'neighbourhood statistics', and 'map calculation') and by heuristic rules operation (e.g. if rule 1 and rule 2 ... then do) based on visual programming. GIS visual functions can help modellers test their systematic thinking, i.e. whether this rule can create ideal sites for a planned project.

(3) Local growth model

This model seeks major spatial determinants for interpreting local spatial processes based on bottom-up CA simulation. CA are dynamic discrete space and time systems. A CA system consists of a regular grid of cells, each of which can be in one of a finite number of possible states, updated synchronously in discrete time steps according to a local, identical interaction rule. In this model, the cell state is binary (1 – land cover transition from non-urban to urban, 0 – not), limited in the cellular space of each project. CA simulation is carried out by the dynamic evaluation and updating of the development probabilities at each cell in the cellular space. The cells selected in each iteration will be changed from 0 to 1. The development potential of each cell *j* at time *t* is defined as:

$$P_j(t) = \sum_{i=1}^{k} W_i(t) * V_{ij}(t) \prod_{i=k+1}^{m} \omega_i \qquad (3)$$

Where $P_j(t)$ refers to the development potential of cell *j* at time *t*. It is assumed that a total of *m* constraints ($1 \le i \le m$) are considered, comprising *k* non-restrictive and *m-k* restrictive constraints – when $k+1 \le i \le m$, ω_i is a binary variable (0 or 1) representing restrictive constraints from local, regional and global levels (equation 3). $\omega_i = 0$ means that a cell is absolutely restricted from transition into urban use in relation to constraint *i*, e.g. the centre of a large lake.

When $1 \le i \le k$, they are non-restrictive constraints or named factors in order to be distinguished from restrictive constraints. These factors complementarily contribute to the development potential of a cell. The potential for transition depends on a linear weighted additive sum of development factors. $W_i(t)$ is the relative weight value of factor *i* to be calibrated from data. Largely, $W_i(t)$ interpret the causal-effects of the local growth process. In the case of global temporal dynamics, $W_i(t)$ is treated temporally as a constant W_i . The functions $W_i(t)$ will be discussed in detail in the next section on local temporal dynamics. $V_{ij}(t)$ is the standardised score (within the range 0~1) of factor *i* at cell *j* at time *t* according to equation 4. In equation 4, $X_{ij}(t)$ is the value of factor *i* at cell *j* at time *t; min and max* are the minimum and maximum of $X_{ij}(t)$ among the cells to be evaluated in relation to factor *i*. In urban growth, the frequently considered factors include transport accessibility, urban centres/sub-centres accessibility, suitability, planning input and dynamic neighbourhood (e.g. White et al., 1997; Clarke and Gaydos, 1998; Wu, 1998c; Ward et al., 2000a).

Suitability analysis has been implemented at the stage of site selection. The other four factors are selected for evaluating $P_j(t)$ at this stage. The quantification of master planning will be explained in the section on implementation. Accessibility measurement, such as the accessibility to a major road, is a very active field in GIS and modelling. Numerous methods have been published (e.g. Miller, 1999). In this study, a negative exponential function is employed to quantify the distance-decay effect (equation 5). Urban models based on economic theory (Muth, 1969) and discrete choice theory (Anas, 1982) made widespread use of the negative exponential function. Previous research for the same case study (Cheng and Masser, 2003) confirmed its effectiveness, although the inverse power function has also frequently been successfully employed for quantifying the distance-decay effect (Batty and Kim, 1992).

$$V_{ij}(t) = (X_{ij}(t) - min) / (max - min), \qquad 0 \le V_{ij}(t) \le 1, \quad 1 \le i \le k \qquad (4)$$

$$X_{ij}(t) = e^{-\phi\, dij} \qquad (5)$$

Where d_{ij} is the distance from cell *j* to any spatial element defined in factor *I*, such as to a major road network. ϕ is a parameter controlling the decay effect of distance. Usually, $0<\phi<1$, and ϕ varies with factor *i*. A higher value of ϕ means that the influence on land transition will decrease more rapidly. The parameter ϕ can be determined by a global exploratory data analysis of the urban growth patterns (Cheng and Masser, 2003), where ϕ is a slope value of the log-linear relationship between probability of transition and distance d_{ij}. Equation 5 calculates the potential for land conversion contributed by any proximity factor. In this study, accessibility factors are fixed or static during the modelling period as the spatial factors (e.g. road networks) are not updated temporally, so $V_{ij}(t)=V_{ij}$.

In our model, neighbourhood size is not globally universal but locally parameterised, and varies with different projects as each project has distinguishing social and economic functions. The neighbourhood effect (action-at-distance) is represented as a non-restrictive factor in equation 3, which indicates the spatial influences of developed cells on land conversion in surrounding sites. Developed cells come from the previously transited cells or the old urban area. Strictly speaking, the former reflects the local spatial self-organisation of land conversion in each project as a dynamic variable that is updated in each iteration, i.e. $V_{ij}(t)\neq V_{ij}$. The latter depends on existing global urban activities as a fixed spatial factor. They are treated as two independent factors in this research.

In practice, restrictive and non-restrictive constraints are a relative classification. They are temporally varied. For example, ponds may be a restrictive constraint in 1950 but become non-restrictive in 2000 as no large quantity of developable land is available in the later period.

$$P_{j'}(t) = (1+ln(\S)^{a})\, P_j(t) \tag{6}$$

$$\Delta L(t)=L(t)-L(t-1), \quad L(0)=0 \tag{7}$$

Principally, land conversion is allocated according to the highest score of the potential; however, practically, this is subject to stochastic disturbance and imperfect information. To generate the patterns that are closer to reality, a stochastic disturbance is introduced as $(1+\ln(\xi)^{\alpha})$ (Li and Yeh, 2001a). ξ is a random variable within the range [0~1]. α is a parameter controlling the size or strength of the stochastic perturbation. Like other CA applications (White et al., 1997; Wu and Webster, 1998; Ward et al., 2000a), $P_{j'}(t)$ in equation 6 represents the probability of land transition in cell *j* at time *t*, which is the major driving force of local growth.

Whether a cell is to be transited or not from time *t-1* to *t* depends on the probability $P_{j'}(t)$ at each iteration. Selection will start from the maximum of $\{P_{j'}(t)\}$ until it reaches the required number of cells, i.e.$\Delta L(t)$, for the iteration between time *t-1* and *t*. The demand of land consumption $\Delta L(t)$ in equation 7 will be calculated from the stage of temporal control as $L(t)$ is the accumulative amount of land development until time *t*.

(4) Temporal control model

Previous studies suggest that urban development process *L(t)* in equations 1 and 7 follows a logistic curve over time (Herbert and Thomas, 1997). For example, Sui and Hui (2001) simulated the expansion trend of the desakota regions between 1990 and 2010 by using a logistic equation, where the total number of converted urban pixels was a logistic function of the year. Here, the same principle is applied for the temporal control of each project. A standard logistic curve is illustrated in equation 8.

$$L(t) = \frac{a}{1 + b * e^{-ct}} \tag{8}$$

Where *a*, *b* and *c* are unknown parameters, *t* (1~n) the time step and *L(t)* the amount of land development till time *t*. If it is assumed that $L(0)=L_0=a/(1+b)=1$, $L(n)=L_n=a/(1+be^{-cn})=L_d$, Here, *n*, L_d are the same definition as in equation 1; equation 8 can be revised as in equations 9 and 10:

$$z = \frac{L_d(e^{-cn} - 1)}{e^{-cn} - L_d} \tag{9}$$

$$L(t) = \frac{z}{1 + (z - 1) * e^{-ct}} \tag{10}$$

z in equations 9 and 10 implies the long-term limit of *L(t)* behaviour. The shape of the logistic curve usually represents the speed of project development over time, which is controlled by the parameters *c*, *n* and L_d. Here, for simplicity, temporal control is classified as three types: slow growth, normal growth and quick growth, which indicates three distinguishing scenarios. If it is assumed that $L(t) = L_d/\lambda$ when t = n/2, c = 2log $[(L_d-\lambda)/(\lambda-1)]/n$. Further, *L(t)* can be the function of both time *t* and parameter λ when *n* and L_d are set. Consequently, the value of λ will determine the shape of the logistic curve. As such, we can define slow, normal and quick growth in equation 11 according to λ. Of course, we can define more classes such as 'very slow' and 'very quick' by assigning a different λ value.

$$\begin{cases} \text{"Quick growth":} & \lambda = 4/3 \\ \text{"Normal growth":} & \lambda = 2 \\ \text{"Slow growth":} & \lambda = 4 \end{cases} \tag{11}$$

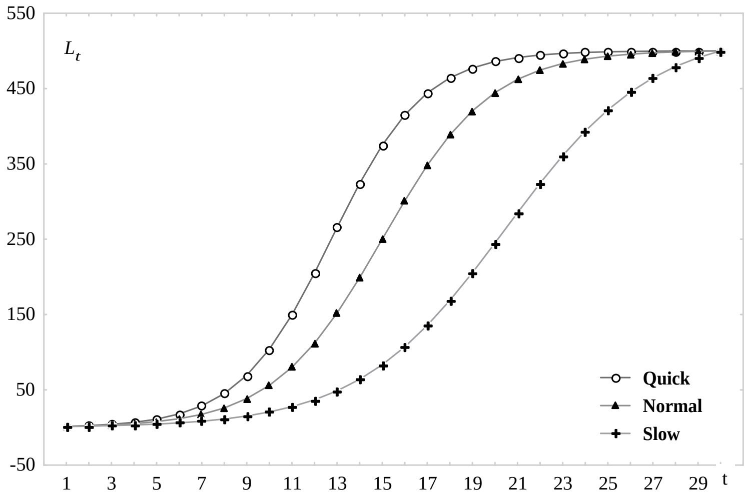

Figure 6.2 An illustration of temporal development patterns

Figure 6.2 is an example of three modes, where $L_d=500$, $n=30$, and λ is equal to 4/3, 2 and 4 respectively for the three patterns. However, iteration time t (1~n) in simulation is different from the real time: year *y* (*1~m*) such as 1993 (*y*=0) and 2000 (*y*=7). If $L_i(y)$ denotes the total growth of project *i* until year *y*, a transition from $L_i(t)$ *to* $L_i(y)$ should be established as equation 12.

$$L_i(y)=h(L_i(t)) \quad y=1, 2,...m; \quad t=1, 2, ...,n; \quad n>m \tag{12}$$

In previous research on CA applications, a linear function is applied, i.e. $t=\Delta * y$. Here Δ is assumed to be a constant, which means equal growth rate. For example, when y=5 years, t=20 iterations; in the case of a linear relationship, it can be defined as t = 4*y. So $y(1)=\sum L(t)$, $0<t<5$. In reality, function *h* could be a non-linear function of iteration number *t*, which can be tested experimentally through qualitative understanding and visual exploration of the difference between actual and simulated processes.

6.2.4 A conceptual model for local temporal dynamics

The multi-stage method can understand the global temporal dynamics of the whole study area rather than the local dynamics of each project. The latter requires a different perspective, focusing on more detailed spatial and temporal processes.

