Abstract

Cellular automata (CA) have been in popular use for urban geosimulation. However, CA modeling in urban geosimulation is still in its infancy and at a development phase, being faced with many challenges, such as grid size selection, land use category identification, modeling neighborhood interactions as well as appropriate calibration approach. Urban area has grown greatly in the last century in the Tokyo metropolitan area, and the trend would continue according to the population projections. Due to this rapid urban growth, a lot of environmental changes have occurred. This study aims at modeling spatial process of urban growth in the Tokyo metropolitan area using CA so as to improve the methodology in the application of CA coupled with Geographical Information System (GIS) to urban modeling. In particular, this research focuses on three fundamental elements of the CA - the grid size, the cell state, and the neighborhood effect.

The situation and limitation of urban analysis using remote sensing technique is discussed. The data set “Detailed Digital Information (10m grid land-use) Metropolitan Area” of Tokyo (DDIMA10m) is chosen as basic data set for this research. Based on the data set, fractal dimension and spatial metrics are adopted to analyze the characteristics of spatial process of urban growth in the Tokyo metropolitan area. The results illustrate the characteristics of compact growth or conglomeration of the existing urbanized area, and indicate that urbanized area takes bifractal structure in the period from 1974 to 1994.

Grid size and cell state are most important elements in the definition of CA. How to theoretically identify grid size and cell state of CA is explored in this research. The results illustrate that grid size of CA and urban land-use classification systems affect the understanding of spatial process of urban growth. This research provides theoretical justification approaches for selecting grid size and land-use classification system in CA-based urban models.

Traditionally, modeling urban growth always deals with study areas into binary categories of land use: urbanized area and non-urbanized area. The fact is omitted that urban growth is the results of the emergence of various urban activities as well as their interactions and competition. In this research, urbanized area is divided into detailed land-use types, and the emergence, interaction, and competition of these land-use types yield the fact of urban growth. An alternative neighborhood effect model is proposed based on the integration of the theory of Tobler's First Law of Geography with Reilly's gravity model and coupled with logistical regression approach. This model provides a new method to calibrate the neighborhood interactions in the spatial process of urban growth instead of traditional "trial and error" approach.

Constrained CA model is used to simulate the urban growth in the Tokyo metropolitan area in 1994. Compared with actual land-use pattern in 1994, the results of simulation are discussed at both of macro classification scale and micro classification scale in four ways: quantitative comparison through cell-by-cell, comparison of spatial form of urbanized area through fractal dimension, comparison of urban landscape through spatial metrics, and regional characteristics analysis. The results indicate that urban geosimulation model proposed in this research can visually and well simulate the spatial process of urban growth of the Tokyo metropolitan area, and can be applicable in others regions for predicting the spatial process for the future by urban planners.

Keywords: cellular automata; urban growth; geosimulation; geographic information system and science; neighborhood interactions; the Tokyo metropolitan area; spatial model; complex systems

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Chapter one

Introduction

1.1 Problem statement and research questions

Land-use and Land-cover Changes (LUCC), as one of the main driving forces of global environmental change (Fresco *et al.*, 1997; Turner II *et al.*, 1997), significantly affect key aspects of Earth System functioning (Lambin *et al.*, 2001). They directly impact biotic diversity worldwide (Sala *et al.*, 2000); contribute to local and regional climate change (Chase *et al.*, 2000) as well as to global climate warming (Houghton *et al.*, 1999); are the primary source of soil degradation (Tolba *et al.*, 1992); and, by altering ecosystem services, affect the ability of biological systems to support human needs (Vitousek *et al.*, 1997). Therefore, LUCC undoubtedly have become a central theme of global environmental change research (Turner II, 1994; Vitousek *et al.*, 1997) and attracted sweeping attentions of scientists with background in different disciplines, ranging from anthropology to mathematical programming.

Generally it is recognized that natural forces and human activities are two factors of main driving forces on LUCC at a local and global scale. However, at short time scale (Several dozens years or even one hundred years), the effect of natural forces is comparatively less than that of human activities (Ye and Fu, 1994), and the most striking human-induced land transformation of the current era is that of urbanization (Clarke *et al.*, 1997). Traditionally, urbanization was recognized as a process of population concentration (Tisdale, 1942), which is mainly derived

from industrialization and modernization (Smailes, 1975). It proceeds in two ways: the multiplication of the points of concentration and the increase in size of individual concentrations. Nevertheless, with the development of modernization, another manifestation of urbanization has come into being, which was associated with the transformation of the socio-economic life of settlements inherited from the former agrarian pattern, especially in metropolitan area in developed countries (Smailes, 1975). Villages in these areas have become settlements of people who have urban associations by reason of their work or background, manifestations of which may well be seen as a further step in a continuing process of urbanization (Smailes, 1975). However, no matter which kinds of manifestation, the process of urbanization brings on the spread of urbanized area into the surrounding countryside of cities and towns, and spawning suburbs and swallowing up farms and villages, which are the idioms of modern urban growth (Qadeer, 2004). Therefore, urbanization has been primarily a phenomenon of urban growth (Qadeer, 2004).

Past centuries were such a period with rapid urbanization all over the world, in which most people quickly congregated in the urban area or metropolitan area. In a longer timescale, 200 years, total global population has increased six times and the earth's urban population has increased over 100 times (Hauser *et al.*, 1982). The urban population in the world was estimated at 2.4 billion in 1995 and is expected to double at about the year 2025 (Antrop, 2000). Increasing population and urbanization result in the most complex process of land-use and land-cover changes from local to global scale. Pond and Yeates (1994) estimated for a growing country in Canada that, in addition to the actual urban area, 20% of the land was in the process of the urban transition and 2% was in ex-urban uses, fully dependent on the urbanized areas (Pond and Yeates, 1994). This process, in turn, has profoundly disrupted the structure and function of ecosystems. While the urbanized areas taken by the huge population account for only 2% of the Earth's land surface (Grimm *et al.*, 2000), they consumed more than 75% of its resources (May, 2004), and land-use and land-cover changes caused by the rapid urbanization have greatly impacted the

local (Lin and Ho, 2003; McKinney, 2006; Paul and Meyer, 2001) and global environmental changes (Grimm *et al.*, 2000; Lambin *et al.*, 2001). Consequently, to effectively discern and interpret spatiotemporal patterns, relationships, and interactions among features, activities, and events in the process of urbanization have long been hot topics in multi disciplines, especially in geography. In addition, city planners also greatly pay attention to the understanding of urbanization process as they try to learn how to plan urban land-use more effectively by systematically evaluating the outcomes of past planning attempts (Kaiser *et al.*, 1995). Ideally they would like to see the possible consequences of the plans and policies they may have under consideration.

Early efforts achieved by geographers, economists, and social scientists with regard to understanding the morphology and evolution of cities coming from urbanization were three classic theories: the concentric zone theory (Burgess, 1925), the sector theory (Hoyt, 1939), and the multiple nuclei theory. Since the 1960s, a variety of new theories and methods have been used for describing the form and formation of urban systems. These include catastrophe theory (Wilson, 1976), chaos theory (Wilson, 1981; Wong and Fotheringham, 1990), dissipative structure theory (Allen and Sanglier, 1979b), fractals (Batty and Longley, 1989; Frankhauser and Sadler, 1991; White and Engelen, 1993), and theory of self-organization (Portugali, 2000; Schweitzer, 1997).

Many of the theories developed are more accurately described as models, as they consist of a series of interconnected hypotheses, rather than a set of empirically validated laws (Macmillan, 1989). A model is often an idealized representation of reality, in order to demonstrate certain of its properties. Such idealized representations are abstractions of reality and omit certain unimportant details. The process of model building, therefore, represents a procedure for making these abstractions (Thomas and Huggett, 1980).

Modeling, especially if done in a spatially-explicit, integrated and multi-scale manner, is an important technique for the exploration of alternative pathways into the future, for conducting

experiments that test our understanding of key processes, and for describing the latter in quantitative terms (Lambin *et al.*, 2000). Batty (1971) pointed out three principal roles for mathematical models of cities can be distinguished. First, such models have been developed to help in refining and experimenting with hypotheses about the structure of cities; they form an essential part of theory development in urban research. Second, models have been used to provide methods for educating planners in urban theory. Third, and perhaps most important, the models can be used in practical planning studies to help predict the likely consequences of planning or not planning the future of cities (Batty, 1971). Like other geographic phenomenon, urban growth is not easily experimented with on the ground. Realistic but synthetic computer simulation based on spatial explicitly models can be built as a laboratory for exploring ideas and plans that we would not otherwise be able to effect on the ground. Modeling can be used as a planning support system (PSS), to pose what-if question and evaluate likely or alternative outcomes.

In contrast with the static models of urban morphology developed in 1950s, new approaches in urban modeling after 1960s emphasized the dynamics of urban form and its relation to generating processes. Also in sharp contrast with the traditional views, these new approaches were based on non-equilibrium and nonlinear systems perspectives. In addition, from fractals to cellular automata and to self-organization, bottom-up and local interactions were viewed essential for the formation of urban systems.

The thing that cellular automata (CA) were introduced into urban modeling has been deemed as an important innovation in the field of urban modeling. The cellular automaton is a rule-based algorithm that has been long employed in computer science to explore social and physical phenomena (Wolfram, 2002). For some time now, CA have been in popular use for urban geosimulation (Barredo *et al.*, 2003; Batty, 1998; Batty *et al.*, 1999; Clarke and Gaydos, 1998; Clarke *et al.*, 1997; White and Engelen, 2000; White *et al.*, 1997; Wu, 1998a; Wu, 2002; Xia and Yeh, 2000; Yeh and Xia, 1998; Yeh and Xia, 2002). CA have many advantages for

modeling urban phenomena, including their decentralized approach, the link they provide to complexity theory, the connection of form with function and pattern with process, the relative ease with which model results can be visualized, their flexibility, their dynamic approach, and also their affinities with Geographic Information Systems (GIS) and remotely sensed data (Torrens, 2000). However, although CA have been largely adopted in urban geosimulation, there are several key areas on which those working with urban CA might focus future efforts and build upon existing success: exploration in spatial complexity, infusing urban CA with theory, exercises in education and outreach, the development of hybrid model structures, and new strategies for validating cellular urban models, proposed by Torrens and O'Sullivan in 2001.

Nevertheless, aside from these peripheral problems, some intrinsic techniques in the application of CA to urban geosimulation also have not been well dealt with. Formally, a finite cellular automaton A can be represented by means of a finite set of states $S = \{S_1, S_2, \ldots, S_N\}$ and a set of transition rules T, which is associated with a neighborhood configuration R neighboring A:

$$A \sim (S, T, R) \tag{1-1}$$

The state of cellular automaton A changes over time based on its internal transition rules T and external input. Up to date, how to identify appropriate size of automaton A and the states S to represent the objects' behavior in urbanized area has not been theoretically justified yet in the field of urban geosimulation using CA. The neighborhood R also has no theoretical configuration. These problems undoubtedly influence the understanding of urban growth process (Claire and Scott, 2005; Yeh and Li, 2006).

As one of top megacities in the world, urban land-use has greatly changed in last century in the Tokyo metropolitan area as the population has grown largely, and the trend would continue according to the population projections. Table 1 shows the change trend of population of 12 megacities in the world in period of 40 years from 1975 to 2015. Because of the rapid transformation of urban land-use, many kinds of environmental changes have occurred

Table 1.1 Top megacities in the world

Rank	City	Population (millions)		
		1975	2004	2015 (estimated)
1	**Tokyo**	**26.6**	**35.0**	**36.2**
2	Mumbai	7.3	17.4	22.6
3	Delhi	4.4	14.1	20.9
4	Mexico City	10.7	18.7	20.6
5	Sao Paolo	9.6	17.8	20.0
6	New York	15.9	18.3	19.7
7	Dhaka	2.2	11.6	17.9
8	Jakata	4.8	12.3	17.5
9	Lagos	1.9	10.1	17.0
10	Calcutta	7.9	13.8	16.8
11	Karachi	4.0	11.1	16.2
12	Buenos Aires	9.1	13.0	14.6

Source: May, 2004

(Ichinose *et al.*, 1999; Kondoh and Nishiyama, 2000; Saitoh *et al.*, 1996). Therefore, it is very essential to understand the mechanisms of urban growth in the Tokyo metropolitan area and make exploration of alternative pathways into the future through modeling the urban dynamics under the support of new theory and technology, CA, for instance. Moreover, since Japan is two or three decades or more time ahead of most of the developing countries of Asia (Sorensen, 2000), a better understanding of the Japanese case, especially the Tokyo metropolitan area, may be special interest to geographers and planners in those countries, and more generally to those interested in comparative urbanization and urban planning study.

Urban modeling for the Tokyo metropolitan area has been experienced for several decades. In 1983, the group of Nakamura at the university of Tokyo implemented the hierarchical Computer-Aided Land-Use Transport Analysis System (CALUTAS) for the Tokyo metropolitan area (Nakamura *et al.*, 1983). The group later spread to Yokohama, where Miyamoto independently developed the Random-Utility URBAN model (RURBAN), an equilibrium land market model (Miyamoto and Kitazume, 1989; Miyamoto *et al.*, 1986). These models typically belong to large-scale urban models. In 1993, Murayama adopted Markoff's chain model to predict aggregated changes of the land-use at micro-level scale for the Tokyo metropolitan area, which was divided into several sub-areas according to orientation and distance to the center of the Tokyo (Murayama, 1993). In 2004, Arai and Akiyama estimated the land-use transition potential functions at a high-resolution scale in a case of study area in the northeast of the Tokyo metropolitan region, including the parts of Kashiwa, Abiko, Nagareyama, Matsudo city and Shonan town (Arai and Akiyama, 2004). However, they did not simulate the land-use change in this area using the explored functions.

In 1998, a data set, "Detailed Digital Information (10m grid land-use) Metropolitan Area" of Tokyo was released by the Geographical Survey Institute of Japan. This date set provides essentially abundant information for studying on urban geosimulation using CA. Here, with the help of this kind of data set, this research focuses on the methodology of application of CA to

model spatial process of urban growth using the Tokyo metropolitan area as a case study.

1.2 Objective of this study

The proposed objective of this study aims at gaining experience with the application of CA to model spatial process of urban growth in the Tokyo metropolitan area at high-resolution level so as to improve the methodology of urban modeling by investigating a number of questions:

(1). Spatial scale

According to O'Sullivan and Unwin (2002), as spatial pattern in any time is generated from corresponding spatial process, spatial model which aims at simulating the spatial process can be constructed through analyzing dynamic spatial patterns in time-series (O'Sullivan and Unwin, 2002), which are affected by spatial scale (Qi and Wu, 1996; Turner *et al.*, 1989). How about the effect of spatial scale on the result of pattern analysis of urban land-use changes and how to select appropriate spatial scale for urban geosimulation models?

(2). Land-use classification system

Urban land-use pattern occurs not just at certain scale, but also at certain land-use classification system. Cities are complex emergent systems, consisting of a more or less dense scattering of urban activities in the space which contains them. Land-use classification mostly comes from the understanding of urban activities. Most literatures concerning spatial models of urban land-use change just choose their own urban land-use classification system in terms of their own purpose in their research with no theoretical justification (Barredo *et al.*, 2003; White and Engelen, 1993; White *et al.*, 1997). Klosterman (2005) has pointed out that the number of land-use classes which can be projected and the scale at which they can be projected vary substantially for the different types of models (Klosterman, 2005). How do the different classification systems affect the analysis of urban land-use pattern? How is appropriate land-use

classification system selected for modeling the spatial process of urban growth?

(3). Transition rules

In a CA-based model transition rules describe how the state of each cell change over time based on local scale interactions. The richness of patterns that can be generated is impressive, but at the same time this implies that the selection of the right set of rules is a very critical part of developing the model. Finding a suitable set of transition rules is a tedious procedure which requires much time of the model builder. This research strives hard to make progress in this field, especially in identifying neighborhood interactions.

(4) Model calibration

A spatial model needs calibration. Usually calibration is called as the process of experimentation connected with the design of the model. The chief purpose of calibrating the model is to estimate the value of parameters which control the model's locational simulation, and the repercussions of activity through time. Calibration of high-resolution urban models is complex due to the many interacting coefficients that do not necessarily yield unique solutions: different processes (rule sets) may lead to identical patterns (Verburg *et al.*, 2004).

All the problems mentioned above puzzle the construction of urban geosimulation models using CA coupled with GIS. Study of these problems behind the construction of spatial model, which is an important part of research in GIScience, can even viewed as part of the science, if not part of the system (Goodchild, 1992).

1.3 Structure of the research

This dissertation is organized into five chapters. The research flowchart, which outlines the flow of the study, is illustrated in Figure 1.1.

Chapter one introduces a general overview of the study. This includes the problem

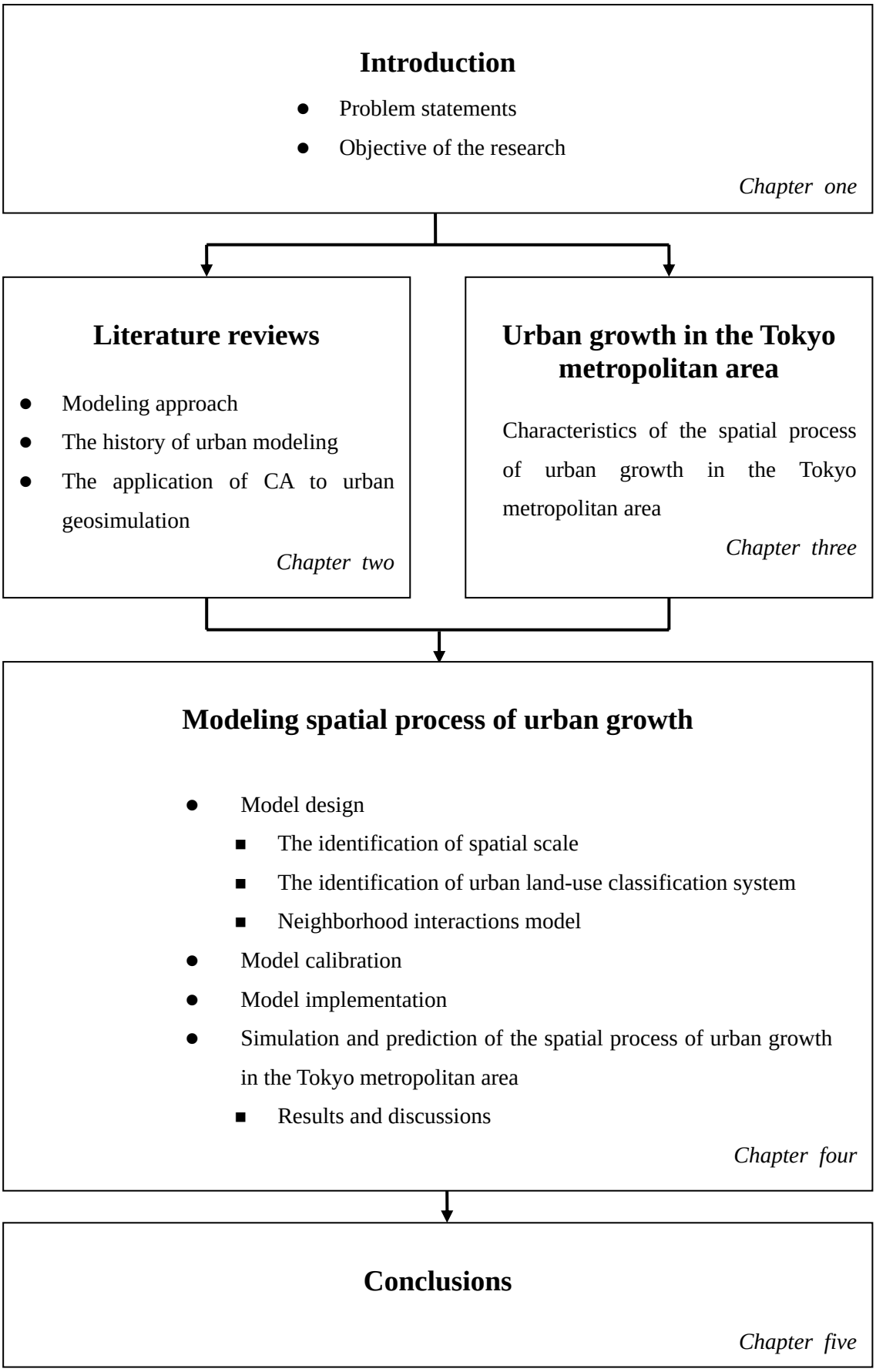


Figure 1.1 Research flowchart

statements, the main objectives and a brief outline of the structure of the research.

Chapter two provides the theoretical and methodological discussions that are relevant to this research. Firstly the necessity of modeling approach in the field of geographical domain is emphasized. Then the history of urban modeling is reviewed. The history of urban modeling can be divided into three phases according to the characteristics and spatial scale level of the models: static urban models, large-scale urban dynamic models, and urban geosimulation models. The characteristics of urban models in every phase are theoretically probed. Especially, from the viewpoint of the complexity of urban systems, this chapter focuses on the necessity and feasibility of the application of CA to modeling spatial process of urban growth. Some representative urban geosimulation models based on CA are reviewed, and the problems, prospects and modifications of CA for urban geosimulation are illustrated.

Chapter three analyzes the situation and limitation of urban analysis using remote sensing technique, and introduces the advantages of the data set “Detailed Digital Information (10m grid land-use) Metropolitan Area” of Tokyo in urban analysis. As a case study, the characteristics of urban growth in the Tokyo metropolitan area are addressed in terms of fractal dimension and spatial metrics respectively.

Chapter four looks at the construction of the spatial model proposed in this research for catching the spatial process of urban growth. Based on the principle of the application of CA to urban geosimulation, the concept of constrained CA-based model is put forward in this chapter. Two essential problems – identification of spatial scale and urban land-use classification system - in the model are theoretically elaborated in terms of spatial autocorrelation index. An alternative model proposed in this research for catching the neighborhood interactions effect in urban geosimulation is discussed in detail. This chapter also describes the processes of calibration for the spatial model. The model is carried out for simulating the spatial process of urban growth in the Tokyo metropolitan area, and the results and discussions are presented in this chapter.

Chapter five concludes the main findings of the study in relation to the research objectives.

Some perspective suggestions for further research are offered in this chapter.

Chapter Two
Theoretical consideration and literature reviews

2.1 Review of urban modeling

2.1.1 Modeling approach

Many of the theories developed by social scientists are more accurately described as models, as they consist of a series of interconnected hypotheses, rather than a set of empirically validated laws (Macmillan, 1989). A model is a simplified representation of an object of investigation for purpose of description, explanation, forecasting of planning (Fotheringham and Wegener, 2000). A spatial model is a model of an object of investigation in bispace (space, attribute). A space/time model (or dynamic spatial model) is a model of an objective of investigation in trispace (space, time, attribute). A model is also an idealized representation of reality, in order to demonstrate certain of its properties. Such idealized representations are abstractions of reality and omit certain unimportant details. The process of model building, therefore, represents a procedure for making these abstractions (Thomas and Huggett, 1980).

Modeling has become an important branch of scientific endeavor as the approach plays a vital role in science exploration (Cadwallader, 1996; Fotheringham and Wegener, 2000) and helps human being to effectively understand and plan the Earth and the world for the future.

Lambin et al. (2000) have pointed out that modeling, especially if done in a spatially-explicit, integrated and multi-scale manner, is an important technique for the exploration of alternative pathways into the future, for conducting experiments that test our understanding of key processes, and for describing the latter in quantitative terms (Lambin *et al.*, 2000).

In geographic domain, as most geographic phenomena are not easily experimented with on the ground, and the data are once-off and observational, with no opportunity to conduct repeated trials, realistic but synthetic computer simulations through modeling can be built, however, as a laboratory for exploring ideas and plans that we would not otherwise be able to effect on the ground. Modeling can be used as a planning support system (PSS), to pose what-if questions and evaluate likely or alternative outcomes.

2.1.2 Urban modeling: theories and practices

Urban models attempt to describe urban system using mathematical equations. They provide a simplified and abstract view of some aspect of the urban system and deal with the allocation and interaction of land-use activity in cities and regions. Urban modeling is a practical approach to urban analysis which firstly seeks to understand and describe the mechanisms which govern the structure and behavior of the urban system and secondly to predict the outcome of future policy decisions (Foot, 1981).

Urban models have quite a short history of development because they deal with large quantities of the data which can only be processed by computer. As the computer has been developed, increase in size and become generally available to all urban analysts, urban modeling has followed a similar course. Prior to the advent of computer in the late 1940s, some significant works about the morphology and evolution of cities had been done and a number of classical theories had been developed. Despite these theories could not been recognized as “true” urban models, undoubtedly they provided basis to further urban modeling (Batty, 1971). Research of urban modeling can be classified into three phases according to the characteristics and scale level

of models: static urban models, large-scale urban dynamic models, and urban geosimulation models.

(1). Static urban models

The early development in urban modeling was in transportation planning in the USA in order to try and study scientifically organized way the traffic problems arising from the enormous increase in car ownership (Batty, 1971; Foot, 1981). These models were representatives of partial models which deals with one part or subsystem of the overall urban system (Foot, 1981). These models were highly successful and led to more ambitious attempts to model other subsystems of the urban system such as the housing market and the location of retailing activity.

Consequently, model builders began to build more general models, which consider a number of subsystems, attempting to integrate the housing, retailing, and industrial sectors with the transport system. These models were first developed in the early 1960s in North America and followed previous developments in transportation systems analysis. The chief focus of this research was on the spatial variation of the pattern of activities such as population and employment and on the interactions between such activities. The technique of modeling interaction using the so-called gravity model, derived by analogy with the Newtonian concept of gravity, like Lowry model (Lowry, 1964) and Garin-Lowry model (Grain, 1966), and with the concept of entropy in statistical mechanics (Wilson, 1968), was central to much of this research and reflected the concern of the model builders with the interdependencies within the urban system (Batty, 1971). These models provided the clearest ideas of urban systems theory, which sough into integrate different activity systems according to spatial interactions that were embedded in demographic-economic frameworks (Batty, 1994).

In these models an important problem exists: concept. Nearly all models designed in this phase describe the city as a static system. Such models simulate the structure of the city at one

point in time but ignore the processes which have generated the structure. This means that these models are static urban models. However, city is a dynamic system (Forrester, 1969). So in building such static models, model builders have encountered severe problems which were concerned with the measurement and observation of certain variables. It is extremely difficult, for example, to find suitable variables which measure locational attraction in a static sense, for continual changes in such variables with time account for the present structure of the city (Broadbent, 1970). Furthermore, because these models lack historical perspective, they are difficult to use in forecasting (Batty, 1970).

Nevertheless, it was not that static model builders were not conscious of the necessity of making dynamic urban models. For instance, Lowry himself clearly understood that his model should become dynamic (Lowry, 1964). Batty (1971) analyzed two reasons of why dynamic models did not come into being in this phase. First, in building such models, cities are usually divided into homogeneous areas or zones, and the smaller the size of zones, the greater is the descriptive power of the model. But as the number of zones increase, more and more detailed data are needed and computer storage requirements increase, often exponentially. Second, it is difficult to collect the necessary time series data required in testing and validating the models. These difficulties in observing the processes of change have also led to problems in formulating meaning hypotheses about the dynamics of cities and setting up relevant experiments.

(2). Large-scale urban dynamic models

With the development of computer science and technology, large-scale urban dynamic models appeared in late 1960s. In this phase, there are two precursors who are worthy of mention: Crecine and Forrester. In 1968, Crecine presented the time oriented metropolitan model which was designed to simulate changes in the structure of activities in time intervals of 5 years or more (Crecine, 1968). Forrester’s model is based on his concepts of industrial dynamics and simulates the processes of change in a hypothetical city in 5 years intervals over a 250 years

period (Forrester, 1969). These models typically yield results that are relatively complex, both temporally and spatially. In this approach, the focus is on the process, which may or may not lead to a stable equilibrium; but, in any case, these models do not depend on an assumption of equilibrium. Figure 2.1 shows the simulation result of one city using Forrester's model of urban dynamics, which is a representative export of large-scale urban dynamic models. The model is, however, not spatial and does not recognize that the structure of activities in a city can be explained in terms of spatial interaction. Moreover, although these models show that the dynamic processes in the cities can be simulated, at least in part, the models are not comprehensive in their treatment of both time and space as essential determinants of the structure of cities (Batty, 1971), and it is impossible to achieve more than a very crude spatial resolution. Subsequently, Wilson (1970) published his dynamic model which modified spatial interaction model by entropy-maximizing methodology (Wilson, 1970). Batty (1971) designed a dynamic model at the University of Reading to simulate the changing structure of activities and interactions between activities at intervals of one year over a 15 years period (Batty, 1971).

The 1970s was also a turbulent time for urban modeling; as a field of research, urban modeling drew heavy criticism in that period and was all but written off as a failure. In 1973, a publication entitled as "Requiem for large-scale models" by Lee (1973) deprecated the equally ambitious attempts to develop large-scale computer models of the metropolis in perspective in urban planning context (Lee, 1973). However, these criticisms did not stop the design of urban models. With the development of computer science and technology as well as the application of new ideas, a lot of new models and demonstrations were implemented by many workers (Allen *et al.*, 1984; Allen and Sanglier, 1979a; Clarke and Wilson, 1983; Dendrinos and Sonis, 1990; Haag, 1989; Nijkamp and Reggiani, 1992; Weidlich and Haag, 1987). Especially, Wegener (1994) indicated the pomp of urban modeling through a world map of urban modeling centers at the twenty years after the Lee's criticisms in 1973 (Wegener, 1994). In his paper, twelve contemporary operational urban models were evaluated, using as criteria comprehensiveness,

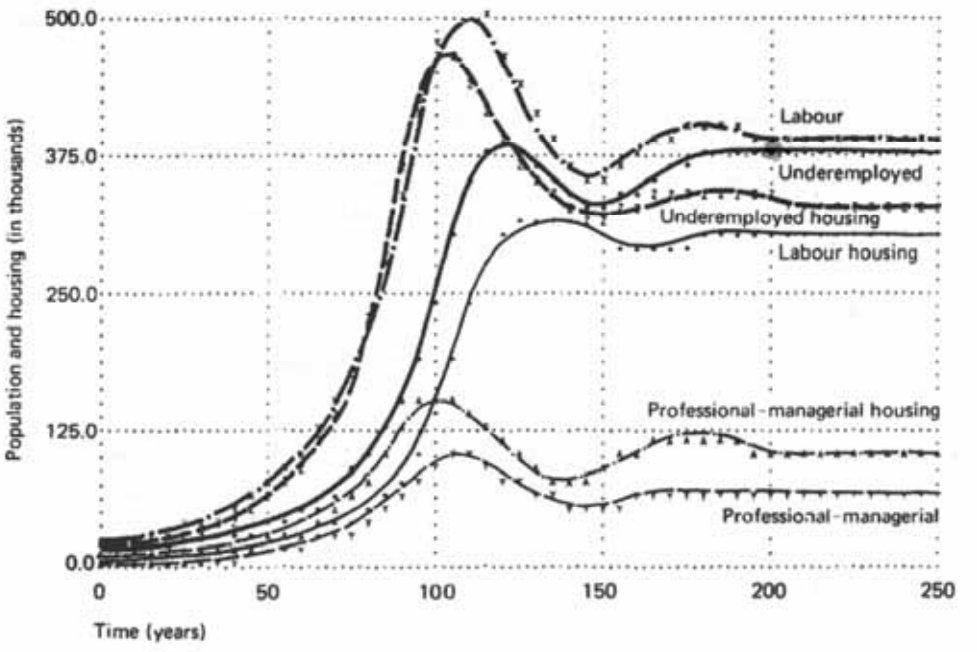


Figure 2.1 Dynamics of population and housing in Forrester's model of urban dynamics (*Source:* Forrester, 1969)

overall structure, theoretical foundations, modeling techniques, dynamics, data requirements, calibration and validation, operationality, and accrual and potential applications. It is shown that most of the criticisms of the Requiem have been made redundant by advances in data availability and computing technology.

Much of these works, however, although alluding to disaggregate locational structures in cities, has been pitched at the traditionally macrolevel and thus it has been hard to develop coherent explanations of the king of changes emerging from the smallest scales which subsequently restructure the macroform of the system (Batty, 1998). This kind of cognition on urban phenomena motivated the emergence of urban geosimulation models at micro-scale level.

(3). Urban geosimulation models

Urban geosimulation models differ from conventional urban models in its constituent "elements". They operate with human individuals and infrastructure entities, represented at spatial nonmodifiable scales such as households, homes, or vehicles. In geosimulation models, these objects behave. Many of these objects are animated (visually and dynamically), and that animation drives the behavior of inanimate objects in a simulation. In Batty's paper, "New ways of looking at cities", published in 1995, he pointed out that those "from top to down" large-scale urban models are being gradually replaced by these "from the bottom up" models which based on local spatial interactions of individual activities (Batty, 1995).