Heterogeneity in a temporal context means that the parameters describing any geographical phenomena vary from phase to phase in the whole period studied. For example, Wu and

Yeh (1997) applied logistic regression methods for modelling land development patterns in two periods (1979-1987 and 1987-1992) based on parcel data extracted from aerial photographs. They found that the major determinants of land development have changed: from distance from the city centre to closeness to the city centre; from proximity to inter-city highways to proximity to city streets; and are more related rather than less related to the physical condition of the sites. This suggests that various factors are changing their roles in the process of land development. Likewise, if we shrink the long period (1979-1992) to a shorter period (such as 1993-2000) and zoom out the spatial extent from the whole city to a smaller part (such as a large-scale project), the same principle should apply as well. Therefore, temporal heterogeneity results in complex spatial and temporal processes, which need to be identified in modelling. As similar patterns can result from numerous different processes, understanding process is more important than understanding pattern. Pattern is only a phenomena but process is the essence.

Figure 6.3 gives an example of spatial pattern and processes involved in urban growth. T_1,T_2,T_3 indicate time series of land development. The grey level means the temporal order of land development; the darker the later. The same spatial pattern results from three (in reality, more) distinct spatial-temporal processes, which reflect the spatial and temporal interactions between road-influenced and centre-based local growth patterns. The arrows indicate the trend of temporal development, from which we can define them as three different processes (convergence, sequence and divergence).

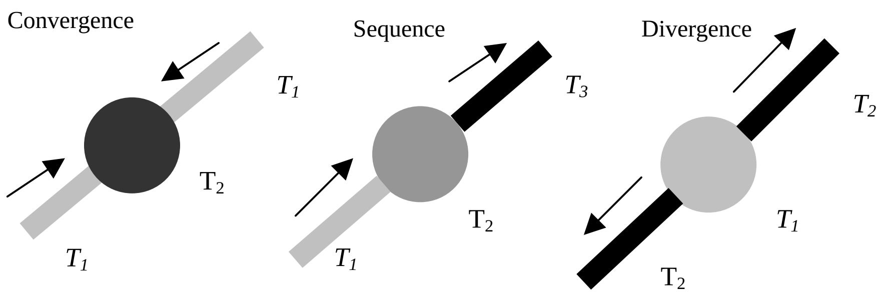

Figure 6.3 Different spatial-temporal processes

Table 6.1 Dynamics in local spatial-temporal processes

Process	T_1	T_2	T_3
Convergence	$W_r \to 1$, $W_c \to 0$ (if $L_t < L_l + L_u$)	$W_r \to 0$, $W_c \to 1$ (if $L_t > L_l + L_u$)	–
Sequence	$W_r \to 1$, $W_c \to 0$ (if $L_t < L_l$)	$W_r \to 0$, $W_c \to 1$ (if $L_t > L_l$ & $L_t < L_l + L_c$)	$W_r \to 1$, $W_c \to 0$ (if $L_t > L_l + L_c$ & $L_t < L$)
Divergence	$W_r \to 0$, $W_c \to 1$ (if $L_t < L_c$)	$W_r \to 1$, $W_c \to 0$ (if $L_t > L_c$ and $L_t < L$)	–

Note: symbol "$\to$" means "approaching to or close to"

The basic principle behind the phenomena is that various physical factors such as roads and centres take temporally varied roles in the course of local growth. In the first one (convergence), the road is more important than the centre at time T_1, but less important at T_2. This means that local growth occurs along the road first and then moves to the centre. The third one has an opposite effect. If we use L to denote the total amount of local growth, L_l for the lower part along road, L_u for the upper part along road, L_c for the centre part and L_t for the continuous development amount till time t, $L = L_l + L_u + L_c$. W_r and W_c represent the weight values of spatial factor ROAD and CENTER respectively. The rules detected are listed in table 6.1. The three cases imply that temporal dynamics can be represented and understood through the dynamic weighting concepts. Dynamic weighting means that factor weight is not a constant but a function of temporal development amount (equation 13).

$$W_i\,(t) = f_i\,(L_t) \qquad i = c,\, r \tag{13}$$

To some extent, this equation suggests a dynamic feedback between $w_i(t)$ and L_t, representing the complex interaction between pattern and process. L_t indicates the temporal pattern in amount, and the process is described by the changing roles of multiple factors $w_i(t)$; actually, L_t is also impacted by $w_i(t)$. In principle, the functions $f_i(L_t)$ should be continuous, which can be a step linear or more complicated non-linear function as $w_i(t)$ is not negatively or positively linear to L_t in most cases. For example, in the case of the sequence (table 6.1), W_r temporally experiences a decrease from 1 to 0 and then an increase from 0 to 1 when t changes from T_1 to T_3. Apparently, W_r is a non-linear function of L_t. When $f_i(L_t)$ is constant in relation to t, w_i is becoming the universe temporally, as applied in most CA applications. However, this treatment is effective for understanding global dynamics in equation 3 but not local dynamics at the project level (illustrated in figure 6.3). The design of function $f_i(L_t)$ is critical. Empirical study can be carried out based on a theoretical understanding of the interaction. Higher temporal resolution such as a series of the actual value L_t can be used to calibrate the temporal rules $w_i(t)$. For simplicity, the functions f_i can be discretised. This implies that the whole period needs to be divided into a few phases $t_1 \sim t_n$, in which varied weight values are defined with the assistance of local knowledge or by calibration from data.

6.3 Implementation

6.3.1 Urban growth

During the last five decades, Wuhan underwent rapid urban growth from 3,000 ha of built-up area in 1949 to 27,515 ha in 2000 (chapter 3). As a result, Wuhan is a good case for understanding the dynamic processes of urban growth in a fast developing country. In this chapter, the urban growth of Wuhan in the period 1993-2000 will be modelled based on the methodology discussed in section 6.2.

Operational CA models need access to real databases for better simulation performance (Li and Yeh, 2001a). The imagery employed here includes SPOT PAN/XS of 2000. The secondary sources include planning scheme maps, traffic/tourist maps, street boundary maps, and the population census and the statistical yearbook. These are used to create the required spatial factors (e.g. proximity and density variables) for CA modelling based on simple GIS operations such as overlay, buffering and neighbourhood statistics. The detailed procedures can be seen in chapter 3.

Table 6.2 Land cover transition from 1993 to 2000 (unit of area*: ha*)

Major types	Water	Town/ Village	Agricultural land	Others	Total
Area in 1993	30,258	8,669	51,585	–	–
Transited area	1,131	1,530	3,527	72	6,260
Transition percent	18.1%	24.4%	**56.3%**	1.2%	100%
Annual transition rate	0.5%	2.3%	0.9%	–	–

The land cover transition from 1993 to 2000 shown in table2 is calculated based on a 10×10 m^2 cell size. This table shows that major land use/cover changes come from water, town/villages and agricultural land, which were physically or functionally transferred into the urban built-up area. Town/villages with the highest annual transition rate were only functionally transferred to urban administration due to the rapid expansion of Wuhan municipality. Agricultural land has the highest transition percentage. Here, the water body includes ponds and lakes. A higher percentage area is taken for transition from ponds than from lakes (see map of actual pattern in figure 6.6). The item 'Others' includes green areas, sands, and mis-classification from image processing etc, which is omitted for modelling.

6.3.2 Project planning and site selection

With the assistance of historical documents, local planners and fieldwork, four large-scale projects, planned before or around 1993 were identified (WBUPLA, 1995). All small-scale projects were merged into one class, which results in five projects (figure 6.6 and table 6.3) as follows:

1) *Zhuankou*: car manufacturing plant (planned from 1988);
2) *Wujiashan*: Taiwanese investment zone (planned from 1992);
3) *Guanshan*: hi-tech development zone (planned from 1988);
4) *Changqing*: large-scale residential zone (planned from 1994);
5) *The rest*: small-scale development (commercial/institutional/residential).

In a GIS environment (ArcView 3.2a), we create the required spatial layers (figure 6.5), including land cover of 1993, distance to road networks and city centres/sub-centres, and population density. These layers are exported into a computational program for testing different site selection rules for each project according to equation 2. As a result of a sensitivity analysis conducted in a visual programming environment, the tested constraints at three levels for each project are listed in table 3. The total amount of development L_d (from the actual urban growth in figure 6.6) and the temporal control mode (from document and interviews) are also displayed in this table.

Table 6.3 Site selection rules of five projects

Project	*Zhuankou (1)*	*Wujiashan (2)*	*Guanshan (3)*	*Changqing (4)*	*The Rest(5)*
Cells - L_d	1,390	314	514	160	3,710
Functions	Manufacturing	Economic zone	High-tech zone	Residential	Mixture
Global constraint	<300 m to major road	<300 m to major road	<300 m to major road; <4.2 km to the university street	<300 m to major road; <3.5 km to sub-centres; >560 (person/ha) in net population density.	Close to city centres/sub centres; Close to road network.
Regional constraint	Density of developable land >62% in a 4.5 × 4.5 km^2 square; & > 90% in a 2 × 2 km^2 square	Density of developable land >69% in a 1 × 1 km^2 square; Density of developed area >18.7% in a 2 × 2 km^2 square.	Density of developable land >68% in a 3 × 3 km^2 square	Density of developable land >60% in a 1 × 1 km^2 square; Density of developed area >10% in a 2 × 2 km^2 square	Higher density of developed areas
Local constraint	Agricultural, village	Agricultural, village	Agricultural, village, hill	Agricultural, pond	Agricultural, village, pond, lake
Temporal control	Quick	Slow	Quick	Quick	Normal

After 1992, Wuhan entered a new wave of development characterised by more actors, diverse functions and a new industrial structure (Cheng and Masser, 2003). From this table, we are able to explain the spatial behaviour of the actors involved in each project. For instance, the dominant actor in the *Zhuankou, Wujiashan* and *Guanshan* projects is Wuhan municipality, which obtained financial resources from the central government, foreign investors and local enterprises. Being the owner of the land, the actor did not need to consider the costs of land utilisation. Hence, for large-scale projects, the first rule is the availability of a certain amount of developable land. Being oriented towards manufacturing and tertiary industry, the second rule is accessibility to major road networks. Strictly speaking, the second one is not only true for large-scale but also for small-scale land development such as commercial use.

Moreover, accessibility to developed areas is crucial for the economic development zone *(Wujiashan)* and the high-tech zone (*Guanshan*). Access to research resources, including nearly 20 universities is a prerequisite to locating a high-tech zone (*Guanshan*). In contrast, the major actors in the *Changqing* housing project are local real estate companies and relevant work units. Land value is becoming an important criterion, which weakens the role of accessibility to the city centres. The low-quality land cover such as ponds is much cheaper than agricultural land. Higher population density can guarantee better market demand as an influential factor for residential development. For small-scale projects, especially inside urban districts, more actors are involved in the decision-making, including local residents, investors, work units, planners and the lower levels of local government. This results in a more stochastic process of site selection as a result of which the constraints become more uncertain and fuzzy. However, generally speaking, accessibility to the city centre/sub-centre and road networks is the key factor.

6.3.3 Local growth

The cell size in this research is 100×100 m^2, which results in a 640×410 grid. A smaller cell size (such as 10×10 m^2) would cause an overload in terms of model computation. The state of cells is binary (1 - change, 0 - nonchange). The initial layer is the 1993 land cover. This includes Developed, Agricultural (A), Village/town (V), Pond (P), Lake (L), and Protected (Green, Park, and Sands). In figure 6.5a, P and L are merged into water bodies, and 'others' include protected. As described in 6.3.1, only four types A, V, P and L, underwent much change. The pattern model from another part of this research (Cheng and Masser, 2003), shown that the major spatial determinants of urban growth in 1993-2000 included major road networks, minor road networks, centres/sub-centres and master planning (as displayed in figure 6.5). They are selected here as non-constrictive factors for evaluating the potential for land conversion.

It should be noted that the classification of each layer is of great importance and modelling is sensitive to the classification, particularly when the study area is large and the period is long. For instance, the construction of roads may occur in different phases of the period to be modelled. Their construction time should be taken into account. In this research, a major road connection (linking with the Third Bridge over the Yangtze River) was completed in early 2000. This is clearly visible in the 2000 SPOT images. However, this major road is not included in the major road network layer because it had no practical impacts on urban development in the period 1993-2000. This judgement is also confirmed by very sparse and

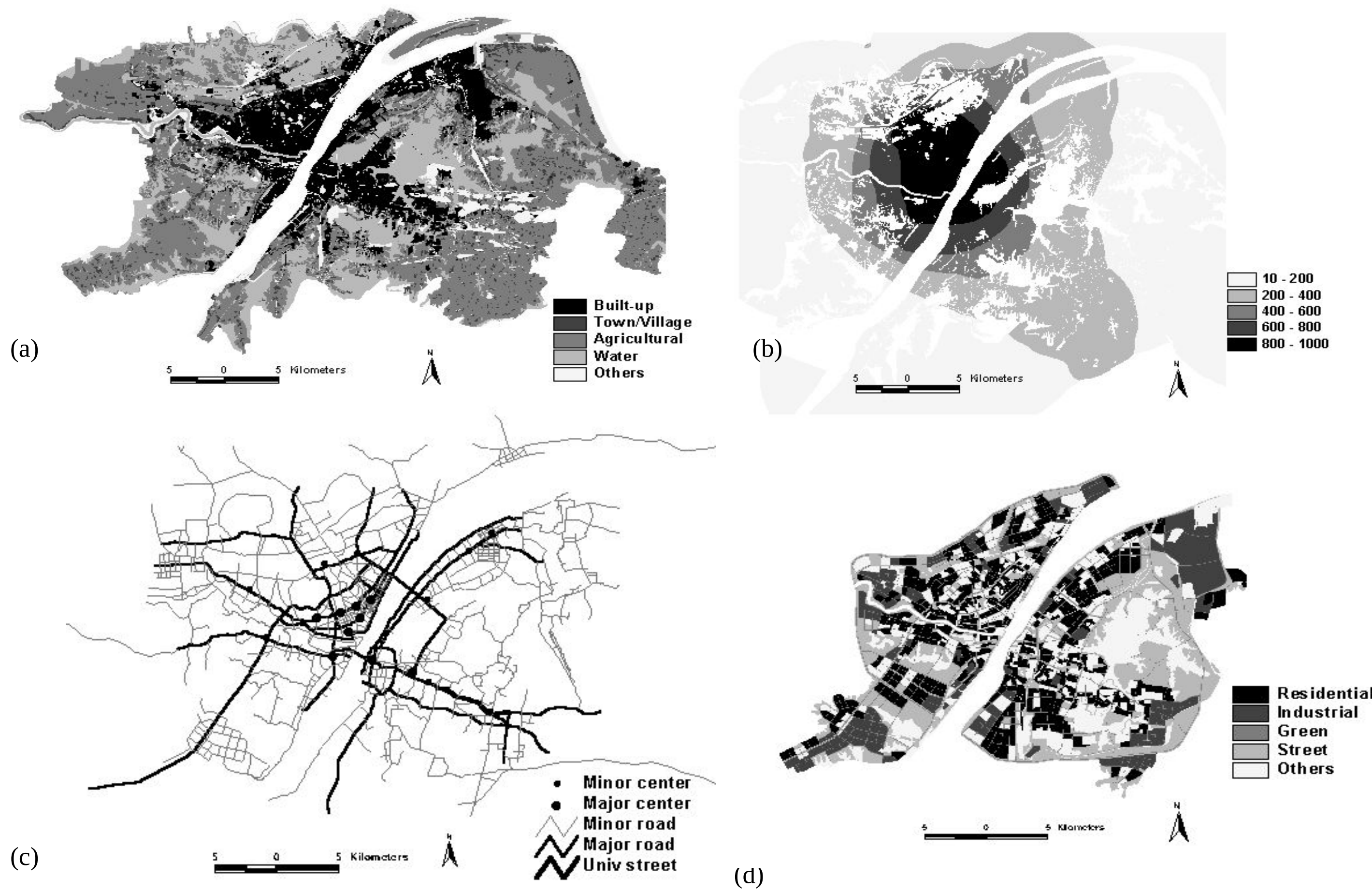

Figure 6.4 Spatial factors and constraints for site selection and CA modelling: a) land cover of 1993; b) population density (persons/ha); c) road networks and centres/sub-centres; d) master plan 1996-2020.

limited land cover change surrounding the road. Other layers are spatially defined by the following similar rules.

Wuhan city can be treated as a flat landscape as its elevation ranges between 22 and 27 m above sea level apart from a few hills. Hence, slope is not an influential factor. Physical constraints principally comprise water bodies (see figure 6.5a). Theoretically, water bodies should be completely excluded. However, in this case study, 18% of the land cover change comes from water bodies, which include ponds and lakes (see table 6.2). As this comes mostly from either small-scale ponds or the fringe of large lakes, a general procedure can be designed for defining a specific layer (exclusion layer):

- Extracting a water body from the land cover layer of 1993;
- Neighbourhood statistics (based on a circular neighbourhood with a 200 m radius);
- Selecting sum > 4 (neighbouring 4 ha area is water)

The layer will be utilised as physical constraint from the water body, defining excluded zones from transition. In the five CA models corresponding to the five projects, a circular neighbourhood is chosen because it does not have significant directional distortion. Its size varies with different projects, ranging from three to nine cells. The selection of neighbourhood size for each project relies on empirical study and sensitivity analysis (see a later section). The heterogeneity of spatial processes is indicated by the varied combination of influential factors, weight values and parameters, which imply distinguishing local spatial behaviour.

Table 6.4 Influential degree of master planning on land cover transition

Code	Classification	*Zhuankou*		*Guanshan*		*The Rest*	
		C_i / M_i	M_i	C_i / M_i	M_i	C_i / M_i	M_i
R_1	Low-rise residential	0.237	265	0.23	57	0.087	1082
R_3	Poorer environment	-	-	-	-	0.1333	149
M	Industry	0.318	508	0.24	172	0.049	419
G_1	Public green	0.27	137	-	-	0.0916	416
G_2	Protected land	0.147	58	0.33	112	0.041	222
G_3	Ecological agriculture	-	-	-	-	0.0216	82
C_1	Administration/Offices	0.26	52	-	-	0.0787	17
C_3	Cultural/Recreational	0.528	16	-	-	-	-
C_4	Sports facility	-	-	0.3	44	0.035	89
C_5	Hospital/Health	0.742	33	-	-,	-	-
S_1	Street	-	-	-	-	0.069	354

"-": M_i <15 (omitted)

Given that local growth is impacted by the master plan to be implemented in this period, we must incorporate the master plan for 1996-2020 as an influential factor (this scheme was initiated in 1990 and approved by the central government in 1996). Due to the rapid urban expansion in the fringe, some projects such as *Changqing* and *Wujiashan* had not even been planned until their construction. These will be excluded from the master planning analysis.

Only the projects covered by master planning are considered i.e. *Guanshan*, *Zhuankou* and *The Rest*. Each cell j is assigned a value X_j, representing the influential degree of the planned land use on its land cover transition in a project. If M_i denotes the total area of land use i in a specific project, C_i denotes the transited part of M_i, C_i / M_i generally indicates the influential degree of land use i. If a cell j was planned as land use i, $X_j = C_i / M_i$. X_j needs to be standardised according to equation 4 $(X_j\text{-}min) / (max\text{-}min)$ before it can be incorporated into the evaluation formula (equation 3). The M_i and C_i / M_i values of the major land uses are listed in table 6.4. The item 'Code' follows the National Urban Land Use Classification Standard (NULCS). Generally, table 6.4 reveals that the master plan was more successful in guiding large-scale projects in the fringe than small-scale ones in urban districts. In figure 6.5d, "Residential" includes R_1~R_3, "Green" G_1~G_3, "Street" S_1, and the rest (C_1, C_3, C_4, C_5) are all merged into "Others".

The calibration of parameters has proved a difficult task in urban CA modelling (Clarke and Gaydos, 1998; Li and Yeh, 2001a), especially when there are many factors and parameters to be considered. The difficulty lies in the fact that most urban CA modelling takes the whole municipality into the calibration procedure, which results in intensive computation overload. In this research, project-based CA modelling has largely reduced the computational time of calibration as the spatial extent of the project is much smaller than the whole study area, as shown in table 6.5 and figure 6.6.

The factors and parameters for model calibration include six spatial factors, neighbourhood size and stochastic disturbance α. Other parameters (e.g. temporal pattern mode parameter λ, iteration time t) are utilised for sensitivity analysis in section 6.4.1. The six spatial factors are "distance to minor road" (OR), "distance to major road" (MR), "distance to centre/sub-centres" (CN), "density of neighbouring developed areas" (DD), "density of neighbouring new development" (DN), and "master planning". Their parameters ϕ (in equation 5) are taken from the global pattern model of logistic regression carried out in another part of this research (Cheng and Masser, 2003). Automatic search for the best-fit parameters is carried out by using a hierarchical means, i.e. to reduce step size for five loops corresponding to six factors at two stages. For example, the step size of loops in calculating the weight values is set as 0.05 first, i.e. from 0.05 to 1 step 0.05. When the parameter scope of the ideal accuracy is determined, e.g. from 0.2 to 0.25, we can set a second step size 0.005 for finer calibration, i.e. from 0.2 to 0.25 step 0.005.

The validation accuracy depends on the approach used to compare simulated and actual patterns. This is traditionally measured by a coincidence matrix generated by a cell-cell comparison of two pattern maps. Some researchers argue that CA simulations should be assessed not just on the goodness of fit (a cell by cell basis) but also on their feasibility and plausibility as urban systems are rather complicated and their exact evolution is unpredictable (Wu and Webster, 1998; White and Engelen, 2000; Yeh and Li, 2001a). Some global measures that have been used for testing the validity of CA simulation include the fractal and Moran I index (Wu, 1998a), fractal analysis (Yeh and Li, 2001a), and landscape metrics (Soares-Filho et al., 2002). Wu (2002) emphasises the need to validate the model through both structural and cross-tabulation measures. Structural measures can only compare the pattern (outcome of process) not the spatial location (or process).