CA - based models (Tobler, 1970), DLA (diffusion-limited aggregation) (Batty and Longley, 1994), percolation model (Makse *et al.*, 1995), and multiagent-based models (Benenson and Torrens, 2004) fall into this kind of urban models. Although other models have their advantages in simulating urban dynamics, undoubtedly CA has led the stream of urban modeling research in this phase as it has attracted the attention of numbers of scientists in both research aspects of theory (Batty, 1998; Batty and Xie, 1994; Clarke *et al.*, 1997; Couclelis, 1985; Couclelis, 1997; Dietzel and Clarke, 2006; Fang *et al.*, 2005; Itami, 1988; O'Sullivan and Torrens, 2000; Phipps,

1989; Tobler, 1970; Tobler, 1979; Torrens and David, 2001; Wagner, 1997; White and Engelen, 1993; White and Engelen, 1997; Yeh and Li, 2006) and application (Batty *et al.*, 1999; Silva and Clarke, 2002; Straatman *et al.*, 2004; Ward *et al.*, 2000; White and Engelen, 1994; White and Engelen, 2000; White *et al.*, 1997; White *et al.*, 1999; Wu, 1996; Wu, 1998a; Wu, 2002; Xia and Yeh, 2000; Yeh and Xia, 1998; Yeh and Xia, 2001; Yeh and Xia, 2002). Compared with other kinds of models, CA have many advantages for modeling urban phenomena, including their decentralized approach, the link they provide to complexity theory, the connection of form with function and pattern with process, the relative ease with which model results can be visualized, their flexibility, their dynamic approach, and also their affinities with geographic information systems and remotely sensed data (Torrens, 2000). This research focuses on the methodology of the application of CA to modeling spatial process of urban growth.

2.2 Cellular automata-based urban modeling

2.2.1 Cellular automata as a framework for modeling complex spatial systems

2.2.1.1 Formal definition of CA

The invention and early development of the CA framework took place in the 1950s and 1960s and is generally associated with famous names and great discoveries of the twentieth century (Benenson and Torrens, 2004). Its former form can ascents to Alan Turing's "Computational machine" (Turing, 1936) and John von Neumann's self-reproducing artificial structures (von Neumann, 1951). The formal definition of cellular automata (originally "cellular space") offered in von Neumann's lecture of 1951 (von Neumann, 1951) is just the same as the definitions used today. Under von Neumann's scheme a CA is defined as a one- or

two-dimensional grid of identical automata cells. Each automata cell processes information, and proceeds in its actions based on the knowledge received from its environment and following rules that it stores or holds internally. Each cellular automata A is defined by a set of states $S = \{S_1, S_2, \ldots, S_N\}$ and a set of transition rules T, as well as a set of cells (in the neighborhood R) neighboring the cellular automata A:

$$A \sim (S, T, R) \tag{2.1}$$

Transition rules define an cellular automaton's state, S_{t+1}, at time step $t+1$ depending on its state, S_t (S_t, $S_{t+1} \in S$), and the neighborhood R, at time step t:

$$T : (S_t, R_t) \rightarrow S_{t+1} \tag{2.2}$$

In a one-dimensional CA, neighborhoods R typically consist of two cells, one on the left and one on the right of a target automaton; wider neighborhoods, including two cells on each more cells on each side are also considered (Benenson and Torrens, 2004) (Figure 2.2).

Two-dimensional CA are usually considered on a square grid, and the neighborhood consists typically of four or eight adjacent cells, which are often referred to as the von Neumann (1951) and Moore (1964) neighborhoods, respectively (Figure 2.3); wider neighborhoods are also often used, especially in applications to natural systems (White and Engelen, 1993).

2.2.1.2 Cellular automata as a framework for modeling complex spatial systems

Early CA were proposed and used to explore the probability of both self-reproducing and computationally universal that is able to reproduce any recursive function, in nature. In this phase Ulam, von Neumann and Turing had done excellent original works (Rucker, 1999; Turing, 1936; von Neumann, 1951). But after that, especially during 1960s, public interest in CA hovered less over mathematic publications, and gradually decayed.

The 1960s and 1970s played host to the rise of general system theory (Benenson and Torrens, 2004). Far-from-equilibrium and self-organizing systems (Haken, 1983; Prigogine, 1967)

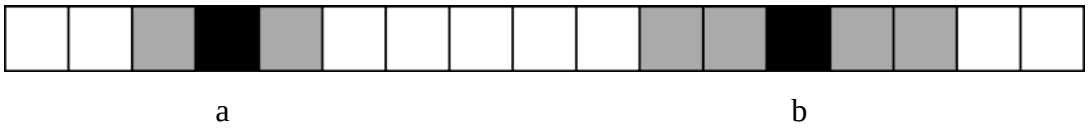


Figure 2.2 Typical neighborhood configurations of one-dimension cellular automata. (a) Neighborhood consists of two cells on the left and on the right of a given cell; (b) Neighborhood consists of two cells on each side of the given cell

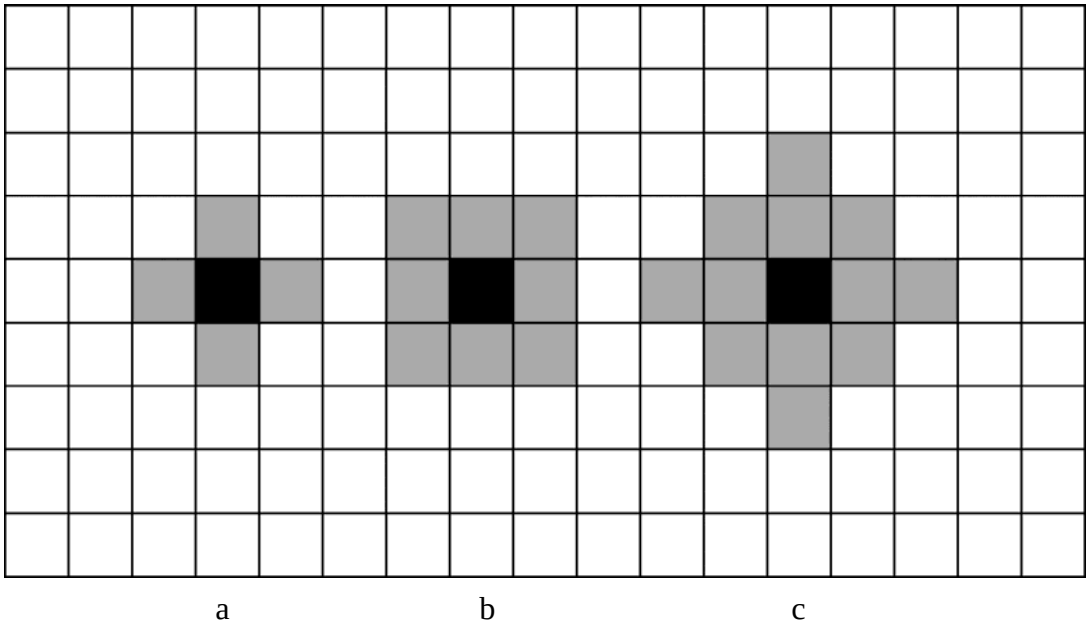


Figure 2.3 Typical neighborhood configurations of two-dimension cellular automata. (a) Von Neumann 3×3 neighborhood; (b) Moore 3×3 neighborhood; (c) Von Neumann 5×5 neighborhood

became hot topics in natural science. Systems of nonlinear differential equations have been applied to socioeconomic systems of all level, from the world as a whole to regional and cities (Benenson and Torrens, 2004). This period provided opportunity for the revival of CA.

Revival in interest came at the beginning of 1970, amid the popularity prompted by Martin Gardner's presentation of John Horton Conway's model of "Life" (Gardner, 1970; Gardner, 1971). Conway's initial motivation was to design a simple set of rules to study the microscopic spatial dynamics of population. Aware of the computational university of CA and their ability to generate complex spatial structures, Conway looked for rules that were simple, but generated population dynamics that were not easily predicted or expected. He succeeded! The simple rules of the Game of Life which was designed by Conway support fantastic variation in patterns of growth in a simulation. Generally stated, the Game of Life introduced CA as an interdisciplinary tool for representing complex spatial systems and investigating their dynamics. Wolfram (1994) has also systematically discussed the relationship of CA and complexity.

2.2.2 Complex urban dynamics

Cities are complex objects (White and Engelen, 1993), like most geographical phenomena, as they always exhibit several of the intrinsic characteristics of complexity: fractal dimensionality, self-similarity, self-organization and emergence (Torrens, 2000; Torrens and David, 2001). From local-scale interactions such as individual movement habits, the geomarketing strategies of retail establishments, social biases, and residential and lifestyle choices, large-scale and at least partially ordered patterns emerge in the aggregate. Peak-hour congestion, specialist retail areas, social segregation, and distinctive neighborhoods may all be regarded as patterns in this sense. These aggregate patterns often emerge apparently and independently of the dynamics driving the individual components of the system.

Cities, like some other social open systems, tend to be ordered, at least in the sense of urban land-use patterns (Barredo *et al.*, 2003). This kind of systems has been defined as self-organizing.

Self-organization in dynamic systems establishes the tendency for system structures to develop ordered patterns, often on a large scale (Krugman, 1996; Torrens, 2000). The ordered properties of cities have been studied by using fractal dimension (Frankhauser and Sadler, 1991; White and Engelen, 1993; White *et al.*, 1997) or radial dimension (Frankhauser and Sadler, 1991) as a measure of order.

The fact that cities do have fractal structure also introduces the concept of self-similarity. By this definition, fractal objects are self-similar. New area in cities shows patterns which often are indistinguishable from the previous patterns and from the whole of the city, moreover the structure of the pattern is independent from scale (Torrens, 2000; Wolfram, 1994).

2.2.3 Cellular automata-based urban modeling

2.2.3.1 Brief review of CA-based urban modeling

In complex emergent systems, like cities, a small number of rules applied at local level are capable of generating surprising complexity in aggregate form (Torrens, 2000). The ordered large-scale patterns of urban land-use are developed from these local-scale interactions. Depending on the nature of these local-scale interactions, the large-scale ordered patterns will take their form, structure, shape and/or behaviors. It is cellular automata, which act as the agency between such large-scale patterns and local-scale interactions. This approach-based models differ from conventional urban models in its constituent ‘elements’ (Benenson and Torrens, 2004). They operate with human individuals and infrastructure entities, represented at spatially non modifiable scale such as households, homes, or vehicles. Many of these objects are animated (visually and dynamically), and that animation drives the behavior of inanimate objects in a simulation. The idea behind using urban CA models to study complexity is to look at the simple ingredients of complexity that was found in cities.

White and Engelen (2000) have analyzed a number of reasons for the attractive application

of CA in urban modeling:

1) they are inherently spatial; typically they are defined on a raster cell space and are thus compatible, or can be made compatible, with most spatial data sets;
2) they are dynamic, and can thus represent spatial processes in a direct way;
3) they are highly adaptable – they can be set up to represent a very wide range of situations and processes;
4) they are rule based, and can thus capture a wide variety of spatial behaviors;
5) they are simple, and thus computationally efficient; and
6) in spite of their simplicity, they can exhibit extraordinarily rich behavior; some simple CA have been shown to be formally equivalent to a Turing machine, i.e. these CA can represent and execute any possible algorithm.

Informal cell-space modeling of urban development was demonstrated by Tobler (1970) in his animation of the growth of Detroit which he eventually formalized in his definition of cellular geography (Tobler, 1975; Tobler, 1979). Albin (1975) also introduced CA and multi-agent system as a tool for investigating complex socioeconomic systems (Albin, 1975).

The 1980s can be classified as the phase of theoretical discussions for the application of CA to urban geosimulation. In this phase, Couclelis was one of trailblazers (Couclelis, 1985; Couclelis, 1988; Couclelis, 1989). She demonstrated how CA might be used as an analog or metaphor to study how different varieties of urban dynamics might arise, and explored the potential of CA in an urban planning environment as well as the theoretical obstacles to incorporating CA models in a geographical context. Subsequently, a few authors (Itami, 1988; Phipps, 1989) also introduced CA, as an approach, to the geographic public. These developments paved the way for acceptance of CA as a modeling tool, capable of substituting regional models.

In the early 1990s, CA-based operational urban models began to appear. Especially in last decade, CA have been in very popular use for urban simulation. Where, three kinds of models are worthy of mention: Constrained cellular automata, Life cellular automata and Self-modifying

cellular automata.

Constrained cellular automata of land-use dynamics firstly came from White and Engelen's work in 1993 (White and Engelen, 1993). The approach merges the cellular space models of the 1960s with Tobler's geographic model (Tobler, 1979) and implements the assumption that the potential of a land cell to undergo a certain land-use transformation in each iteration depends on the states of extended cell's neighborhood. However, this process of transformation of the state of a land cell is subjected to a constraint of urban growth which depends essentially on its position in a larger exogenous urban-economic system (White *et al.*, 1997). This concept provides the probability of connecting the microlevel models with large scale models. This model became the mainstream CA application in geography (Benenson and Torrens, 2004) and widely used in simulation of a lot of regions and cities in the world (Barredo and Demicheli, 2003; Barredo *et al.*, 2003; Straatman *et al.*, 2004; White and Engelen, 1997; White and Engelen, 2000; White *et al.*, 1997; White *et al.*, 1999; Yeh and Xia, 2001; Yeh and Xia, 2002). This research also adopts the concept of constrained cellular automata.

Life cellular automata models were proposed by Batty and Xie (Batty and Xie, 1994). This model is named 'Life' cellular automata here because approach of this model came from the idea of Conway's the Game of Life. They endow the cells in certain area with 'life' like other critters. The life of cells is nondeterministic in that births and deaths amongst the configuration of active cells at time *t* are computed stochastically. Births of cells are determined by the cells acting as single parents and are eventually located with respect to neighborhood, while cells die as a function of a system-wide rate, not as a function of what is happening in their locality. This model mostly aims at explore the characteristics of the emergence, development, and decay of a city as an object (Batty, 1998; Batty *et al.*, 1999).

Self-modifying cellular automata designed by Clarke and co-authors (Clarke *et al.*, 1997) takes a diffusion-based view of urban development, not only assuming unitary cells, but also diffusion of more complex urban entities as a whole. In this model, five factors are designed to

control the behavior of the system: Diffusion, Breed, Spread, Slope resistance, and Road Gravity. Urban growth rate is the sum of the four different types of urban growth defined in the model: spontaneous, diffusive, organic, and road influenced under the action of the five factors above. A general heuristic CA model based on the concept has been built by Clarke and his colleagues, called SLEUTH (*S*lope, *L*and-cover, *E*xclusion, *U*rban, *T*ransportation, and *H*ill shade). Beginning in 1997 with simulations of Santa Barbara in California, the model has now been applied to other regions of the United States, as well as cities elsewhere in the world (Leao *et al.*, 2001; Silva and Clarke, 2002; Xian and Crane, 2005; Xian *et al.*, 2005).

2.2.3.2 Future prospects of CA-based urban modeling

Although CA have become very popular recently in urban geosimulation field, cellular automata modeling is still in its infancy and at a development phase (Torrens and David, 2001). Torrens and David (2001) discussed several key areas on which those working with urban CA might focus future efforts and build upon existing success: explorations in spatial complexity, infusing urban CA with theory, exercises in education and outreach, the development of hybrid model structures, and now strategies for validating cellular urban models. Besides these areas above, other issues, which are associated with the primal definition of CA in urban geosimulation, are discussed here: spatial scale, the cell states, and the neighborhood.

Spatial scale

Rectilinear grid systems adopted in most urban CA models have obvious advantages both in terms of compatibility with raster-based data systems and computational efficiency. However, most grid space is typically assumed to be homogeneous, and usually different models adopted different grid size (Barredo *et al.*, 2003; Clarke *et al.*, 1997; White and Engelen, 1993). Questions like how the difference of spatial scale affects the understanding of urban dynamics and how to select appropriate grid size in the context of cellular automata modeling need to be further investigated.

The cell state

In urban models cell states most commonly represent land-cover and land-use categories although sometime they may be used to represent population density levels (Wu, 1998b) or other features. But the question that how different land-use categories would impact the understanding of urban dynamics, especially in terms of certain spatial scale, still remains.