Table 6.5 CA Simulation of five projects

Projects	*Zhuan kou-1*	*Zhuankou-2*			*Wujia shan*	*Guan shan*	*Chang qing*	*Rest*
Land demand L_d	1,390	1,390			314	514	160	3,710
Accuracy *CC*	*54%*	*54%*			*51.6%*	*53.2%*	*85%*	*55%*
Lee-Sallee index	*0.37*	*0.37*			*0.35*	*0.36*	*0.74*	*0.38*
Neighbourhood size	*6*	*6*			*5*	*8*	*3*	*7*
λ	*4/3*	*4/3*			*4*	*4/3*	*4/3*	*2*
Dynamic weighting	-	*<15%*	*15-55%*	*>55%*	-	-	-	-
Major road (MR)	0.2	-	0.5	0.05	0.325	-	0.1	0.3
Minor road (OR)	0.3	-	0.1	0.15	0.1	0.35	0.55	0.15
Centres (CE)	-	0.7	-	0.5	-	-	-	0.2
Neighbourhood-new	0.3	0.3	0.1	0.15	0.3	0.35	0.35	0.1
Neighbourhood-old	-	-	-	-	0.275	0.25	-	0.2
Master planning	0.2	-	0.3	0.15	-	0.05	-	0.05
Total	100%	100%	100%	100%	100%	100%	100%	100%

Note: α=1%, n=50, ϕ for MR, OR and CN: 0.000765, 0.0012 and 0.000272

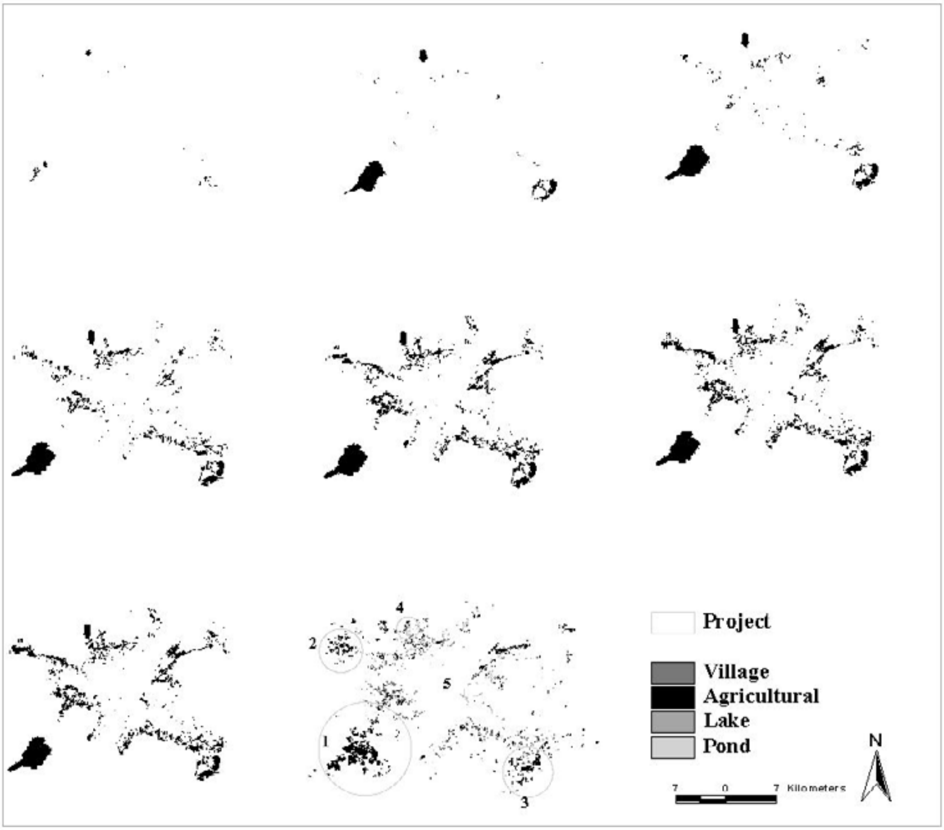

Figure 6.5 Simulated (1994-2000 in order) and actual patterns (last map)

We consider that spatially location match is also of great importance for supporting planning decision-making despite the difficulties imposed by CA modelling. Another reason lies in the fact that local processes at the project level require more accurate cell-based measures, as their morphology is less definite than that of processes at the global level.

Clarke and Gaydos (1998) outline four ways to statistically test the degree of historical fit (three r-squared fits and one modified Lee-Sallee shape index). For the Lee-Sallee shape index (combining the actual and the simulated distributions as binary urban/non-urban, and computing the ratio of the intersection over the union), they reported that the practical accuracy is only 0.3. In this chapter, we use consistency coefficients (*CC*) (the percentage of the matched over the actual) and the Lee-Sallee index (*LI*) for the evaluation of goodness of fit. The total number of pixels is set the same for simulation as the actual pattern, i.e. $L_d = L_n$, $LI=CC/(2\text{-}CC)$. For example, when $CC=0.57$, $LI=0.4$. Following this formula, the Lee-Sallee index for five projects are computed and listed in table 6.5. The overall accuracy based on the weighted combination (L_d) of five projects is 0.554 in *CC* and 0.383 in *LI*, greater than those of Clarke.

6.3.4 Temporal control

With local knowledge, we are able to identify the patterns of temporal development of each project (see table 6.3). In 1993, *Zhuankou* was still completely rural. By 1995 it was nearly half constructed. There was not much change from 1997 and 2000. Therefore, its temporal growth pattern is defined as "Quick". The small-scale projects (the Rest) are a mixture of all three patterns. Some may be quick and others slow. On average, it is reasonable to classify them as "Normal". The number of iterations is defined as *n*=50 because the greater the number, the finer the discriminative capacity of the models.

Figure 6.6 exhibits the trajectories of temporal development of the five projects respectively, according to the results of the validated CA simulation. As described in equation 12, the output of CA simulation is $L_i(t)$ $(1\sim n)$, which is different from the yearly actual amount $L_i(y)$ $(1\sim m)$ for each project *i*. We need a transition from $L_i(t)$ to $L_i(y)$. The transition function *h* in equation 12 should be based on an understanding of the actual temporal development process, which is determined by its socio-economic development. For the sake of simplicity, we use an equal time interval, i.e. a linear function: $y = t/7$. As *t* ranges from 1 to 50 (n=50) and *y* from 1 to 7 (m=7), $L_i(y)= \Sigma L_i(t)$, *t* from $7*(y-1)+1$ to $7*y$. A series of newly created layers for the whole study area, corresponding to the seven-year urban growth (from 1993 to 2000, figure 6.6), have been imported into animation software (Animagic32) for dynamic visualisation. This animation is helpful for exploring and comparing the temporal dynamics of spatial processes.

Table 6.5 shows the spatial heterogeneity of the causal factors, which vary spatially in terms of their weight values. The neighbourhood effect is represented by neighbourhood size, and the weight values of new and old developed areas. This table suggests that there are some similarities and some dissimilarities between the five projects. The weight values of the major roads, minor roads, city centre/sub-centres and master planning also show some differences. Major roads play a greater role in "The Rest" and *Wujiashan*, and less important roles in *Changqing* and *Guanshan*. Conversely, minor roads play a greater role in the latter projects than in the former.

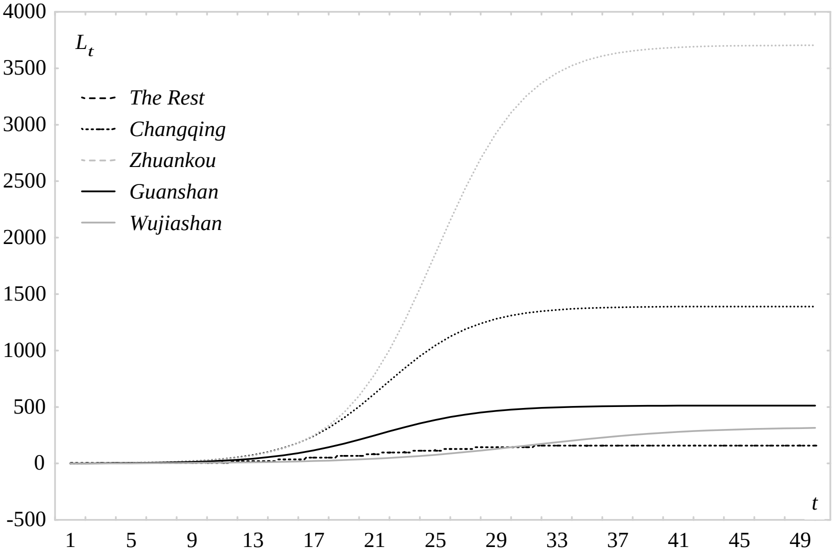

Figure 6.6 Temporal control patterns of five projects

By linking the site selection rules shown in table 6.3, it can be seen that the road networks system actually takes varying roles during different phases of urban growth. The major road network is the key at the stage of site selection and remains important for some areas at the stage of local growth. However, the minor road network is only active at the stage of local growth. This is due to the fact that minor road networks are created after the stage of site selection, together with the new growth. Relatively, city centres/sub-centres are influential only for "The Rest" as the others are located in the urban fringe. Master planning is less influential than others. The spatial heterogeneity described above suggests that the causal effects of urban growth vary from place to place. Local process modelling can offer deeper insights into urban growth processes.

6.3.5 Local temporal dynamics

Local temporal dynamics are focused on each project and are indicated by the following examples:

- Compared with the major road network, minor roads, especially in new zones that are also new development units, may occur temporally at different phases of the period studied, i.e. between T_0 and T_n, but not immediately from T_0;
- The spatial impacts of various factors such as roads and centres are not simultaneous in temporally affecting local growth;
- Neighbourhood effects may suffer from temporal variation; for example, it may be stronger at T_0 than at T_n, or vice versa.

These examples qualitatively show the complex pattern and process interaction as explained in section 6.2.4. Two models of *Zhuankou* in table 6.5 have similar model accuracy and similar patterns. However, their spatial-temporal processes are quite different, as quantitatively shown in figure 6.8. Model 1 exhibits a more random process. Model 2 shows a more self-organised process. Model 2 is based on the assumption that new development in *Zhuankou* first occurred in the centre, then along the major road, and finally spread from the centre. The assumption corresponds to a temporal dynamics that is spatially controlled by three sets of weight values (table 6.5). To calibrate this process-oriented CA model, manual tests based on the modeller's understanding of local growth processes and the visual exploration of model outputs (temporal patterns) are very important for reducing parameter ranges and making rough estimates of dynamic weight values. Limited automatic search can be followed for the best ideal combination of parameters.

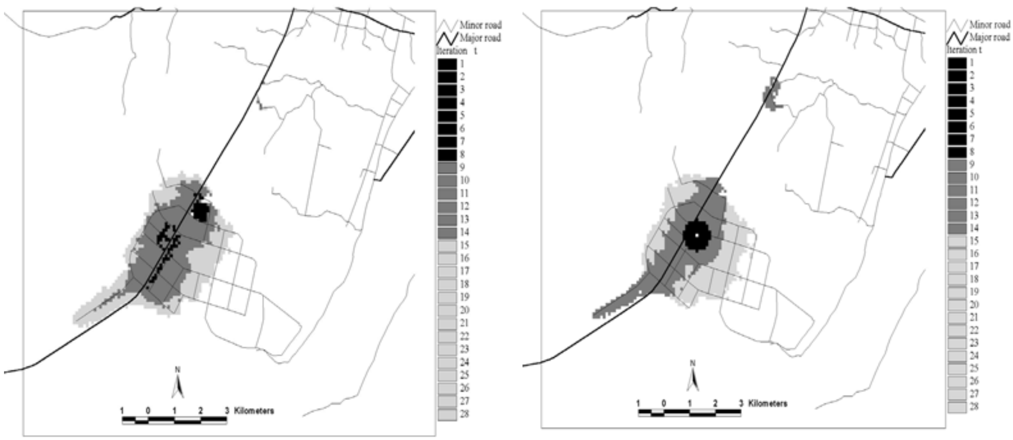

Figure 6.7 Local temporal dynamics (Zhuankou-1 and -2 in table 6.5)

To some extent, the dynamic weighting implies the temporal lag of the spatial influences of locational factors on urban growth. This example suggests that local temporal dynamics can enable us to better understand the organised local growth. If we explore the changes in weight values, it can be found that the major changes are indicated in major roads and centres. As explained in equation 13, the weight values should be non-linear functions of temporal land development demand. Table 6.5 also shows the functions are highly complex in reality. They are frequently phased. Model 2 is actually based on local knowledge. Other projects can be calibrated temporally by the same procedures as in the Zhuankou project.

6.4 Discussion and Conclusions

6.4.1 Model calibration and validation

Li and Yeh (2001a) report a calibration procedure of CA modelling by using an artificial neural network. In their method, the neural network is utilised to obtain the optimal parameter values automatically based on training empirical data, and then the parameter values calibrated are used to carry out CA simulation for new data. In CA models of this kind, the transition rules represented by the neural network structure are not transparent to users. Consequently, this method can be used for prediction by using the same set of rules, but it is not ideal for interpreting the logic of land conversion or spatial-temporal processes as it is a black box (Wu, 2002).

It has been found in this research that visual tests offer a quick and useful way of calibrating and verifying a CA model (Clarke et al., 1997; Ward et al., 2000a), particularly with respect to sensitivity analysis. In this project-based CA modelling, calibration has proved not to be a severe problem in computation time. However, the optimal combination of parameters from automatic search may not give the best results as socio-economic systems essentially produce no best solution. Consequently, the calibrated results need further confirmation according to the interpretation and plausibility of their spatial and temporal processes. In table 6, the *Wujiashan* project is taken as an example to illustrate this issue. When neighbourhood size is set as 5, the optimal parameters with 52.8% accuracy are calculated by automatic search (step of weight value is 0.005), together with the other combination of parameters. However, the spatial processes produced by the weight values (0.2, 0.1, 0.45, 0.25) are not the same as the real temporal pattern based on visual comparison. Conversely, another combination (0.325, 0.1, 0.3, 0.275) can create more satisfactory temporal patterns, although its model accuracy (51.6% in CC) is lower. Consequently, visual tests are still a necessary means for process rather than pattern modelling.

Table 6.6 Calibration of CA modelling and sensitivity analysis (*Wujiashan* project)

Accuracy *CC(%)*	52.8	**51.6**	51.3	50.8	29.5	46	49.7	50	50.8
Neighbourhood size	5	**5**	5	5	5	*8*	*6*	*4*	*5* λ=4.5
Major road (MR)	0.2	**0.325**	0.325	0.225	0.375	0.1	0.325	0.325	0.325
Minor road (OR)	0.1	**0.1**	0.05	0.25	0.3	0.3	0.1	0.1	0.1
Neighbourhood (new)	0.45	**0.3**	0.35	0.15	0.3	0.4	0.3	0.3	0.3
Neighbourhood (old)	0.25	**0.275**	0.275	0.375	0.025	0.2	0.275	0.275	0.275
Total (%)	100	**100**	100	100	100	100	100	100	100

Note: α=1%, n=50, λ=4, ϕ for MR, OR and CN: 0.000765, 0.0012 and 0.000272

Another part of calibration is sensitivity analysis, as the results of CA simulation are very sensitive to the parameter values (e.g. neighbourhood size, weight values, λ and n). This is the issue of uncertainty existing in CA simulation that has not been given enough attention in most applications. For the *Wujiashan* project, before accepting (0.325, 0.1, 0.3, 0.275), we need to test its stability by slightly or greatly adjusting the weight values and the other parameters such as neighbourhood size as listed in table 6.6. The changes (slight or great) in validation accuracy that are identical to those in parameters assure the reliability of this set.

6.4.2 Visualisation of processes

To implement site selection and CA modelling, a loose coupling strategy is frequently adopted for various applications (Clarke and Gaydos, 1998; Bell et al., 2000). Loose coupling means that a data transfer procedure is frequently implemented between a CA model, GIS, and an animation module. This loose coupling strategy sacrifices the friendly interface but improves the computation efficiency of CA simulation. Here the site selection rules and the CA model is programmed in object-oriented programming language. Spatial data analysis and visual exploration tasks are implemented within a GIS environment – ArcView platform. Each layer produced is exported as an ASCII raster file. A sub-procedure is programmed to read and write the ASCII raster files between CA and ArcView. The major parameters include the weight values, the temporal pattern control λ, the neighbourhood size and the stochastic perturbation α. The validation results are stored in a text file and an ASCII raster file. A validated urban growth layer (1993-2000) from the simulation is separated into a series of maps, each corresponding to one year. The layers created are exported as a JPG or any other type of image file. These are inserted as an individual frame into the animation file for visual check of the spatial process. However, a major deficiency of this strategy is that it is not a very friendly environment for the immediate visualisation of spatial-temporal processes, although it is effective for model calibration. In the future, CA modelling tightly coupled with GIS and animation should be further studied to enhance its visualisation of spatial-temporal processes.

6.4.3 Process modelling

To some extent, the accuracy of a simulation model depends on the complexity and stochasticity of the real city and also on the availability of more detailed information. Although the overall accuracy of five CA models is only 55% based on a cell by cell basis, the methodology proposed in this chapter illustrates the potential for understanding spatial processes and their temporal dynamics at the two levels based on the methodology. The spatial clustering of land development projects indicates a self-organising process. The timing schedule of various projects exhibits global temporal dynamics. Dynamic weighting is an important concept for simulating process rather than pattern. Spatial classification based on the project concept is subjective but transparent to urban planners. The spatial-temporal processes explored by project-based modelling can easily be interpreted with reference to socio-economic and decision-making processes. To be a true process model, CA modelling as suggested in this research should incorporate dynamic weighting methods, although there is still much difficulty in systematically defining these functions in practice.

From the local spatial modelling point of view, a possible direction lies in applying a moving window or kernel in defining a project for each cell, so that generalised local process modelling can be repeatedly applied for each cell. This is a similar principle to that applied in geographically weighted regression (GWR) modelling. This idea can result in universally localised process modelling. The parameters for understanding local processes vary with the cell. Users can redefine interesting projects for further interpretation by focusing on some hot spots.

From the perspective of spatial data analysis, the methodology can be utilised to discover the hidden processes from the required integrated spatial database regarding temporal urban growth. This has been one of the major concerns in the field of spatial data mining or knowledge discovery. When socio-economic data at detailed levels become available, project-based CA modelling can be further linked with micro-scale multi-agent and economic modelling. Such integration can explore the spatial and economic behaviour of various actors at the micro scale.

The major purpose of CA simulation is to generate alternative scenarios for decision support in a smart growth management. The methodology developed here can be extended in this direction. In this new case, stages 1 and 4 need to incorporate top-down socio-economic models for predicting the demand for new land development in the future, i.e. L_d in equation 1. Stages 2 and 3 are subject to some modification in quantification. The construction of plan scenarios is based on soft systems thinking, which stresses the role of users' subjectivity. In this way local planners' intentions can be transformed into spatially and temporally explicit weight values and certain parameters (e.g. Wu, 1998c). With a user-friendly visualisation environment, the framework tested in this research can facilitate decision-making of urban spatial development.

We cannot ignore the fact that any advanced modelling technique including CA must be based on a proper understanding and abstraction of the systems studied. The better the understanding the more accurate it is likely to be. Planning will never be a hard science, for it is built on humanistic assumptions, values and goals (Shmueli, 1998). Our understanding of the new urban reality will be ultimately based upon a combination of computers and human judgement (Sui, 1998).

CA is only a simulation tool for testing a decision-maker's understanding. Limited by existing GIS theory and methods, the identification of various spatial and temporal heterogeneity cannot be completed without the assistance of local knowledge. This implies that local knowledge is an important ancillary data source for CA modelling especially within the framework presented in this chapter. During the process of the modelling, project planning, site selection and temporal control need more input from local experts. For dynamic weighting, due to the limited temporal resolution, local knowledge is an essential source of qualitative information. It has been emphasised in this research that a soft system methodology, stressing the roles of decision-makers and feedback both between modellers and users and between stages of the decision-making process, is helpful, especially when complete information resources are not guaranteed.

Chapter 7

Conclusions

7.1 Introduction

This research centres on understanding rather than predicting complex spatial and temporal urban growth, in support of urban development planning and growth management. The study of urban growth processes as a complex system is inherently multidisciplinary and contributes to and benefits from other disciplines. Understanding-oriented modelling needs innovative concepts, reliable and diverse data, and feasible methods of analysis or modelling. This research has put forward a general methodology based on complexity theory and modelling methods, together with remote sensing (RS) and geographical information science (GIS). This methodology is tested with reference to a rapidly growing city, Wuhan, in a dramatically developing country, China. Based on the findings of previous chapters, there is an open general question that needs to be answered: What are the contributions of the new findings to the relevant scientific fields and planning practice? With this question in mind, this chapter falls into five sections. Following this introduction, section 2 focuses on the implications for planning practice in Wuhan city. Section 3 relates to GIS with respect to data and spatial analysis. Section 4 concentrates on modelling, while the final section discusses the findings in terms of complexity theories and methods. Each of these sections includes a discussion of the main findings of the research, as well as some conclusions and suggestions for future work related to its specific theme.

7.2 Implications for Planning in Wuhan

The findings of the case study described in this research have resulted in some significant understanding of the great physical and functional changes that have taken place in Wuhan city over the past five decades despite the existing poor data infrastructure. Chapter 3 gives a detailed evaluation based on some specific indicators. The findings of this chapter reveal that the spatial structure of Wuhan has shifted from a monocentric to a multicentric form, and from a linear pattern along the rivers to an outward spreading pattern along the major road network; moreover, the land development process has become more fragmented and more diverse. Increasing industrial land use and decreasing residential land use show the continuously dominant roles of industry in the economic development of Wuhan city even after the economic reform. The paid transfer of land use rights has led to a relatively more compact pattern of urban growth than that under the free land market before the land reform (chapter 4). The influence of master planning is decreasing over the land development process. Conversely, road infrastructure has played a crucial role in new development, and this grew stronger in the second wave (1993-2000) (chapters 5 and 6). This indicates that Chinese urban growth is still in its early stages, stimulated or guided by physical infrastructure and facilities, and lacks land market legislation. It also suggests that the methods of master planning are not suitable for this new challenge, which needs to deal with rapidly changing environments.

New methods should be based on an understanding of the dynamic processes of urban development. This research has developed a general methodology that falls into three stages: monitoring (chapter 3), modelling (evaluation, measurement, pattern and process, chapters 3 to 6) and planning support (chapter 6). Modelling in this study has produced significant quantitative evidence for comparison, evaluation and interpretation. Consequently, modelling spatial and temporal change should become an important theme in the studies of Chinese urban planning. Understanding-oriented models are able to simplify complicated problems and construct potential scenarios for planning.

In the future, we will first continue to model the spatial patterns and processes in the period 1955-1965 based on the methodology developed in chapters 5 and 6 respectively. These results are expected to be used for systematic comparisons between the two development waves occurring under two different political systems. This is the comparative study in the vertical direction. Second, the multi-stage method based on cellular automata as described in chapter 6 will be extended as a planning support tool for building future urban growth scenarios of Wuhan. Third, as a mega-city in a developing country, the findings of the Wuhan case study will be compared with similar studies in other Chinese cities, and even in other countries, in order to discover the universal and disparate characteristics of the urban growth process. This is the comparative study in the horizontal direction. It is worth noting that urban growth in Chinese cities is dominated by formal development and is quite different from the informal development in other developing countries such as India and Africa (Hall and Pfeiffer, 2000).