The neighborhood

The transition rules are the heart of CA. They represent the logic of the process which is being modeled, and thus determine the spatial dynamics which result. The local interactions for one cell in the neighborhood play a fundamental role in the transition rules of CA-based urban models. However, the neighborhood in different models keeps different in size and shape. The problem of how to evaluate the local interactions should be further explored.

Chapter Three
Urban growth in the Tokyo metropolitan area

The period of High Economic Growth which began in the latter half of the 1950s led to a massive migration of population from rural to urban areas in Japan (Murayama, 2000). The population concentration into Tokyo and its circumjacent prefectures, like the area including Tokyo, Saitama, Ibaraki, Chiba, and Kanagawa prefecture, was particularly noteworthy. Figure 3.1 shows the population increase in this area from 1920 to 2000. It is obvious that the growth rate of population from 1950 to 1975 is higher than that from 1920 to 1950. Although the rate from 1975 to 2000 declined a little, the increment reached more than 5 million in amount. And the increase would keep up from 2000 to 2015 (Figure 3.2). Accompanying the population increase, a rapid expansion of built-up area into the surrounding area occurred. For instance, Figure 3.3 shows the processes of urbanized area encroaching non-urbanized area in the Tokyo wards area from 1910 to 1975. Obviously, the urbanized area almost occupied all the 23 wards by 1975. After that time, the urbanized area mostly grew in the area out of the wards. The urbanized area would keep on extending in the future with the trend of the population increase in this area.

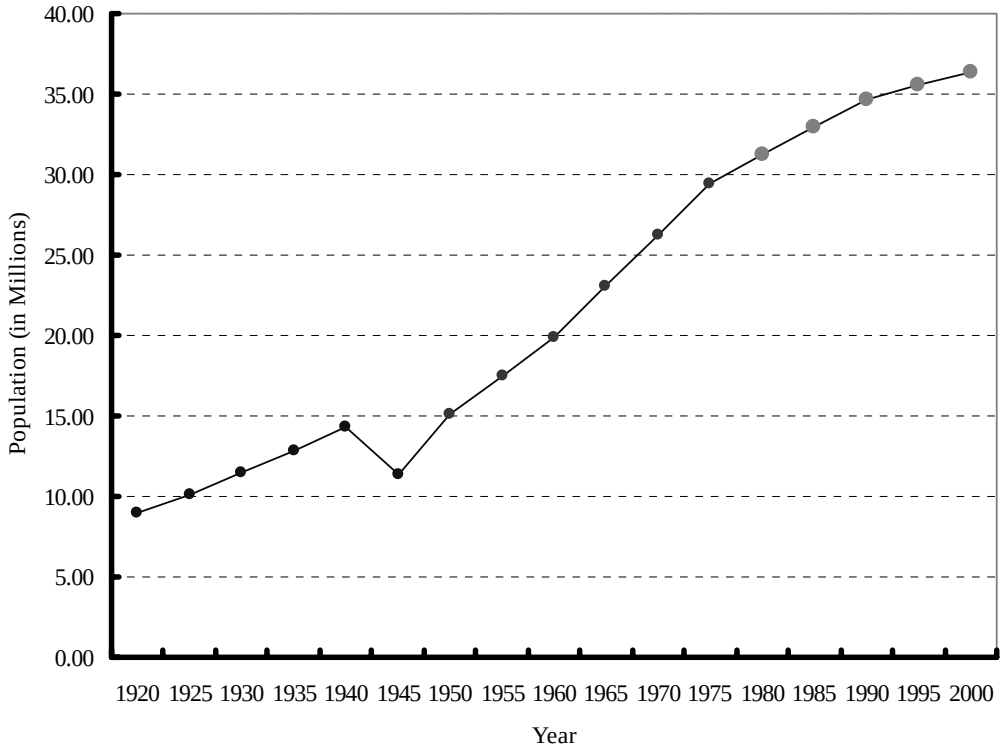


Figure 3.1 The population increase in the area including Tokyo, Saitama, Ibaraki, Chiba, and Kanagawa prefecture from 1920 to 2000

(*Source*: Population Census of Japan)

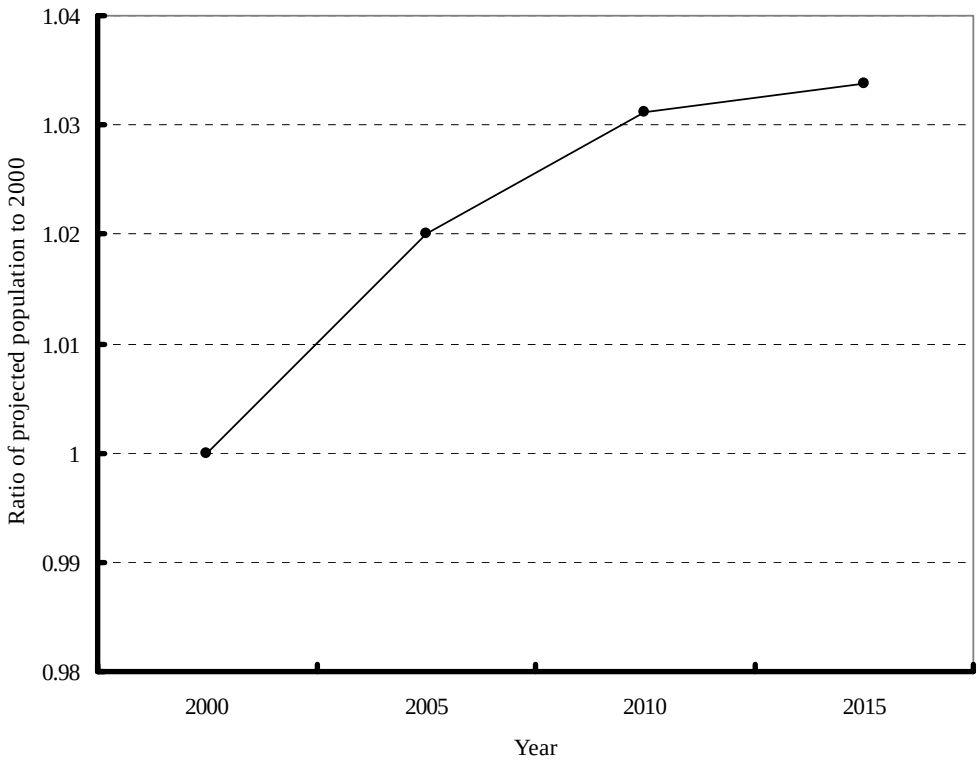


Figure 3.2 Projection of the population in the area including Tokyo, Saitama, Ibaraki, Chiba, and Kanagawa prefecture from 2000 to 2015

(*Source*: National Institute of Population and Social Security Research)

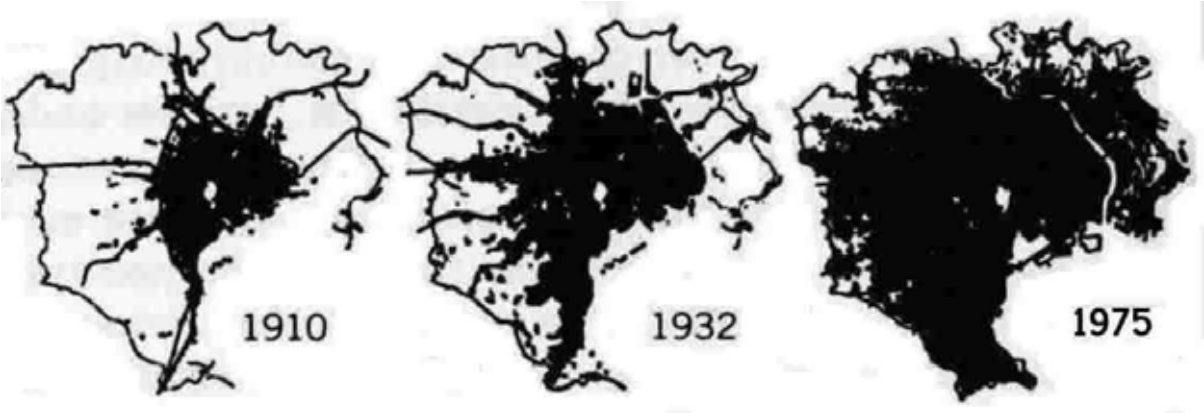


Figure 3.3 Urban growth in the Tokyo wards area from 1910 to 1975

(*Source*: Gallion and Eisner, 1975)

3.1 Study area

The study area in this research consists of the region of restricted urbanization and suburban development zones governed by the National Capital Region Development Act (Figure 3.4). This area is located in the area including Tokyo, Saitama, Ibaraki, Chiba, and Kanagawa prefecture, 192 cities (towns) with 8264 km^2 (Geographical Survey Institute, 1998). Here, this area is defined as the Tokyo metropolitan area. It is assumed that this kind of definition does not affect the cognition of CA-based model of spatial process of urban growth proposed in this research.

Urban growth is a direct result of population concentration or life-style changes of people (Qadeer, 2004; Smailes, 1975), which can be expressed as the expansion of urbanized area, also the increase and diffusion of population density in urbanized area (Li *et al.*, 2003; Tobler, 1970). Because this research is mostly concerned about modeling spatial processes of the land-use changes from agricultural or forest land to built-up or resort area where is related with people who do not lie on the traditional agrarian works any more, urban growth is interpreted as the first expression, viz. the transformation of land-use from agricultural or forest land (non-urbanized area) to built-up or resort area (urbanized area).

3.2 Data set

Although land-use and land-cover always are mentioned together, the definition of them is different. Barnsley et al. (2001) refer to land-cover as “the physical materials on the surface of a given parcel of land (e.g. grass, concrete, tarmac, water),” and land-use as “the human activity that takes place on, or makes use of that land (e.g. residential, commercial, industrial)” (Barnsley *et al.*, 2001). Land-use can consist of varied land-covers, (i.e. a mosaic of biogeophysical

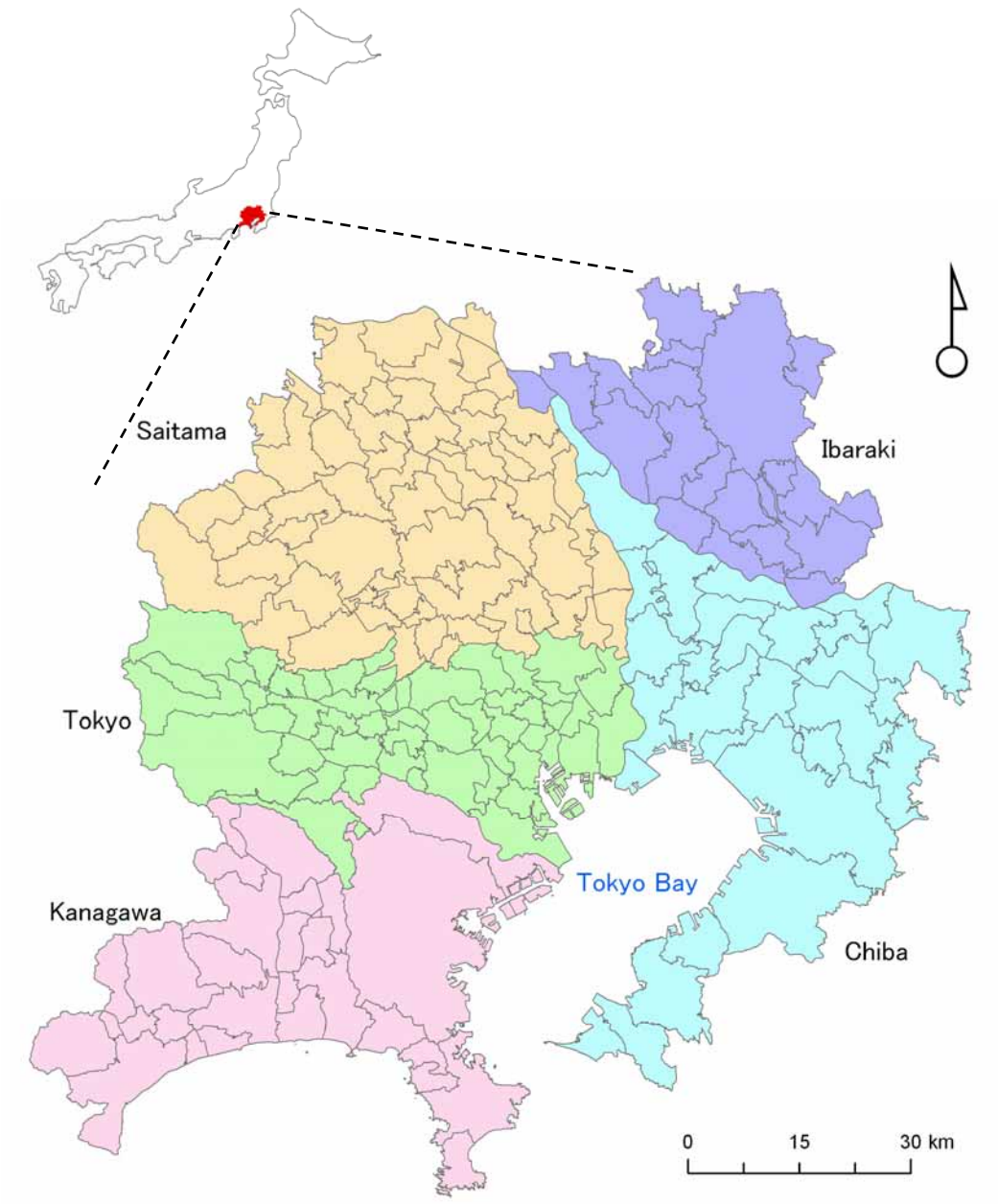


Figure 3.4 Study area

materials found on the land surface). For instance, a single-family residential area consists of a pattern of land-cover materials (e.g. grass, pavement, shingled rooftops, trees, etc.). The aggregate of these surfaces and their prescribed designations (e.g. park) determine land-use (Andersen *et al.*, 1976). Therefore, land-use is an abstract concept, constituting a mix of social, cultural, economic and policy factors.

Cities are reflection of economic, environmental, technological, and social processes. Urban growth intuitively leads to the land-cover change at the macro or regional scale. However, the growth is the result of a complex process of land-use in nature considering the interaction and the change of different urban land-use types, such as industrial, residential, commercial and so on. Therefore, understanding, representation and modeling of the complex urban system entail very detailed data ranging from environmental and ecological parameters to socioeconomic information, and land-cover and land-use data with known spatial and temporal accuracy (Clarke *et al.*, 2002). Important data sources are the censuses collected by governments, and by planning agencies (Fagan *et al.*, 2001; Foresman *et al.*, 1997; Wegener, 1994). However, there are problems associated with such spatial social data. Herold et al. (2003) discussed such problems including: they do not have a uniform global availability – they are frequently unavailable for developing nations; spatial social data may be classified or available only through private or restricted government sources; they can have poor temporal accuracy and consistency, and they often contain the wrong thematic representations for objective urban analysis.

Remote sensing techniques have already showed their value in mapping urban areas, and as data sources for the analysis and modeling of urban growth and land-use change (Batty and Howes, 2001; Clarke *et al.*, 2002; Treitz and Rogan, 2004). Remote sensing provides spatially consistent data sets that cover large areas with both high spatial detail and high temporal frequency. Batty and Howes (2001) have emphasized the importance of remote sensing as a "unique view" of the spatial and temporal dynamics of the process of urban growth and land-use change. However, land-use has little physical importance with respect to reflectance properties,

and hence has a limited relationship to remote sensing. Remote sensing data record the spectral properties of surface materials, and hence, are more closely related to land-cover. In short, land-use cannot be measured directly just from remote sensing, but rather requires visual interpretation or sophisticated image processing and spatial pattern analyses to derive land-use from aggregate land-cover information coupled with other ancillary data (Cihlar and Jansen, 2001). Integrated analyses within a spatial database framework (e.g. GIS) or field works are often required to assign land-cover to appropriate land-use designations. This is a tiresome work taking cost and time. Especially in urban areas it is more difficult due to the heterogeneity and small spatial size of surficial materials, which leads to significant subpixel mixing (Foody, 2000; Ridd, 1995). This problem becomes exacerbated when discrimination of multiple classes is necessary (Stefanov *et al.*, 2001). This may be one of the reasons why the study area was always divided as built-up area and non-built-up area only in many literatures of urban growth modeling.