7.3 Data and GIS

Process-oriented planning rather than blueprint planning involves three general procedures: urban growth monitoring, process modelling and then scenario building. They involve remote sensing, GIS, modelling and PSS (planning support systems) respectively. The quantification of dynamic processes first requires a large quantity of data and a number of data analyses. Undoubtedly, the accuracy of both the data and the analysis will determine the final success of the modelling. The major findings regarding data and spatial analysis are summarised as follows.

7.3.1 Data

As described in chapter 2, urban growth ***G*** dynamically interacts with three systems ***P***, ***N*** and ***U.*** Consequently, the data required for urban growth modelling must cover all four domains (***G***, ***P***, ***N***, ***U***) at certain spatial and temporal resolutions. In this research, a wide range of data sources is utilised, including remotely sensed imagery, topographic maps, plan schemes, socio-economic data and historical documents. The primary data sources come from timely, cheap and multi-resolution imagery (SPOT images and aerial photographs). SPOT imagery has proved an ideal source for mapping land cover in the fringe, as applied for the two years 1986 and 2000 (chapter 3). This imagery can produce land cover maps at the 1:50,000 scale. Aerial photography is still a means for extracting urban land use information, as used for the year 1955 (chapters 3 and 4). Although supervised classification of images improves the accuracy of land cover mapping, temporal data consistency in a series of changes requires human interpretation, especially when images and aerial photographs are employed together for change detection. When interpreting past urban land uses from imagery, detailed historical documents such as the historical records of urban planning and urban construction provide the valuable references to temporal events (chapter 3). In most cases, interviews with local planners and developers are also needed for further confirmation.

However, in contrast to physical data (space attributes), functional data (activities attributes) have proved a major barrier to modelling in this research (chapter 4). This is due to the lack of local data infrastructures, particularly in the developing world. This also limits this research in the exploration of spatial pattern and process. Further exploration of spatial behaviour, temporal complexity and the decision-making process, particularly on a micro scale, will become possible only with improved data infrastructures. The new IKONOS imagery offers great potential for urban land cover and land use mapping at detailed levels.

7.3.2 Data analysis

GIS in urban growth modelling has three objectives: to provide an integrated spatial and temporal database, to develop spatial indicators, and to facilitate spatial analyses. The majority of urban growth models applied in this research are based on raster data structures directly from imagery. These have a number of limitations. First, image classification and visual interpretation unavoidably contain uncertainties such as the classification of low-density or high-density residential areas that can be treated as fuzzy spatial objects. Second, a pixel is not an independent social and economic entity in spatial modelling. Consequently, raster-based modelling is weak in explaining social and economic activities. This leads to a requirement for a process-oriented temporal data model, which can represent dynamic spatial and temporal relationships between spatial objects (e.g. Cheng, 1999). New data models should be able to represent the events of spatial and temporal changes.

Spatial analysis in this study includes both explanatory and exploratory data analysis. The basic objective in spatial analysis, particularly in large-scale modelling, is to quantify spatial or spatio-temporal indicators such as proximity, accessibility, density, intensity and entropy. These indicators can be measured from various perspectives, representing different understandings of physical and socio-economic processes. A typical example is an indicator of accessibility. Many methods have been developed to quantify accessibility to meet the demands of particular applications. An inappropriate indicator may affect the accuracy and effectiveness of modelling. Not enough attention seems to have been paid to this point in

GIS or in the application fields. On the other hand a great deal of effort is often devoted to developing new and advanced modelling methods such as spatial regression and local analysis. However, overly simple GIS operations such as buffering, overlay and neighbourhood statistics frequently fail to satisfy the requirements of modelling. These deficiencies in spatial data analysis can be seen in this research in the case of the proximity-based and neighbourhood-based variables in chapters 5 and 6. For example, a proximity variable such as the distance to the road network is too simple to represent the economic influences of infrastructure. It must be recognised that the understanding of space and spatial relationships in current GIS is not rich enough in its semantics to represent complex spatial and temporal phenomena in various applications. The spatial concepts representing spatial relationships are limited to five types: distance, direction, topology, scale and similarity. The majority of spatial or spatio-temporal measurements are based on some of these combinations such as kernel density functions and spatial weight matrices in spatial regression. The temporal measurement based on the relative space concept that is described in chapter 4 is a significant development in this direction. Data disaggregation can improve the spatial measurement of the density index by integrating social and economic activities. Landscape metrics have been developed in the field of landscape ecology to quantify the structural and functional properties of landscape units, which can explain underlying ecological processes. These indicators have been extended to quantify urban functional features such as land uses, as shown in chapter 3 of this research.

Spatial explanatory analysis incorporates spatial statistics into traditional statistical analysis in order to explain complex spatial cause-effect relationships. As spatial phenomena frequently violate the assumptions of traditional statistics, spatial sampling is a necessary step to remove or reduce spatial dependence, as shown in chapter 5. Spatial logistic regression has also proved effective in interpreting spatial patterns as a non-linear modelling method.

Spatial exploratory data analysis aims to explore the spatial distribution of any indicator that can suggest a significant pattern for further modelling. Spatial auto-correlation is frequently used for pattern detection with respect to a spatial variable. This approach can compare and evaluate the sprawling pattern of urban growth, as implemented in chapter 4. In this study, the exploratory data analysis carried out in chapter 5 can detect spatial outliers for the redefinition of a spatial layer and can compare the spatial effects of each variable. This analysis can strengthen the transparency of further explanatory data analysis. Animation as applied in chapter 3 offers visual and dynamic snapshots of urban growth and other spatial factors such as roads network and city centres. This exploratory analysis can help modellers develop potential hypotheses of urban growth processes.

Chapter 6 has shown that cellular automata (CA) can supply powerful and convenient spatial modelling functions, especially when they are integrated within a GIS environment. GIS offers CA a large volume of spatial and other socio-economic data. CA provide GIS with a strong process modelling function. The integration of both has proved successful in simulating the spatial and temporal processes of urban growth and in discovering the mechanisms of urban evolution.

7.3.3 Planning support systems (PSS)

Process-oriented planning requires a user-friendly environment to build or simulate "what-if" policy scenarios. As a result, the process of modelling should be transparent to decision-makers. For scenario building, we need PSS techniques to stimulate decision-makers' thinking and to help them use these models. Recent developments in virtual reality (VR), web-GIS, participatory GIS, group MCE (multi-criteria evaluation) and visualisation have considerable potential for spatial decision-making. It should be borne in mind that quantitative analysis needs to be combined with a certain degree of subjectivity, particularly in the domain of urban planning, as planning is an organised human activity. In addition the users of modelling need to participate in, or at least get involved in, the procedures of modelling in order to confirm the outcomes of modelling. The transparency of the modelling process and a user-friendly interface become an important criterion for PSS. In urban growth, animation is widely utilised for exploratory analyses of dynamic processes. This enables users to understand and imagine possible hidden processes and construct potential scenarios. The multi-stage method in chapter 6 is transparent in its process of modelling when incorporating spatially and temporally explicit decision-making processes. It can be extended to a PSS environment in order to help planners to simulate planning scenarios.

7.4 Spatial and Temporal Modelling

7.4.1 The concept of a model

The concept of a model has also been changing since the 1960s. In the past, it usually referred to mathematical algorithms or equations, which are typically represented by some parameters. This type of modelling aims to choose the types of equation and to calibrate these parameters according to real data. A typical example is the Lowry model (1964), which consists of about a dozen equations and several more parameters. However, in an information society urban systems continually become more complex than in an industrial society as the interactions among the increasing number of components are strengthened. The hard-system methodology used before is not suitable for these new urban systems that require a soft-system methodology (Barry and Fourie, 2002). This new philosophy emphasises the process of thinking towards solving complex issues. This is particularly useful for applied sciences such as urban planning where human knowledge has a dominant effect. In this sense, the content or connotation of the model is broadened and extended to include more conceptual components. A typical example of this modelling is the conceptual multi-stage model presented in chapter 6. In this case the process of decision-making in urban growth is divided into four steps, each related to one or more approaches such as CA. Hence, modelling indicates a methodology. As reality is complicated in essence, we cannot expect mathematical models to directly solve all complex or ill-structured issues. Human thinking is the most complex process of modelling, which can structure complex issues into simple form. This modelling to some extent results in the steps or procedures to simplify complex issues. In this study, such modelling includes new perspectives (for example, the integration of multiple indicators in chapter 3, relative space in chapter 4, multi-scale in chapter 5, and global and local dynamics in chapter 6) to deepen insights into spatial and temporal urban growth phenomena. These new perspectives have proved successful in linking modelling with urban planning.

7.4.2 Modelling methods

To understand the complexity of the urban growth process, a number of modelling methods can be qualified as evaluated in chapter 2. Each method has both advantages and disadvantages. The most important criterion is the purpose of modelling, which is focused on understanding system ***G***, i.e. dynamic interactions between ***G*** and the three systems ***P***, ***U*** and ***N*** in this study. Understanding means interpretation. This requirement results in the selection of fractals, landscape metrics, spatial auto-correlation, spatial logistic regression and CA. These methods all can be operated on raster data.

Fractals, spatial auto-correlation and landscape metrics are only quantitative spatial indicators rather than integrated modelling. They are limited to spatial variables and are not applicable to other socio-economic variables such as planning and administrative boundaries. Nevertheless, they are frequently used for exploratory data analysis.

Spatial logistic regression has proved very successful in quantifying the probability of land conversion. Its dependent variable corresponds to the two states of land conversion, the independent variables to the determinants of spatial patterns. Under the multi-scale framework set out in chapter 5, the method can also explain the probability of spatial self-organisation (i.e. the density of change).

As an effective spatial simulation tool, cellular automata itself cannot model the spatial and temporal processes of urban growth. It needs to integrate various variables that enable to interpret the causal effects of the processes. Its major advantage in modelling is dynamical updating the value of variables and its flexibility in the definition of transition rules. In this study, the transition rules are defined at two scales: municipality and project. This results in its strong interpretative capacity for understanding global and local temporal dynamics. However, these findings in this research do not mean that other methods cannot be applied for modelling. A key point is how to integrate these methods into the process of modelling and how to develop new methodologies to satisfy the requirements of urban growth panning.

As modelling aims to support the decision-making of various actors, the risks or reliability of modelling should be evaluated or estimated before using it. The accuracy of modelling is impacted by a number of factors such as data accuracy, data completeness, analytical techniques, model interpretability and modelling scale. Modelling scale refers to the number of variables considered in an integrated model. When modelling is carried out on a large scale such as 100 variables, certain points need to be considered. First, the computational time is likely to be massive. For instance it is difficult to imagine the computational hours needed to run an artificial neural network or CA model with 100 variables. Second, error propagation can be accumulated to a significant level, particularly when the data accuracy of most variables cannot be guaranteed. The more variables there are, the more errors they may accumulate. Third, sensitivity analysis will be difficult or even impossible to implement. Fourth, when a model calibrated in one time period is used for prediction in the next period, the model will undergo much change as a number of variables in the new period are already revalued. For this reason the accuracy of prediction modelling cannot be satisfactory especially in a long period of modelling. Consequently, modelling scale should be limited to an acceptable level for the selected modelling method.

7.4.3 Future work

This research focuses on spatial and temporal modelling, although it is important to take the economic processes underlying dynamic urban growth into account. Consequently, CA modelling is less successful in *explaining* the human behaviour that leads to the spatial processes/outcomes of urban growth, especially in explaining the spatial economic processes of land use change at the detailed level. Furthermore the unit of analysis in this study is either an individual pixel or some aggregation of structural or functional units, rather than the individual decision-maker.

The next step towards understanding complex dynamic processes is how to integrate economic behaviour and decision-making actors into spatially disaggregated simulation modelling. The CA-based modelling used in this research is disaggregated, dynamic, spatially and temporally explicit and globally linked to the decision-making process. However, it still has a number of limitations. For example, the probability of development or land conversion is determined principally by spatial constraints or factors, which are the spatial projection of socio-economic variables. However, the latter can be better linked to decision-makers (actors) to better interpret spatial behaviour. This model is also very little involved with the economic processes of urban growth, especially on a micro scale such as an individual or building level. As a result, it needs to be integrated with other methods such as multi-agent and micro-economic process modelling. The integration of the three methods can link spatial simulation with disaggregated spatial behaviour and the economic process.

To implement the ideas mentioned above, we need a data framework to locate spatial behaviour and represent the micro-economic process. The major spatial units should be able to integrate social and economic information in as disaggregated a manner as possible and spatially to locate micro-level decision-makers. The lowest census unit can be ideal for integrating socio-economic information and the land parcel can be the ideal spatial object to link with decision-makers. The individual parcel, which in most cases is the decision-making unit in the context of land use change, makes possible the use of micro-economic theory as well as micro-level theories from other sciences.

However, while parcel-based land information systems are technically feasible, they are still lacking in developing countries such as China. In China, the hierarchical administration structure is the primary source of socio-economic data (chapter 4). Figure 1 illustrates a spatial data framework to integrate parcel-based with socio-economic information for Chinese cities on which the proposed process modelling framework can be developed. This data framework links the decision-makers at parcel level with the social and economic information constraints at the block level. The latter is aggregated and disaggregated from administrative units.

With this data framework in mind, we are able to first develop a CA model based on the pixel level, which can have a similar size to that of buildings. A multi-agent (MA) model can be designed to simulate the decision-making behaviour of the parcel owner and other actors. Then an economic process model (EP) can be developed based on the block level. Finally, the heuristic rules (decision-maker behaviour constraints) from the MA and the socio-economic constraints from the EP can be incorporated into the CA transition rules. The units of parcel and block (the black box in figure 1) will become the major carrier of the spatial, behaviour and socio-economic information. The methodology can be tested with reference to an urban growth project in the period 1993-2000, as described in chapter 6.

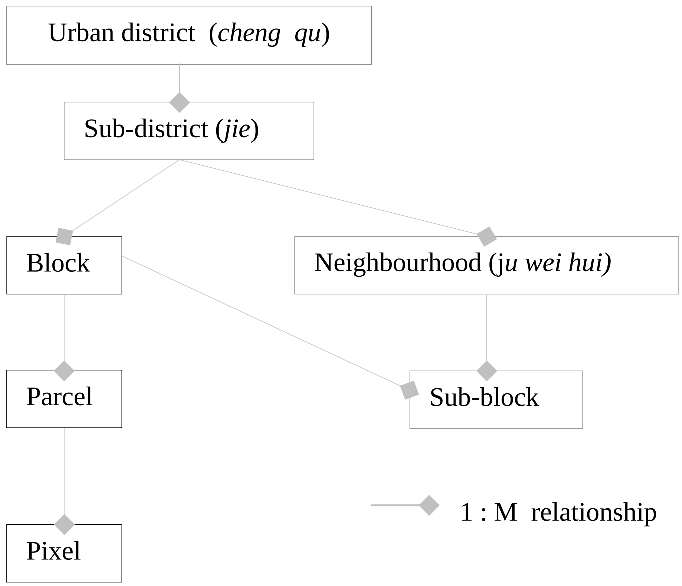

Figure 7.1 An integrated spatial data framework for process modelling in Chinese cities

However this method may lose the advantages of disaggregation. Another more promising approach treats parcel-based data as the socio-economic and decision-making constraints for CA or MA modelling at the pixel level. This treatment is actually a two-level modelling. At the parcel level, a socio-economic or transport/land use model is implemented to calculate the probability and density of new transitions that are determined by the spatial behaviour of actors and socio-economic demands. The proposed spatial data framework can provide detailed socio-economic data at the level of block for parcel-based modelling. At the grid level, the spatial and temporal pattern with each parcel will be simulated by CA or MA models.

7.5 Complexity theory

7.5.1 Understanding system G

As explained in chapter 2, urban growth ***G*** is a system resulting from the dynamic interactions between the three systems ***U***, ***P*** and **N**. This definition provides a theoretical framework for modelling and understanding complex urban growth systems. For example, chapter 3 examines the temporal changes that have taken place in Wuhan in five different periods from 1955 to 2000. These changes are systematically quantified using fractals, landscape metrics and other methods to indirectly evaluate temporal urban growth ***G***. Here, the system ***G*** from t_1 to t_2 was actually transformed into the system ***U*** in t_2. In chapter 4, the measurement of temporal urban growth ***G*** (t_1 - t_2) is based on both ***G*** itself and the system ***U*** in t_1. The relative degree of urban sprawl is impacted by the spatial relationship or interaction between ***G*** and ***U***. Chapter 5 focuses on the spatial pattern of system ***G*** as determined by the systems ***U***, ***P*** and ***N***. The independent variables in the pattern model are defined from these three systems. This is a multivariate pattern for understanding the spatial distribution of system ***G***. In chapter 6, the spatial and temporal processes of system ***G*** are also linked with these three systems. An important distinction from the pattern model lies in the fact that the process of ***G*** is also influenced by the dynamic iterations of ***G*** itself.

To sum up, system ***G*** cannot be modelled or understood independently without the support of the three systems. Among these four chapters, chapters 3 and 4 explore the functional aspects or activity components of system ***U***, which are represented by urban land uses. The activity component provides a more detailed socio-economic explanation for physical change ***G***.

Chapter 3 touches on the structural and functional complexity of system ***G***. Structural complexity aims to quantify the spatial form and morphology of the new system ***U*** transformed from ***G***. The system ***U*** is divided into the urban built-up area and the road network. Understanding the structure of the spatial system depends on the perspective of the modeller, different angles resulting in different interpretations. Chapter 3 examines two angles: dynamic development axes and space-fill, which develop into two structural analyses: dynamic morphology analysis and information-dimension-based fractal analysis. Fractal analysis is able to quantify the heterogeneous degree of the spatial distribution of system ***U***. Morphology analysis can reveal the temporal trend of ***U***. Functional complexity aims to quantify the spatial relationships among functional units. In this chapter, the functional unit means urban land use type. Each land use type is treated as a landscape unit. The landscape metric change can infer some of the social and economic processes shaping the functional landscape.

In chapter 4, temporal complexity is indicated by the temporal incompatibility of changing spatial objects. Comparative measurement is the first step towards understanding the temporal process, particularly in the long term. This complexity is transformed into a spatial complexity represented by the relative spatial relationship between systems ***G*** and ***U*** based on the concept of "relative space". A methodology consisting of four steps is developed to measure spatial complexity based on exploratory spatial data analysis. A major advantage is the integration of the physical space (system ***G***) with the activities (system ***U***), which results in an improvement in interpretative capacity.

In chapter 5, spatial complexity in pattern is indicated by spatial hierarchies (based on hierarchy theory), which leads to a multi-scale framework for understanding the spatial determinants of urban growth ***G***. The spatial hierarchies comprise planning, analysis and data, which are interrelated. The analysis hierarchy includes the probability of change, the density of change and the intensity of change. These provide more detailed information support for different levels of urban development planning. As a non-linear analysis method, spatial logistic regression (incorporating spatial sampling) together with exploratory data analysis is ideal for explaining the spatial impacts (static) of the three systems ***P***, ***N*** and ***U*** on system ***G***.

In chapter 6, complexity in process (spatial/temporal/decision-making) is indicated by the self-organisation of urban growth projects (based on the self-organising theory), and bottom-up and top-down decision-making processes. Self-organisation theory is able to explain the emergence of global spatial patterns from dynamic local interactions. This is one of the most important contributions of complexity theory to the social sciences, including urban planning. Based on this theory, cellular automata are shown to be ideal for simulating and understanding the temporal dynamics of the urban growth process at both the global and project levels. The multi-stage framework proposed makes the process of modelling more transparent to users and the process of decision-making more explicit. Dynamic weighting contributes to the understanding of the interaction between pattern and process. The methodology in this chapter can be utilised to explain the dynamic interactions between system ***G*** and the three systems ***P***, ***N***, ***U***.

7.5.2 Conclusions

In this research, the "project" has proved to be an important concept for representing urban growth as a basic unit. It is the carrier of the complex interactions between systems ***U***, ***P*** and ***N***. The self-organisation of social and economic processes in urban growth is projected on to the spatial clustering of new projects. Spatial self-organisation is represented by density (chapter 5) and neighbourhood (chapter 6) respectively. Chapter 3 focuses on the global description of all projects. Chapter 4 moves to the interaction between projects and the system ***U***. Consequently, the spatial and temporal organisation of projects is crucial to understanding the dynamic process of urban growth in this study.

This research has found that complexity theories such as hierarchy theory in chapter 5 and self-organising theory in chapter 6 are very helpful in conceptually and methodologically understanding the specific complexity of a complex system under study, e.g. ***G***. In reality, hierarchical structure and self-organising processes exist not only in spatial and temporal processes but also in social and economic processes. They are typically represented by the scale of land development and the density of local growth. Clusters of development projects are generated by cumulative and aggregated self-organizing processes. These ideas form the general theoretical basis for spatial modelling. However, when applied to any specific topic, they should be linked to the purpose of modelling and the specific complexities under study. For example, in this research, the purposes of modelling include what information should be produced to support various levels of urban development planning (chapters 3, 4 and 5) and what environment should be offered to support the process of development planning (chapter 6). Specific complexity includes spatial/temporal and decision-making processes as described in detail in chapter 2.

As a generalised universal systematic philosophy, complexity theory is an emerging science that has not received enough attention, particularly in the fields of urban planning and management. On the one hand, the discipline itself is still in its infancy; the theories and modelling methods currently available are not adequate for completely understanding a complex system. On the other hand, there is also a big gap between theory and practice. In reality, no required data exist for testing and developing new theories. Despite these barriers, the applications of complexity in relevant disciplines such as ecology and economics have made great progress. The limited empirical studies described in previous chapters have shown the great potential of complexity theory and methods for urban growth planning and management. First, they facilitate systematic thinking about complex phenomena with qualitative and conceptual understanding and knowledge. Second, they provide advanced methods for developing practical and quantitative methodologies to support the process of decision-making. Third, however, the complexity in urban growth indicates that current theories and methods need further development. Complexity research can take urban growth as a typical example of human-nature interaction including its spatial, temporal and decision-making complexity.