The data set "Detailed Digital Information (10m grid land-use) Metropolitan Area" of Tokyo (DDIMA10m) provides abundant and detailed urban land-use classifications including a variety of socio-economic information at a series of time. This data set was produced by the Geographical Survey Institute, the Ministry of Construction of Japan. It has the data on the category of land-use of each 10 meters square cell, surveyed in 1974, 1979, 1984, 1989, and 1994. In this data set, the land-use classification system has a hierarchical structure, and is divided into three levels: levels one, two and three. The number of the categories is 15 in level three, namely (A) forest & wasteland, (B) paddy field, (C) dry field & other farmlands, (D) land under construction, (E) vacant land, (F) industrial land, (G) low-storey residential land, (H) densely developed low-storey residential land, (I) medium and high-storey residential land, (J) commercial land, (K) road, (L) park, (M) public facility, (N) water, and (O) the others. The land-use classification system is shown in Table 3.1.

The DDIMA10m is selected as a primary data set for this research.

Table 3.1 Land-use classification system in the data set of DDIMA10m

Code	Land-use classification system			Description
	Level one	**Level two**	**Level three**	
A	Forest or agricultur-al land	Forest & wasteland		Forest area, bamboo forest, weed area (abandoned cultivation area is included), barren land and golf-course etc.
B		Agricultural land	Paddy field	Paddy field for paddy rice, lotus and so on. Short-term fallow field and cropland with season are included
C			Dry field & other farmlands	Dry field, orchard, mulberry field, tea garden, nursery stock field, ranch, and other farmlands associated with pasturage, barn and greenhouse
D	Arranged land	Land under construction		The land where artificial alteration is under the way towards residence, industry or commerce
E		Vacant land		The land where rearrangement was done artificially, but is not utilized presently. The outside parking zone, golf practice place, tennis coat and the materials yard etc. are included
F	Building land	Industrial land		Including production factory, fabrication plant, repair shop, the warehouse, the raw materials yard, the products yard and the welfare facilities etc.
G		Residential land	Low-storey residential land	Build-up area for residence with buildings below three floors, where area of one division is more than 100 sq. m. Homestead woodland is included
H			Densely developed low-storey residential land	Build-up area for residence with buildings below three floors, where area of one division is less than 100 sq. m.
I			Medium and high-storey residential land	Build-up area for residence with buildings more than 3 floors
J		Commercial land		Including retail store, supermarket, wholesale store, restaurant, hotel, cinema and theater, bank, amusement area, hotel and lodging, office of enterprise such as bond, insurance and trading company, newspaper company, circulation facility etc.
K	Public land	Road		Road with effective width more than 4 meters, open space before station. Purchased land for road is included
L		Park		Park, zoo, arboretum, athletic competition facility, the hippodrome, baseball field, graveyard, recreational area, temple etc., which possess the public character
M		Public facility		Public office area, education and cultural facility, supply processing facility, social welfare institution, railroad site, bus center and garage, airport etc.
N	Water			River, lake, marsh and the reservoir, fish farm, and seaside area etc.
O	The others			Defense facility, USA military facility, training ground, facility and residential area which are related to the Imperial Family

Source: Geographical Survey Institute, 1998

3.3 Characteristics of urban growth in the Tokyo metropolitan area

City is a complex system (White and Engelen, 1993) which possesses its intrinsic characteristics like fractal dimensionality, self-similarity, self-organization and emergence (Torrens, 2000; Torrens and David, 2001). Purpose of urban model is to grasp the characteristics of the complex system. As this research focuses on the transformation of land-use from agricultural or forest land (non-urbanized area) to built-up or resort area (urbanized area) as discussed in section 3.1, in order to catch main characteristics of spatial process of urban growth in the Tokyo metropolitan area at the series of time from 1974 to 1994, when the data were provided in the data set of DDIMA10m, the study area is aggregated into three types of land-use: non-urbanized area, urbanized area, and water from land-use classification system at level three. Land-use category of (A) forest & wasteland, (B) paddy field, (C) dry field & other farmlands are aggregated into non-urbanized area; (N) water is retained; others are aggregated into urbanized area. Table 3.2 indicates the aggregation of land-use categories.

In this study area, as the data in some cities were not surveyed in 1974, in order to keep consistency of urban growth analysis, the surveyed area in 1974 (about 6,300 km^2, as shown in Figure 3.5) is set for analyzing. It is assumed that this setting would not greatly affect the understanding of main characteristics of the urban form changes in the Tokyo metropolitan area as this region which is set here covers main components of urbanized area.

Spatial metrics and fractal dimension have shown advantages in catching characteristics of urban dynamics and been used to assess urban models (Barredo *et al.*, 2003; Herold *et al.*, 2005; Herold *et al.*, 2003; White and Engelen, 1993; White and Engelen, 1994; Zhao and Murayama, 2006b). Here both of them are selected to interpret the characteristics of spatial process of urban growth in the Tokyo metropolitan area for providing useful information to this research.

Table 3.2 Categories in original data set of and in urban growth analysis

Categories in original data set	*Categories in urban growth analysis*
A. Forest & wasteland	1. Non-urbanized area
B. Paddy field	
C. Dry field & other farmlands	
D. land under construction	2. Urbanized area
E. Vacant land	
F. Industrial land	
G. Low-storey residential land	
H. Densely developed low-storey residential land	
I. Medium and high-storey residential land	
J. Commercial land	
K. Road	
L. Park	
M. Public facility	
O. The others	
N. Water	3. Water

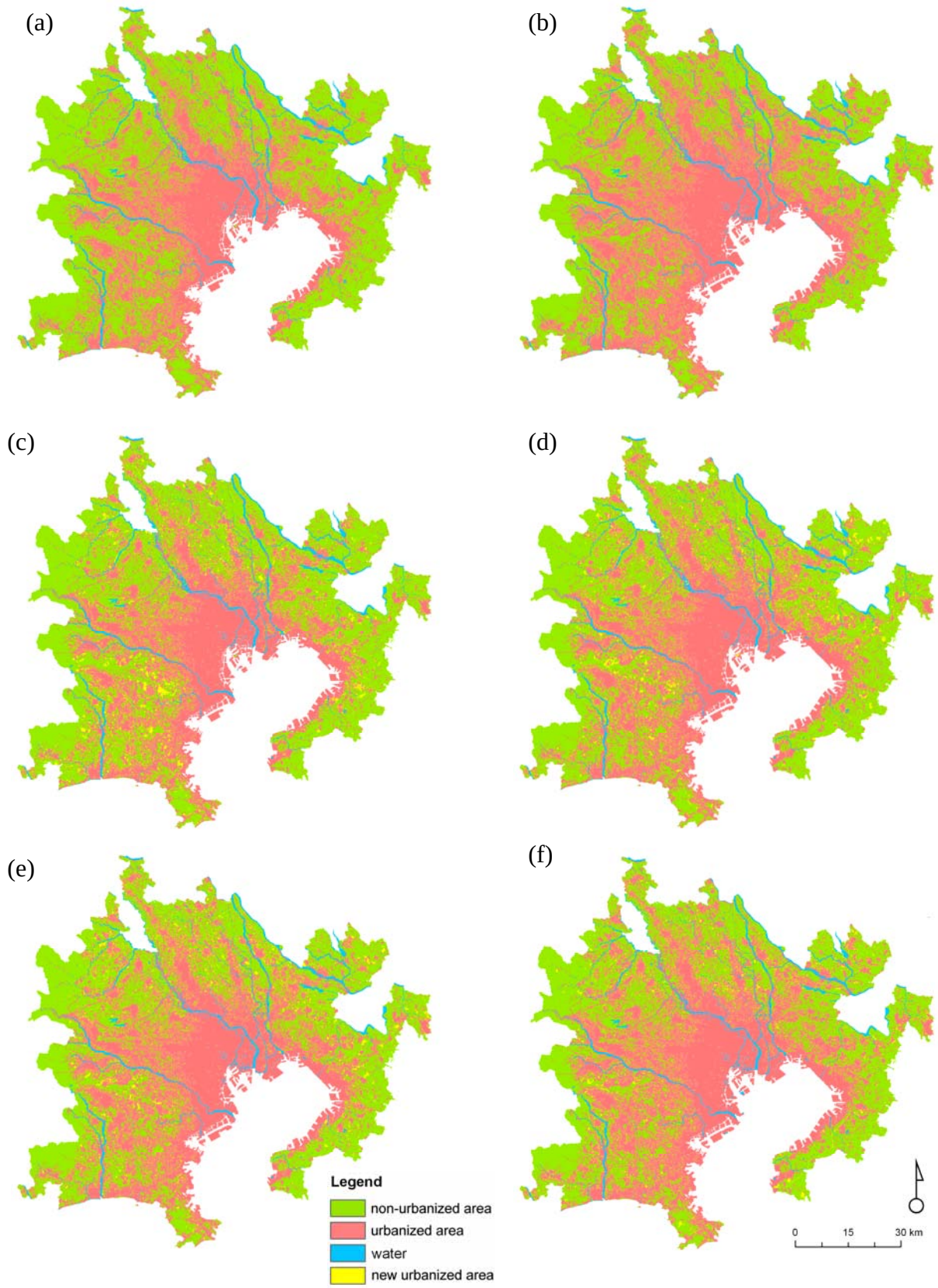


Figure 3.5 Land-use and urban growth in the Tokyo metropolitan area from 1974 to 1994. (a) land-use in 1974; (b) land-use in 1994; (c) urban growth from 1974 to 1979; (d) urban growth from 1979 to 1984; (e) urban growth from 1984 to 1989; (f) urban growth from 1989 to 1994

3.3.1 Characteristics of urban growth in terms of fractal dimension

As non-linear systems, the dynamics and rules of pattern generation and evolution of cities show their own characteristics. Self-organization is one of the main characteristics, which establishes the tendency for system structures to develop ordered patterns, often on a large scale (Krugman, 1996; Torrens, 2000). Fractal dimension (Appendix) has been as a measure to study the ordered properties of cities (Frankhauser and Sadler, 1991; White and Engelen, 1993). Based on the obtained fractal dimensions, cities can be defined as bifractal objects into two zones. The inner zones is more organized and the outer zone less organized or still evolving. In the inner zone, the transformation process has reached, or it is near to, the maximum level of organization accessible to the system. It means that the system has reached a sort of equilibrium and the urban pattern is relatively stable. In the outer zone, the process of urbanization still continues, thus it shows a less degree of organization than the inner zone. Here the system is still evolving. Frankhauser and his group (1991) have analyzed the urbanized areas of a number of cities in Europe, North American, and Australia, and found that most of them have a bifractal form.

The measure of fractal dimension which shows the fractal structure of cities also introduces the characteristics of self-similarity of complex systems. It means that new areas in cities show patterns which often are indistinguishable from the previous patterns and from the whole of the city, moreover the structure of the pattern is independent from scale (Torrens, 2000; Wolfram, 1994). These patterns are fractal structures and can be characterized through fractal dimension (Torrens, 2000).

Here, the measure of fractal dimension is adopted to analyze the characteristics of urban growth in the Tokyo metropolitan area from 1974 to 1994. Tokyo station was chosen as the origin point for calculating the fractal dimensions. Firstly, the area-radius relationships for the

urban area of the Tokyo metropolitan area at the series of time from 1974 to 1994 were calculated and shown in Figure 3.6. In this process, urbanized areas which are far more than 50km from Tokyo station were omitted because cell counts for these areas are dominated by boundary effects. As the relationship remains stable under the radius of 7km, Figure 3.6 just shows that more than 7km.

From Figure 3.6 it can be found that in any time section the urbanized area displays a bifractal structure; in each case the area relationship is a little kinked, with a steep inner segment (1-15km) and a little flatter outer part (15-50km). The fractal dimensions of the urbanized area for these two parts in different time section were calculated respectively, shown in Figure 3.7. It clearly shows that the fractal dimensions of inner part are near biggest numerical value of 2.0 and has changed hardly from 1974 to 1994. It indicates that the inner part consists of the area within which the urbanization process was essentially complete. The fractal dimensions of outer part were smaller than that of inner part and have grown up gradually from 1974 to 1994 but kept the characteristics of fractal structure, meaning that the outer part was the area in which stochastic effects remained important and the process was still full active, so that the urban structure has not stabilized.

3.3.2 Characteristics of urban growth in terms of spatial metrics

Spatial metrics come from the concept of landscape metrics which were developed in the late 1980s and incorporated measures from both information theory and fractal geometry (Mendelbrot, 1983; Shannon and Weaver, 1964) based on a categorical, patch-based representation of a landscape. Patches are defined as homogenous regions for a specific landscape property of interest, such as “agricultural land”, “lake” or “urban area”. Therefore, landscape metrics are used to quantify the spatial heterogeneity of individual patches, of all

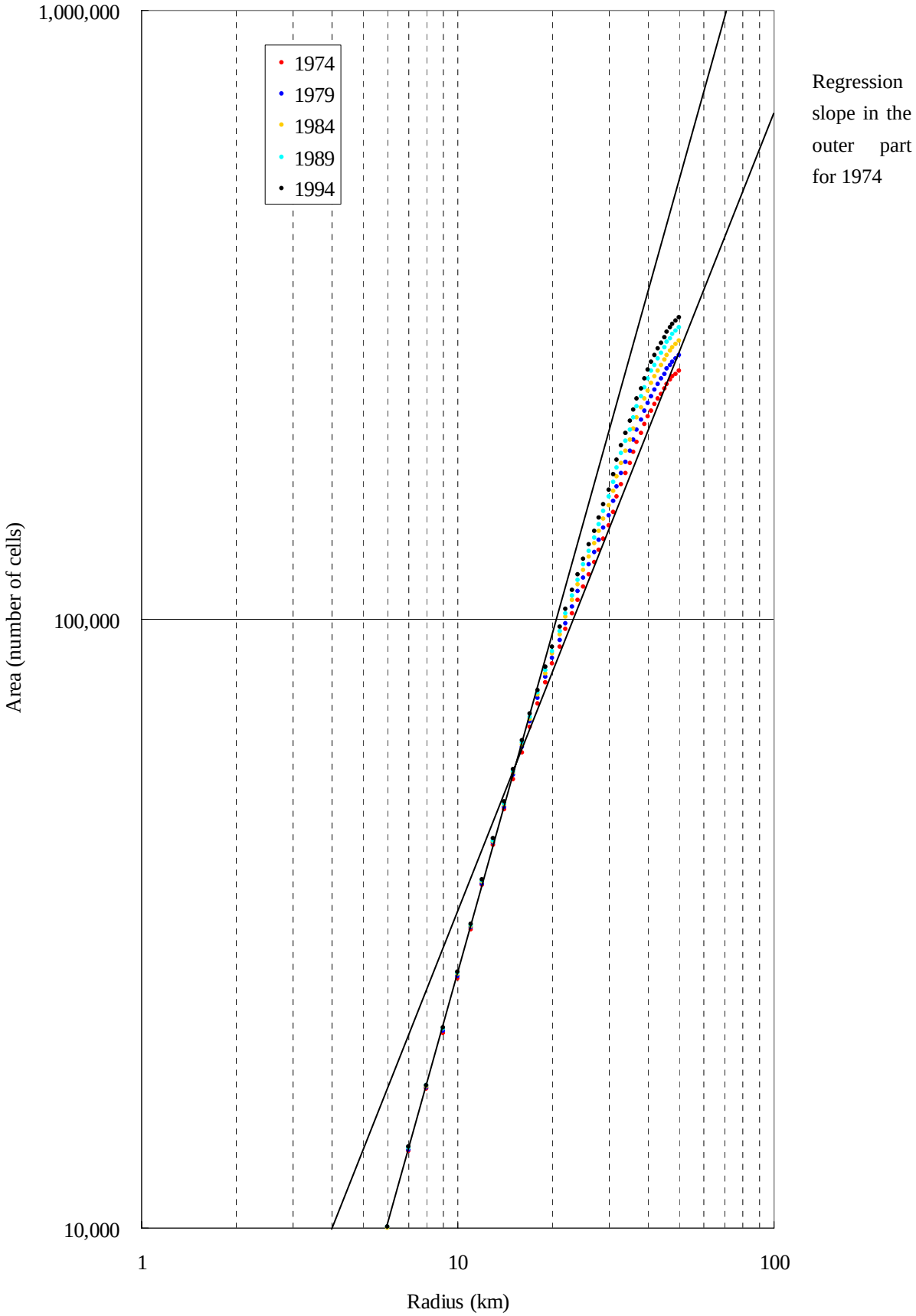


Figure 3.6 Evolution of the area-radius plots of urbanized area in the Tokyo metropolitan area through the series of time from 1974 to 1994

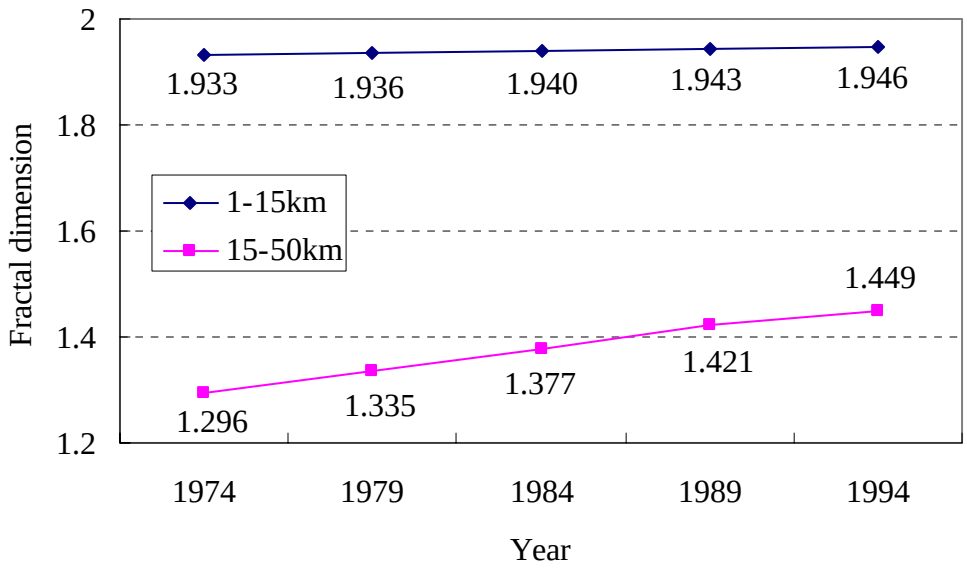


Figure 3.7 Evolution of the inner (1-15km) and outer (15-50km) fractal dimension of the urbanized area in the Tokyo metropolitan area from 1974 to 1994

patches belonging to a common class, and of the landscape as a collection of patches. When applied to multi-scale or multi-temporal datasets, the metrics can be used to analyze and describe change in the degree of spatial heterogeneity (Dunn et al., 1991; Wu et al., 2000). Given to apply in urban domain, Herold et al. (2003) pointed out that the approaches and assumptions might be more generally described as “spatial metrics”.

Interest in using spatial metric concepts for the analysis of urban environments is starting to grow. In 1997, Geoghegan et al. firstly explored spatial metrics in modeling land and housing values. Alberti and Waddell (2000) substantiated the importance of spatial metrics in urban modeling. They proposed specific spatial metrics to model the effects of the complex spatial pattern of urban land-use and cover on social and ecological processes. Parker et al. (2001) summarized the usefulness of spatial metrics with respect to a variety of urban models and argue for the contribution of spatial metrics in helping link economic processes and patterns of land-use. Herold et al. (2003) proposed the integration approach of remote sensing and spatial metrics in spatiotemporal analysis and modeling of urban growth. In 2005, Herold et al. systematically analyzed the role of spatial metrics in the analysis and modeling urban growth and argued that spatial metrics definitely deserve a place in the urban dynamics research agenda.

Here four spatial metrics, CA, NP, PLAND, and LPI, which are defined as in Table 3.3, are adopted as measures to analyze the characteristics of spatial process of urban growth in the Tokyo metropolitan area from 1974 to 1994 in terms of the change of spatial heterogeneity. Class area (CA) is a measure of urbanized area. Change in CA across time can present the change in urbanized area. The number of patches (NP) metric quantifies the number of individual urban areas. The dynamics of NP coupled with CA can describe the degree of fragmentation of the urbanized area. The largest patch index (LPI) describes the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance and presents the extent of the aggregation of urbanized area. Percentage of landscape (PLAND) quantifies the proportional abundance of urbanized area in the landscape. Chang of PLAND can express the

Table 3.3 Spatial metrics used in this study

Metrics	Description	Units	Range
CA-Class Area	CA equals the sum of the areas (m^2) of all patches, divided by 10,000 (to convert to hectares).	Hectares	CA>0, no limit
NP-Number of patches	NP equals the number of patches in the landscape.	None	NP>=1, no limit
LPI-Largest patch index	LPI equals the area (m^2) of the largest patch of the corresponding patch type divided by total area (m^2), multiplied by 100 (to convert to a percentage).	Percent	0<LIP<=100
PLAND-Percentage of the Landscape	PLAND equals the sum of the areas (m^2) of all patches of the corresponding patch type, divided by total landscape area (m^2), multiplied by 100 (to convert to a percentage).	Percent	0<PLAND<=100

Source: McGarigal *et al.*, 2002

growth or decay of the urbanized area.

The results of spatial metrics calculation are shown in Figure 3.8, which presents diagrams of temporal growth significance of four different spatial metrics. The metrics shown were calculated using the software of FRAGSTATS for the year of 1974, 1979, 1984, 1989, and 1994 respectively. The value of CA for this area gradually increased and approximately kept the same speed. It indicates the fact of urban growth of the Tokyo metropolitan area in this period. The change of the value of PLAND also shows the same characteristics. However, the value of NP kept gradual decline with time. This shows the characteristic of the compact growth or conglomeration of the existing urbanized area in the Tokyo metropolitan area. There are two reasons which can yield the results. One is that new urbanized areas always emerge along the fringe of existed urbanized area. Gradually some urbanized area patches grow conjunctively so that new bigger patch comes into being. This phenomenon indicates the effect of neighborhood in the process of urban growth. The other reason is that new urbanized areas would appear in new place firstly, but with their growth, they connect with existing urbanized area and yield new bigger patch of urbanized area. However, no matter what any reason produce the structurally compact growth of urbanized area. This trend is confirmed by the increase of the LPI metric.

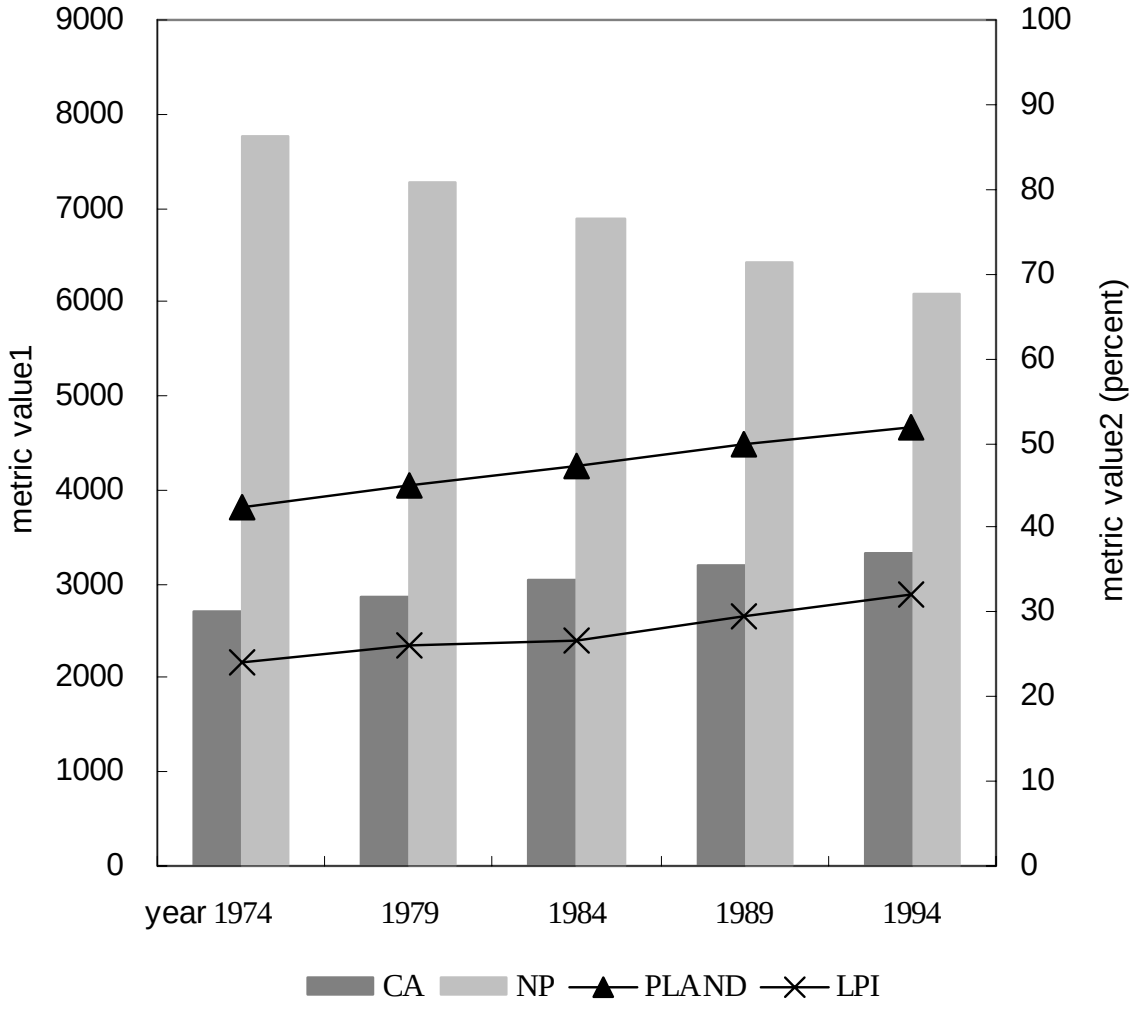


Figure 3.8 Temporal urban growth significance of spatial metrics in the Tokyo metropolitan area from 1974 to 1994

(**Note**: the PLAND and LPI metrics to the secondary *y*-axis)

Chapter Four

Modeling spatial process of urban growth

According to O'Sullivan and Unwin (2002), as spatial pattern in any time is generated from corresponding spatial process (O'Sullivan and Unwin, 2002), spatial model which aims at simulating the spatial process can be constructed through analyzing dynamic spatial patterns in time-series. Modeling spatial process of urban growth also takes the same procedure. This approach represents the link from spatial pattern to spatial process.

Traditionally, research on modeling urban growth always deals with study area into binary categories of land-use: urbanized area and non-urbanized area (Clarke *et al.*, 1997; Herold *et al.*, 2003; Silva and Clarke, 2002; Wu, 1998b; Wu, 1998a). It is assumed that urbanized area grows up as one homogenous object and the form of city is generated under exogenous conditions. However, they omit the fact that urban growth is the results of emergence of urban activities as well as their interactions and competitions. Based on this kind of cognition, in this research urbanized area are divided into more detailed land-use categories, and the emergence, interaction, and competition of these land-use categories yield the fact of urban growth. The model in this research is constructed based on this assumption.

4.1 Constrained cellular automata-based model

4.1.1 Factors of spatial process of urban growth

From a practical point of view, several land-use allocation factors have been identified for urban activities in the science of spatial decision-making (Carver, 1991; Eastman *et al.*, 1993; Voogd, 1983) and applied in geosimulation of urban dynamics (Barredo *et al.*, 2003). Spatial process of urban growth is the result of urban dynamics which are decided by these factors. Five groups of factors can be identified:

- environmental characteristics;
- local-scale neighborhood characteristics;
- spatial characteristics of the cities (i.e. accessibility);
- urban and regional planning policies;
- factors related to individual preferences, level of economic development, socio-economic and political systems.

The first group is related to environmental characteristics. It may be represented as constraints for urban growth. For example, slopes, land conditions, and natural barriers belong to the first group.

It should be noted that the second factor is related with Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). It can be defined as the present and past land-use patterns and their dynamics. Land-use patterns usually represent the strongest influence for the dynamics of land-use. Distance from new features to existing land-uses and the type of these land-uses drive the urban dynamics at local scale.

It is logical to think that new residential areas usually grow near or adjacent to existent residential areas. However, they are also influenced by other land-uses. For example, in this case,

the commercial land-use could represent an attractive factor. As a result a sort of equilibrium is reached between all actual land-uses and their dynamics in a defined neighborhood.

The third group of factors is related to the spatial characteristics of cities. Factors such as distance to the centre, accessibility, flows or transport networks, are included in this group. For example, new links in the road network might contribute enormously to urban dynamics as an attractor for urban land-uses.

The fourth group is related to urban and regional planning policies. From a practical point of view, this group is represented by land-use zoning status. Through land-use zoning plans the city is regulated to be occupied by land-uses in space and time.

The fifth group comprises factors related to individual preferences, level of economic development and socio-economic and political system. These are the most complicated to understand and model. This group of factors is also related to human decision-making processes, which in most cases are qualitative, evolve in time and can be intransitive and therefore difficult or almost impossible to predict. For example, a new residential area could be located in a place because it is more “beautiful” than other places. Usually human decision-making processes include some level of unpredictability. Couclelis (1988) defined human systems as “terribly complex”. From a practical point of view the related complexity of human systems could be modeled as some degree of stochastic in a probabilistic schema. Therefore, it can be considered as a stochastic factor in urban dynamics modeling. The problem arises in how it can be defined and calibrated.

The sum of all the factors which participate in urban dynamics, plus the human decision component, generates a complex dynamic system whose behavior is influenced by some degree of stochastic. Where and when some features will change in a city is a spatio-temporal multi-factor process which necessarily includes some stochastic degree. Therefore, the process of urban dynamics can be defined as an iterative probabilistic system (White *et al.*, 1999) in which the probability (p) that a place (i) in a city is occupied by a land-use (k) in a time (t), is a function

of the concerned factors measured for that land-use: suitability (*S*), accessibility (*A*), land-use zoning status (*Z*), neighborhood influence (*N*) and a stochastic perturbation (*v*):

$$ {}^{t}p_{ik} = f({}^{t-1}S_{ik}, {}^{t-1}A_{ik}, {}^{t-1}Z_{ik}, {}^{t-1}N_{ik}, v) . \qquad (4\text{-}1) $$

Considering this approach, the probability that an area changes its land-use is a function of the five groups of factors working together in time, plus a stochastic degree. In this schema the neighborhood factor (*N*) makes the city works like a non-linear system. Their dynamism and interactive behavior can be understood as the basis of spatial process of urban growth.

4.1.2 Cellular automata-based model for spatial process of urban growth in the Tokyo metropolitan area

Cities are complex systems, which are characterized by collective properties that define the behavior of the system as a whole. As a joint product of the science of complexity and the computational revolution (Couclelis, 1986), CA are excellent models which deal with these complex systems (Torrens and David, 2001). In CA-based model the state of each cell in an array depends on the previous state of the cells within a neighborhood, according to a set of transition rules (White *et al.*, 1999). This is the fundamentals of the application of CA to urban goesimulation. This also is the key point connecting CA with urban modeling, as the neighborhood effect initiate a non-linear dynamics process in which the current land-use pattern and the local-level interactions combine to create the distribution of new urbanized areas and changes from one urban land-use type to another in urban dynamics. Land-use types interact at neighborhood local scale as non-linear feedbacks producing a dynamic system. Each change in urban land-use affects future land-uses at local scale, changing the local equilibrium every time when a land-use change takes place. All this makes the process very dynamic and interactive.

However, urban configuration comes from not only neighborhood interactions, but also other factors as discussed in section 4.1.1. A set of factors, like suitability, accessibility, and

land-use zoning, behaving in a linear deterministic way produce a subset of areas prone to be occupied by some land-use. In this process, the factors are not very dynamic and remain stable for some period until some external action modifies it. For example, the creation of a new railway station will modify the accessibility parameter. Moreover, Cities are most social and economic processes show some degree of stochastic. Because of the stochastic nature of the system some places that been highly ranked in neighborhood interactions or non-dynamic processes may be discarded or can be occupied by a less proper land-use due to human-related decisions.

Following the theoretical considerations above, a vector of transition potentials (one potential for each function) is calculated for each cell from the suitability, accessibility, zoning status, and neighborhood interaction, and the deterministic value is then given a stochastic perturbation using a modifies extreme value distribution, such that most values are changed very little but a few are changed significantly:

$$ {}^{t}P_{ik} = (1+{}^{t-1}N_{ik})(1+{}^{t-1}S_{ik})(1+{}^{t-1}Z_{ik})(1+{}^{t-1}A_{ik})^{t-1}v \,. \qquad (4\text{-}2) $$

Where ${}^{t}P_{ik}$ is the CA transition potential of the cell i for land-use k at time t; ${}^{t-1}N_{ik}$ the neighborhood space effect on the cell i for land-use k at time $t-1$; ${}^{t-1}S_{ik}$ the intrinsic suitability of the cell i for land-use k at time $t-1$; ${}^{t-1}Z_{ik}$ the zoning status of the cell i for land-use k at time $t-1$; ${}^{t-1}A_{ik}$ the accessibility of the cell i to transportation for land-use k at time $t-1$. ${}^{t-1}v$ is the scalable random perturbation term at time t; it is defined as:

$$ v = 1 + [-\ln(rand)]^{\alpha} \,. \qquad (4\text{-}3) $$

Where, (0 < rand < 1) is a uniform random variable, and α is a parameter that allows the size of the perturbation to be adjusted. The stochastic term v has a highly skewed distribution, so that most values are near unity, and much larger values occur only infrequently. Thus most of the potentials ${}^{t}p_{ik}$ are close to their unperturbed, deterministic values.