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Summary

In an effort to better understand the complexity inherent in the urban growth process, the aim of this research was to develop a theoretical framework and methodology that focused on:

1. Analysing the complexity of the urban growth system and evaluating the current methods available for modelling this complexity;
2. Monitoring the urban growth of a fast growing city (Wuhan) in a rapidly developing country (P.R.China), based on remotely sensed imagery, and evaluating its structural and functional changes by modelling;
3. Developing and demonstrating a quantitative method for the comparative measurement of long-term temporal urban growth;
4. Developing and demonstrating an interpretable method for urban growth pattern modelling;
5. Developing and demonstrating a spatially and temporally explicit method for understanding the urban growth process.

First, urban growth is defined as a system resulting from the complex dynamic interactions between the developable, developed and planned systems. Its complexity can be distinguished by projecting onto the spatial, temporal and decision-making dimensions. The specific complexity is linked with the major current methods of modern urban modelling, such as cellular automata, fractals, neural networks, multi-agent and spatial statistics. This confrontation makes it possible to indicate the possibilities of various modelling methods to understand urban growth complexity. Based on the theoretical and operational consideration, this study concentrates on the complexity in structural and functional change, temporal comparability, spatial patterns and spatial-temporal processes.

Second, with remotely sensed imagery (SPOT and aerial photographs) and secondary sources, this research presents a methodology for monitoring and evaluating structural and functional changes in the last five decades. This methodology primarily comprises morphology analysis, urban land use structure change and spatial pattern analysis, using fractal and landscape metrics approaches. The findings show that the integration of multiple spatial indicators can improve the capacity for interpretation, such as evaluation. This case study reveals temporal variations in the spatial urban growth process.

Third, this research presents an innovative method for the temporal measurement of long-term urban growth for the purpose of comparing urban sprawl. By using the concept of relative space, the temporal complexity can be transformed into spatial complexity, indicated by the complex spatial interactions between urban sprawl and urban social and economic systems. The method comprises temporal mapping, data disaggregation, integration on spatial gravity, and global evaluation. The findings reveal that the macro patterns of urban sprawl can be interpreted and compared from micro urban activities, as activities are directly linked with actors and their behaviour. This research also shows that

pattern, process and behaviour must be integrated into a whole towards understanding the complexity in urban growth.

Fourth, this research presents a preliminary multi-scale perspective for understanding spatial patterns based on spatial hierarchical theory. The spatial hierarchies comprise planning, analysis and data, which are interrelated. Multi-scale in analysis hierarchy refers to the probability of change (macro), the density of change (meso) and the intensity of change (micro). The multi-scale analysis seeks to distinguish spatial determinants on each of the three scales, which are able to provide deeper insights into urban growth patterns shaped by spontaneous and self-organised spatial processes. The framework is implemented by using exploratory data analysis and spatial logistic regression. This combination is proven to have a strong capacity for interpretation. The scale-dependent and scale-independent determinants are found significantly on two scales.

Fifth, this research presents an innovative method for understanding spatial processes and their temporal dynamics on two interrelated scales (municipality and project), using a multi-stage framework and dynamic weighting concept. The multi-stage framework aims to model local spatial processes and global temporal dynamics by incorporating explicit decision-making processes. It is divided into four stages: project planning, site selection, local growth and temporal control. These four steps represent the interactions between the top-down and bottom-up decision-making involved in land development for large-scale projects. Project-based cellular automata modelling is developed for interpreting the spatial and temporal logic between various projects forming the whole urban growth. As a non-linear function of temporal land development, dynamic weighting is able to link spatial processes and temporal patterns at the project level. The findings from this research suggest that this method can facilitate and improve the temporal and transparent interpretation and visualisation of the dynamic process of urban growth globally and locally.

Finally, this research has found that complexity theories such as hierarchy theory and self-organising theory are very helpful in conceptually and methodologically understanding the specific complexity of a complex system. Spatial and temporal modelling based on complexity methods such as cellular automata can improve the analytical functions of GIS with the aid of remotely sensed imagery.

Samenvatting (summary in Dutch)

Met het oog op het begrijpen van de complexiteit die kenmerkend is voor stedelijke groei, is het doel van deze studie het ontwikkelen van een theoretisch kader en een methodologie gericht op:

1. Het analyseren van de complexiteit van het stedelijke groeisysteem en het evalueren van gangbare methoden om deze complexiteit te modelleren.
2. Het volgen van de stedelijke groei van een snelgroeiende stad, Wuhan, in een zich snel ontwikkelend land (China), op basis van aardobservatie en door middel van het modelmatig evalueren van structurele en functionele veranderingen.
3. Het ontwikkelen en toepassen van een kwantitatieve methode voor het vergelijkend meten van stedelijke groei over lange periodes.
4. Het ontwikkelen en toepassen van een interpreteerbare methode voor het modelleren van stedelijke groeipatronen.
5. Het ontwikkelen en toepassen van een tijdruimte-expliciete methode voor het begrijpen van het stedelijke groeiproces.

Eerst wordt stedelijke groei gedefinieerd als een systeem dat de uitkomst is van complexe en dynamische interacties tussen ontwikkelbare, ontwikkelde en geplande territoriale systemen. De complexiteit kan begrepen worden door uit te gaan van ruimtelijke, temporele en besluitvormingsdimensies. De specifieke complexiteit komt tot uiting in de belangrijkste methoden die thans gebruikt worden voor stedelijke modellering, zoals celautomaten, fractals, neurale netwerken, multi-actor systemen en ruimtelijke statistiek. Deze confrontatie van methoden resulteert in het aangeven van de mogelijkheden van de verschillende vormen van modelbouw voor het begrijpen van de complexiteit van stedelijke groei. Gebaseerd op theoretische en operationele overwegingen, richt dit onderzoek zich op structurele en functionele veranderingen, vergelijkingen in de tijd, ruimtelijke patronen en tijdruimte-processen.

Gebaseerd op aardobservatiebeelden (SPOT en luchtfoto's) en op secundaire bronnen, presenteert deze studie vervolgens een methodologie om structurele en functionele veranderingen in Wuhan voor de afgelopen vijf decennia te monitoren en te evalueren. Deze methodologie is voornamelijk gebaseerd op ruimtelijke vormanalyse, grondgebruikanalyse en ruimtelijke patroonanalyse met behulp van fractal en landschapmetrie benaderingen. De uitkomsten tonen aan dat de integratie van meervoudige ruimtelijke indicatoren de mogelijkheden voor interpretatie kunnen verbeteren, bijvoorbeeld ten behoeve van evaluaties. De gevalstudie laat de temporele variaties in het ruimtelijke groeiproces van de stad Wuhan zien.

Om stedelijke groei over langere perioden te kunnen meten, met name om verstrooiing van grondgebruik en functies te vergelijken, is een innovatieve methode ontwikkeld. Door uit te gaan van het concept 'relatieve ruimte' kan temporele complexiteit vertaald worden naar ruimtelijke complexiteit, bepaald door ruimtelijke interacties tussen stedelijke verstrooiing en het stedelijke sociaal-economische systeem. De methode bestaat uit temporele kartering, disaggregatie van gegevens, integratie op basis van ruimtelijke zwaartekracht en algemene

evaluatie. De resultaten laten zien dat de macropatronen van urbane verstrooiing vergeleken en geïnterpreteerd kunnen worden vanuit activiteiten op microniveau omdat ze direct te verbinden zijn met het gedrag van bepaalde actoren. Ook wordt aangetoond dat analyses van patronen, processen en gedrag geïntegreerd moeten worden om de complexiteit van stedelijke groei te kunnen begrijpen.

Het vierde onderdeel van de studie is de ontwikkeling van een voorlopig meerschalig, op de theorie van ruimtelijke hiërarchieën gebaseerd, perspectief voor het begrijpen van ruimtelijke patronen. De ruimtelijke hiërarchieën hebben betrekking op planning, analyse en gegevens in onderlinge samenhang. Meerschaligheid in de gegevenshiërarchie verwijst naar de waarschijnlijkheid van verandering (macro), de dichtheid van verandering (meso) en de intensiteit van verandering (micro). De meerschalige analyse tracht ruimtelijke determinanten te onderscheiden op elk van de drie niveaus om meer inzicht te krijgen in stedelijke groeipatronen die ontstaan onder invloed van spontane en op zelforganisatie gebaseerde ruimtelijke processen. Het kader is geïmplementeerd door verkennende gegevensanalyse en ruimtelijke logistische regressie te gebruiken. Deze combinatie heeft bewezen krachtige mogelijkheden voor interpretatie te bieden. De schaalafhankelijke en schaalonafhankelijke determinanten blijken significant te zijn op twee schaalniveaus.

Een meerfasen-benadering en een dynamisch wegingconcept worden vervolgens toegepast voor een nieuwe methode om ruimtelijke processen en hun temporele dynamiek op twee samenhangende niveaus (gemeente en project) te begrijpen. De meerfasen-benadering is bedoeld om locale ruimtelijke processen en algemene temporele dynamiek te modelleren door expliciet besluitvormingsprocessen mee te nemen. Er wordt een onderscheid in vier fasen gemaakt: projectplan, locatiekeuze, locale groei en uitvoeringsbeheer. Deze vier stappen representeren de interacties tussen neerwaartse en opwaartse besluitvorming bij de ruimtelijke ontwikkeling van grootschalige projecten. Een projectgebaseerde modellering op basis van celautomaten is ontwikkeld om de ruimtelijke en temporele logica tussen de verschillende projecten die de stedelijke groei bepalen te kunnen interpreteren. Dynamische weging is, als een niet-lineaire functie van de ontwikkeling van grondgebruik, in staat ruimtelijke processen te verbinden met temporele patronen op projectniveau. De resultaten van het onderzoek geven aan dat deze methode een verbeterde inzichtelijke interpretatie en visualisatie van dynamische processen van plaatselijke en algemene stedelijke groei oplevert.

Tenslotte kan geconstateerd worden dat complexiteitstheorieën, zoals hiërarchietheorie en zelforganisatietheorie, waardevol zijn om zowel conceptueel als methodologisch de specifieke complexiteit van een systeem te begrijpen. Tijdruimtelijke modelbouw op basis van methoden zoals celautomaten kunnen de analytische mogelijkheden van GIS verder verbeteren, in het bijzonder met behulp van aardobservatiegegevens.

Het plannen van stedelijke groei en het beheersen van stedelijke verstrooiing zijn belangrijke vraagstukken in de geografische wetenschappen geworden. Ze zijn ook van belang voor andere wetenschapsgebieden en leiden tot een behoefte aan wetenschappelijk begrip van dynamische processen.

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Curriculum Vitae

Jianquan Cheng was born on October 5, 1966 in Shucheng, Anhui, P.R.China. He completed his secondary education at the No:1 High School of Luan in 1984. He received his Bachelor of Science degree in Mathematics from University of Shandong in 1988. He joined Wuhan Technical University of Surveying and Mapping (WTUSM) from 1988. In his early years at WTUSM, he took part in various projects involving remote sensing and geographic information system for urban applications. He undertook the Master of Science (MSc) course (GIS for Urban Application) in September, 1993. He earned his MSc degree with a thesis entitled 'GIS for Urban Redevelopment in Transformation, a case study of Wuhan City, P.R.China'. After returning to WTUSM, he has been involved in "urban systems engineering" lecturing and GIS applications and relevant projects regarding GIS construction.

With the financial aid of the DSO project between China and the Netherlands, he started his doctoral research in April, 1999. This research has resulted in about ten scientific papers in international peer-reviewed journals (published or submitted) and in the proceedings of the international conferences/symposia in which he participated.