Once all transition potentials are calculated, each cell is converted to the state for which it has the highest potential. In this conversion procedure, only potentials for transformation to the

same function are compared. Potentials for transformation to different functions are not meaningful as the potentials for different functions are scaled arbitrarily with respect to each other. However, this process is subject to an important constraint. Unlike the case in conventional CA, the number of cells in each state at each iteration is not left to be determined incidentally by the application of the state transition rules based on equation (4-2). Because the growth of a city depends essentially on its position in a larger urban-economic system (large scale urban models) and the proportion of various land-use types can change only slowly and within certain limits. In this model the total number of cells in each state to be equal to totals supplied exogenously at each iteration. This is achieved by converting each cell to the state for which its potential is highest, starting with the highest potential – but only until the required number of cells for a given state is attained. Once that the point is reached, the potential of all other cells for that state is set to zero, so no further cells are converted to that state. This kind of models was called constrained CA model by White et al. (1997).

4.1.3 Identification of grid size of CA

As mentioned in section 2.2, CA is defined as a two-dimensional grid of identical automata cells in urban modeling. Now, one of the problems with which this research is being confronted is how to identify appropriate grid size of land-use map for modeling spatial process of urban growth in the Tokyo metropolitan area. Up to now, for example, various types of grid size of land-use map have been used in many literatures: 500m×500m (White and Engelen, 1993), 300m×300m (Clarke *et al.*, 1997), 250m×250m (White *et al.*, 1997), 240m×240m (Yang and Lo, 2003), 100m×100m (Barredo *et al.*, 2003), and so on. It seems that no theoretical justification can be given to adopting any specific grid size. In fact, grid size is associated with spatial scale. Spatial scale encompasses both grain and extent (Turner *et al.*, 1989). Grain refers to the resolution of the data, i.e., grid size in CA models. Extent refers to the overall size of the study area. As usually study area is fixed, spatial scale can be deemed as grid size, or spatial resolution.

Understanding of spatial process comes from the analysis of spatial pattern (O'Sullivan and Unwin, 2002). Generally it is recognized that in the field of landscape ecology, spatial pattern and spatial scale are inseparable in theory and in reality. Spatial pattern occurs on different spatial scales, and spatial scale affects spatial pattern to be observed (Qi and Wu, 1996; Turner *et al.*, 1989). Accordingly, the results of urban land-use pattern analysis also show difference in different spatial scales, and it would affect understanding of spatial process of urban growth. Jantz and Goetz (2005) have demonstrated the issue in urban modeling.

Some scholars have paid attentions to the relationship of spatial scale and spatial model of land-use changes. Turner (1987) has studied the difference of results of simulating landscape changes in Georgia by comparing three transition models. He argued that it would be useful to incorporate variable scales of land-use transitions into the model of land-use changes (Turner, 1987). De Koning et al. (1998) have discussed the spatial scale effects on land-use model. They found different driving factors of land-use changes in Ecuador at different aggregation levels using multiple regression models (De Koning *et al.*, 1998). Veldkamp et al. (2001) have elaborated on a multi-scale approach as used in CLUE (Conversion of Land-use and its Effects) framework and argued the need for scale sensitive approaches in spatially explicit land-use change modeling (Veldkamp *et al.*, 2001). However, little systematic investigation has been done as to how changing spatial scale affects analysis of urban land-use pattern. Zhao and Murayama have paid attention to this issue (Zhao and Murayama, 2005; Zhao and Murayama, 2006a).

Three principles were set in order to identify appropriate grid size for the model:

1) the grid size should be relatively small compared with some literatures in order to keep the model with high-resolution.
2) urban land-use pattern under the grid size selected should be widely representational.

   As the understanding of spatial process of urban growth comes from the analysis of urban land-use pattern changes, this principle ensures that land-use pattern does not greatly change in certain range near the selected grid size.

3) loss of the area of land-use category should be kept as small as possible in the process of grid size conversion.

The original data set possesses very high-resolution with 10m. The area of land-use category would lose in the process of grid size conversion from 10m (Moody and Woodcock, 1994). This principle tries to keep high-precision for the model.

Under the control of three principles above, an experimental area was chosen for identifying appropriate grid size for modeling spatial process of urban growth by analyzing the effect characteristics of grid size (or spatial resolution) effect on the urban land-use patterns.

Experimental area and data set

One experimental area located in the Central Business District (CBD) of the Tokyo with area 3×4km was selected for the empirical analysis as the date set of DDIMA10m (in 1994) provides the probability of changing spatial resolution of urban land-use map from high resolution (10m) to low resolution (200m, according to the first principle) in analyzing urban land-use pattern. As this research does not discuss how to classify land-use, the land-use classifications in original data set were aggregated into 10 categories for the discussion (Table 4.1) in order to reduce workload. It is assumed that this process does not affect the understanding of spatial scale effect on land-use pattern analysis.

In order to allow a systematic analysis of spatial scale effect, the original grid cells (basic cell unit, BCU, here 10m×10m) were aggregated into larger grid cells in the following way. Each BCU was treated as one basic unit, and therefore the grid size at this scale was expressed as 1 by 1. A 2×2 areal unit, then, corresponded to the grid size that contained four BCUs (two on each side). This was accomplished by aggregating four adjacent basic cell units into one larger grid cell in majority rule. Figures 4.1a and b indicate the schematic process of aggregation of four BCUs into one cell with 20m×20m in single-state structure (one cell only possesses one state). In Figure 4.1a, as the sate of all the BCUs is park and woods, the aggregated cell is assigned land-use type of park and woods. In Figure 4.1b, the proportion of park and woods, road,

Table 4.1 Categories in original data set and in grid size study

Categories in original data set	*Categories in grid size study*
A. Forest & wasteland	1. Park and woods
B. Paddy field	2. Agricultural land
C. Dry field & other farmlands	2. Agricultural land
D. Land under construction	3. Vacant land
E. Vacant land	3. Vacant land
F. Industrial land	4. Industrial land
G. Low-storey residential land	5. Low-storey residential land
H. Densely developed low-storey residential land	5. Low-storey residential land
I. Medium and high-storey residential land	6. High-storey residential land
J. Commercial land	7. Commercial land
K. Road	8. Road
L. Park	1. Park and woods
M. Public facility	9. Public land
N. Water	10. Water
O. The others	9. Public land

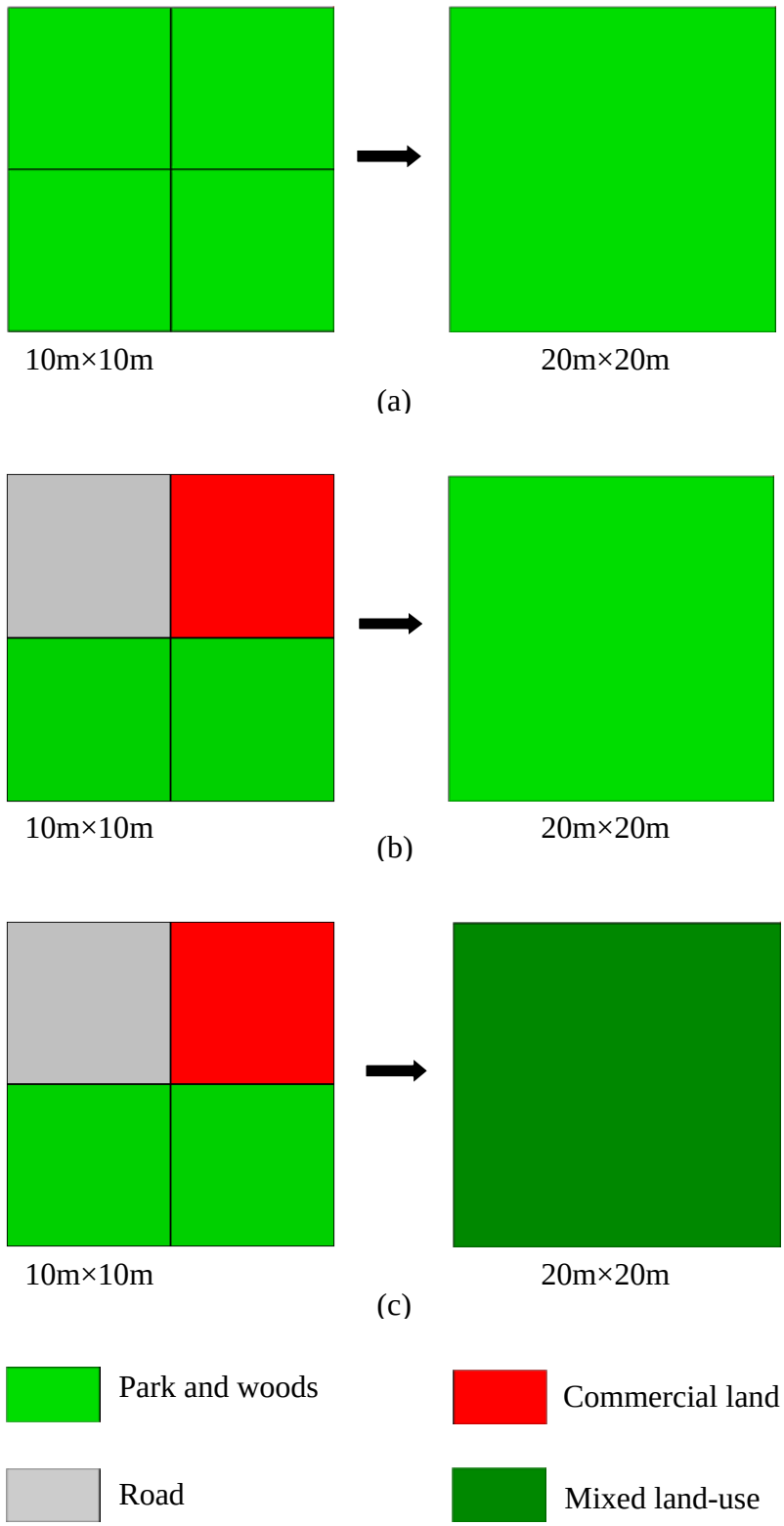


Figure 4.1 Schematic process of the aggregation of four BCUs into one cell. (a) Four BCUs with same category of land-use in single-state structure; (b) four BCUs with different categories of land-use in single-state structure; (c) four BCUs with different categories of land-use in multi-state structure

commercial land to the area of four BCUs is 50%, 25% and 25% respectively. As the proportion of park and woods is more than that of others, the aggregated cell is assigned land-use category of park and woods. This procedure was repeated until the entire region of the data sets was covered. In total, 20 different grid sizes (spatial resolution) were created, ranging from 1×1 through 20×20 BCUs (i.e., 1, 2^2, 3^2 …, 20^2). That is, a series of urban land-use map with spatial resolution from 10m×10m through 200m×200m come into being for this study. Figure 4.2 shows the spatial patterns of urban land-use in some scales. In order to investigate the area change of land-use category in the process, this procedure also was carried out in multi-state structure (one cell possesses multiple states, with proportion of every state) (Zhao and Murayama, 2006a), shown in Figure 4.1c.

In the aggregation process, sometimes the original data set had to be modified (edge rows or columns were omitted) to obtain integer numbers of rows and columns. While this kind of modification was necessary only for technical convenience, it was assumed that this modification would not greatly affect the results of the analysis because of the relatively large size of the data at high spatial-resolution level.

Analysis

Here, spatial autocorrelation index was selected to represent the general pattern of urban land-use. Spatial autocorrelation is a general geographical phenomenon in nature, which indicates spatial association and spatial dependence of geographic phenomenon (Anselin, 1988; O'Sullivan and Unwin, 2002). Although spatial autocorrelation could be seen as a methodological disadvantage, but on the other hand it is exactly what gives us information on spatial pattern, structure and processes and fundamental to much geographical work (Gould, 1970).

Measures of spatial autocorrelation work by examining how objects at one location are similar to objects located nearby. If features situated close together have similar attribute information, then the pattern in the data can be described as exhibiting positive autocorrelation.

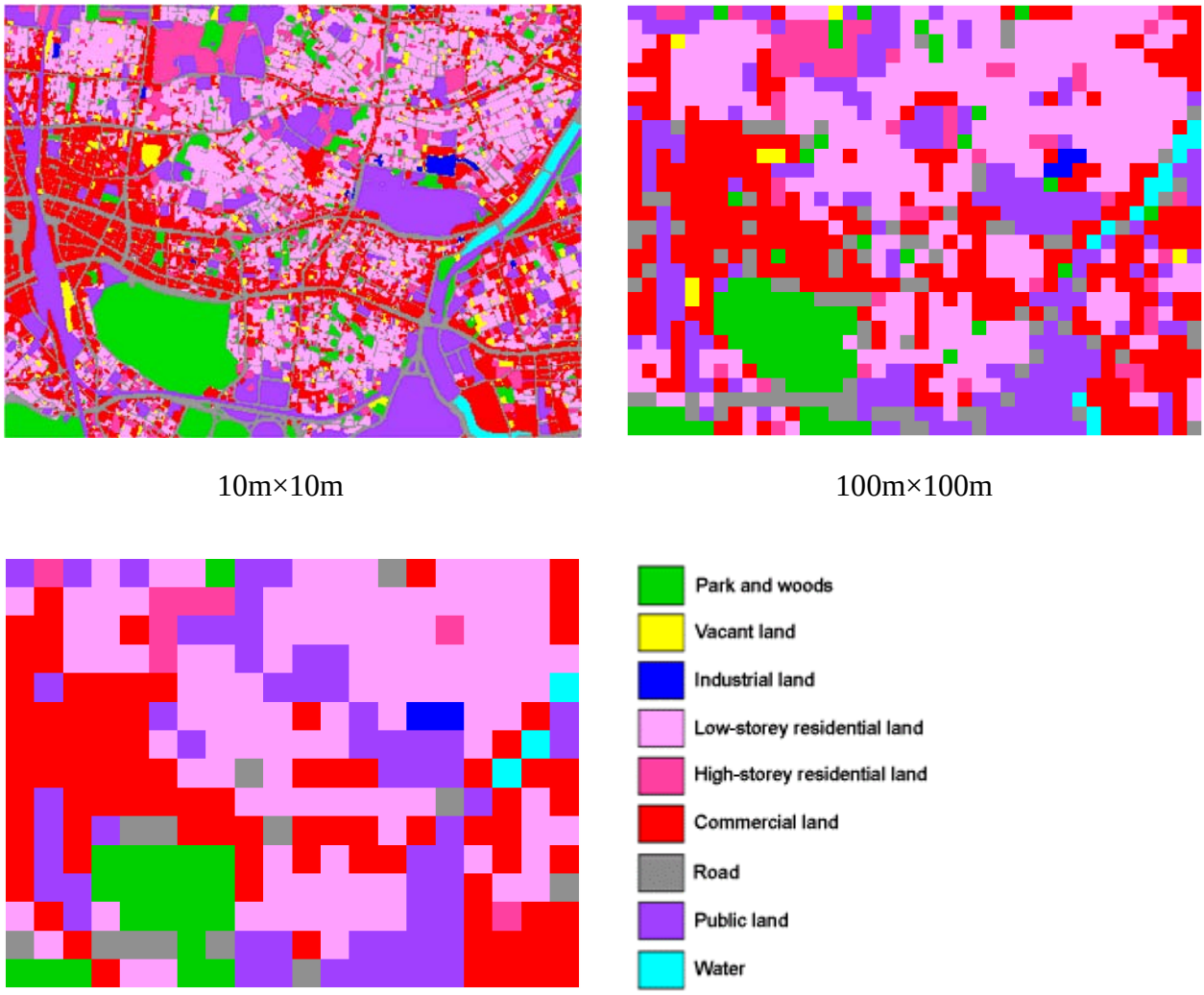


Figure 4.2 Spatial patterns of urban land-use at some scales for experimental area in 1994

When features close together are more dissimilar in attribute value than features further away, pattern in the data is negatively auto correlated. Zero autocorrelation exists when attributes or their values are independent of location (Goodchild, 1986).

Moran's *I* and Geary's c are two common indices for detection of spatial autocorrelation (Cliff and Ord, 1981; Goodchild, 1986; Moran, 1950). Qi and Wu (1996) have used both the indices to analyze the effect of changing spatial resolution on the results of topography and biomass pattern in 1972 of Peninsular Malaysia. They found no appreciable difference among them with regularly grid data sets. Therefore, Moran's *I* was selected as analysis index in this research. Moran's *I* is defined as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(X_i - \overline{X})^2} \qquad (4\text{-}4)$$

Where, X_i *and* X_j stand for feature value of two cells nearby; $\overline{X}$ average value of feature of all the study area; *n* total number of cells; *W* weight (connectivity) matrix. When cell *i* and cell *j* are neighboring, W_{ij}=1, otherwise W_{ij}=0. By convention, W_{ii}=0. The value of Moran's *I* generally varies between 1 and -1, although values lower than -1 or higher than +1 may occasionally by obtained. Positive autocorrelation in the data translates into positive values of *I*; negative autocorrelation produces negative values. No autocorrelation results in a value close to zero (Goodchild, 1986).

Definition above shows that the value of Moran's *I* is mostly determined by two factors: the value of cell and weight matrix. Here, the value of cell adopts the proportion that stands for the extent to which the cell belongs to one or more land-use categories. The weight matrix is constructed in queen case (i.e., a grid cell is adjacent to the neighboring cells in eight directions: left, upper-left, upper, upper-right, right, lower-right, lower, lower-left), similar to Moore neighborhood in cellular-based model of urban dynamics (Figure 2.3).

Figure 4.3 indicates land-use structure of study area. And the value of Moran's *I* (VMI) of

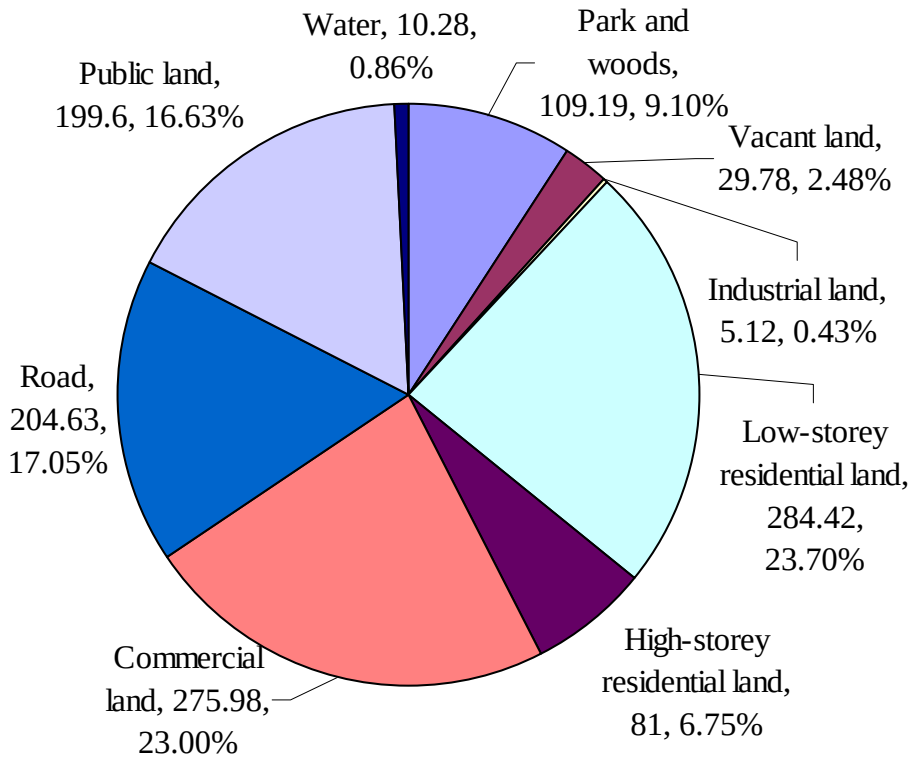


Figure 4.3 Land-use structure of the experimental area in 1994

(**Note**: The label stands for the category, area in ha. and the proportion to the experimental area respectively)

the land-use categories at all the levels of scale are calculated using Geoda software. Figure 4.4 illustrates the variogram of the VMI of all the land-use categories at the series of spatial resolution using single-state structure.

Figure 4.4 indicates that all the data sets show a positive spatial autocorrelation across a range of grid size except land-use type of vacant land at the level of size more than 100m×100m. That is, almost all the types of urban land-use exhibit characteristics of spatial association across the range of scale. It also indicates that the spatial autocorrelation of all the land-use types are scale-dependent as the VMI of all the types of urban land-use decrease with increasing grid size. In the extent from 10m×10m to 50m×50m, the VMI of all the categories of urban land-use decreases rapidly. This indicates that the spatial pattern of all the categories of urban land-use shows strong scale-dependence in this extent. In the scale range of more than 50m×50m to 100m×100m, while any one of the land-use categories is different from the other in the variation of VMI, all the variogram of VMI decreases slowly. That is, scale-dependence in this extent is not as obvious as that in extent from 10m×10m to 50m×50m. In the range of more than 100m×100m, land-use pattern of all categories, except vacant land and industrial land of which are very few in this experimental area, keep relatively stable.

However, the effect of grid size shows different characteristics on different urban land-use category. In order to analyze the differences of effect characteristics, the variogram of VMI of all the urban land-use categories was divided into three groups according to the VMI at original grid size (Figure 4.5).

In Figure 4.5a, the VMI of four types of urban land-use are highest, more than 0.75, at level of original grid cell. The VMI of industrial land and water decrease rapidly across the range of grid size but that of public land decrease not so rapidly. The VMI of park and woods decreases rapidly till spatial resolution of 80m, then keep approximately stable. The VMI of three types of urban land-use in Figure 4.5b keep between 0.6 and 0.7 at level of original grid size. The VMI of low-storey residential land till 20m×20m, commercial land till 30m×30m and high-storey

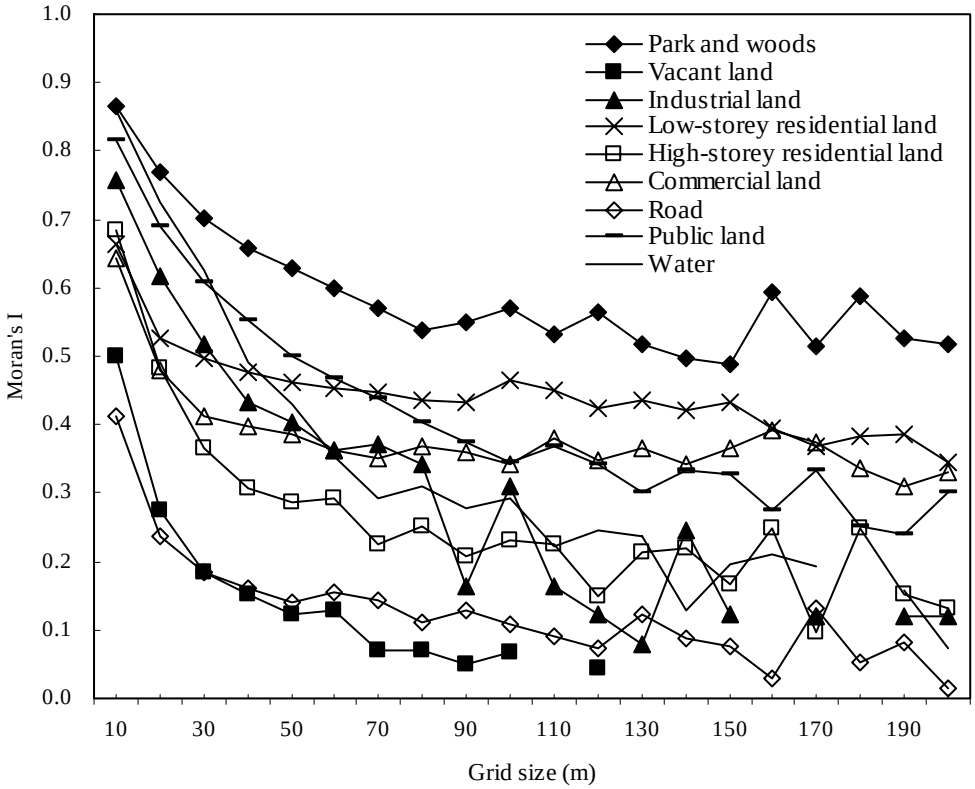
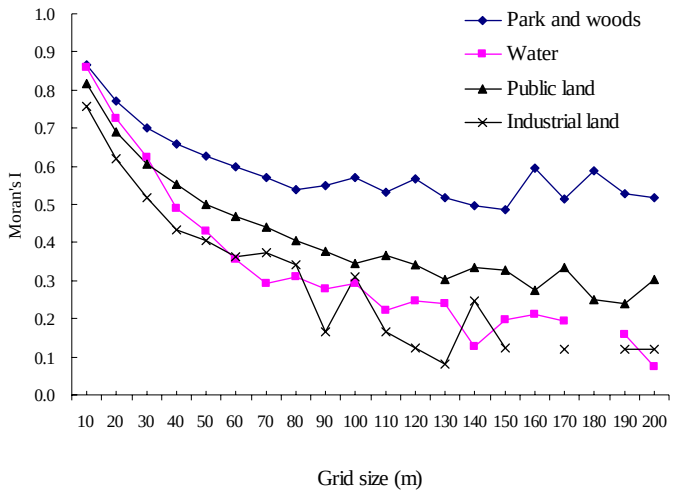
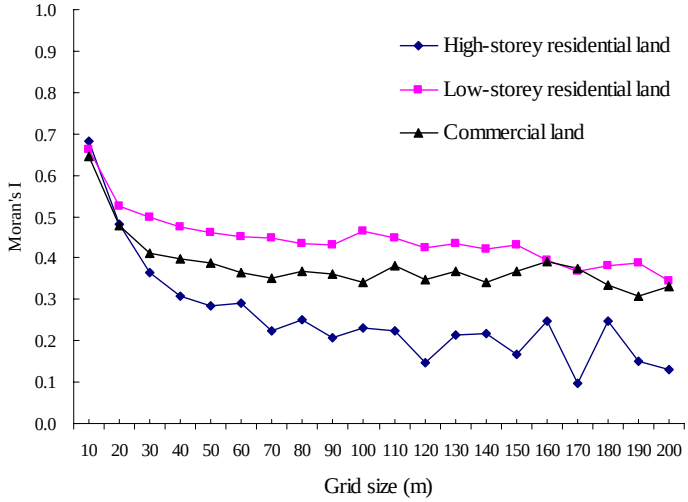


Figure 4.4 Variogram of the VMI of land-use category in the series of grid size in 1994

(a)



(b)



(c)

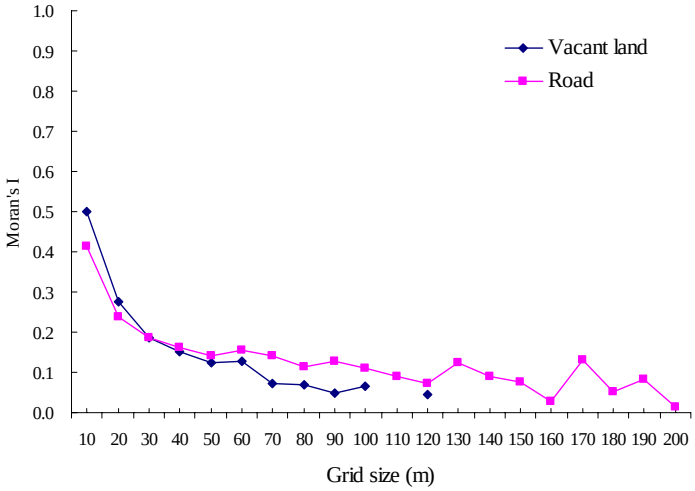


Figure 4.5 Three groups of the variogram of the VMI. (a) park and woods, water, public land, and industrial land; (b) high-storey residential land, low-storey residential land, and commercial land; (c) vacant land and road

residential land till 50m×50m of grid size decrease rapidly, then slowly after that. The VMI of two types of urban land-use in Figure 4.5c are low and decrease rapidly from 10m×10m to 50m×50m of grid size then keep relatively stable. However, the VMI of vacant land disappears from 100m×100m of grid size.

From Figures 4.3 and 4.5 it can be found that effect characteristics of changing grid size on urban land-use pattern is determined by the proportion of urban land-use type to the whole study area and spatial association in general. Spatial autocorrelation of urban land-use with low proportion and dispersed association decreases rapidly with increasing grid size, even disappear. But for high clustered (e.g., park and woods), the spatial autocorrelation decreases slowly, even does not decrease any more (more than 80m×80 grid size). Spatial autocorrelation of urban land-use with high proportion decrease rapidly in a high-resolution range (10m×10m to 50m×50), then show no much effect in a low-resolution range.

Analysis above shows that in the grid size range from 10m×10m to 200m×200m, urban land-use pattern in grid size of 100×100m to 150m×150m can satisfy the second principle for identifying the appropriate grid size.

Change of the area of urban land-use categories in the procedure of aggregating cells was investigated towards the third principle. Figure 4.6 illustrates the results of the investigation under the help of multi-state structure. It is obvious that the area of all urban land-use categories vary with changing grid size in single-state structure. The loss of the area of land-use category in high-resolution grid size is less than that in low-resolution level. It means that area precision of land-use category in the grid size with 100m×100m is higher than that more than 100m×100m. Therefore, 100m×100m was selected as basic grid size for this research. The data set with 100m×100m was produced by aggregating the original 10m×10m cells in majority rule.

4.1.4 Cell states as urban land-use categories

The second problem which should be dealt with in this research is how to identify the state

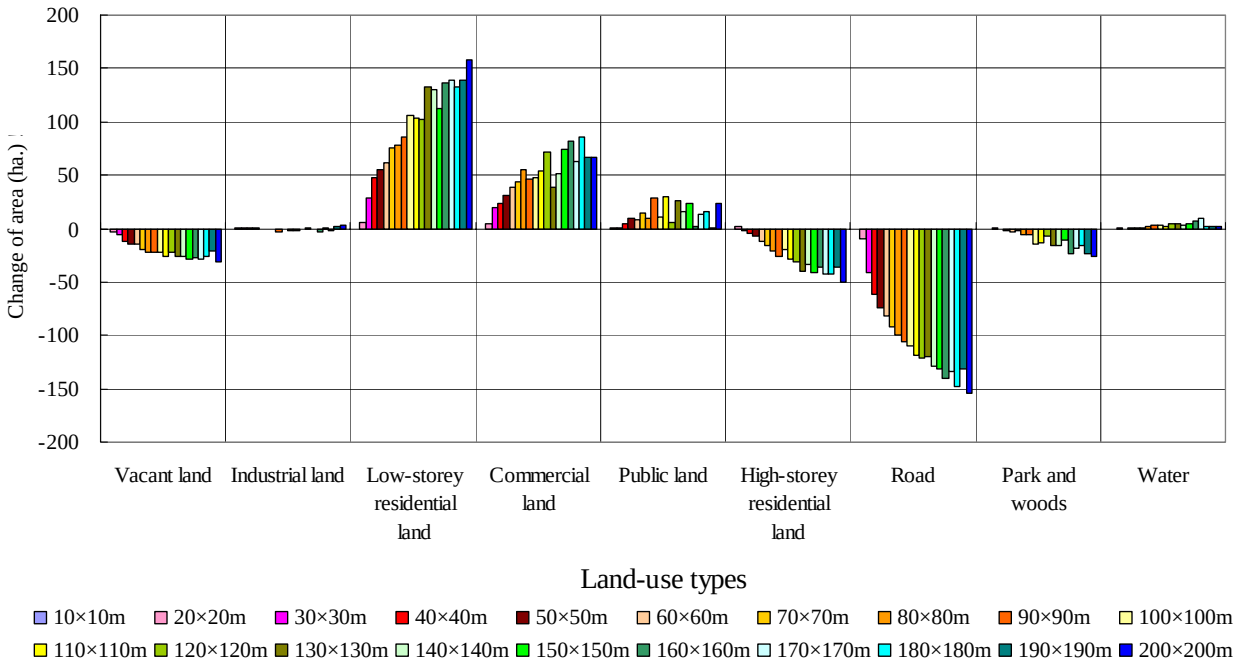


Figure 4.6 Change in histogram of the area of land-use type across a range of grid size (**Note:** For every land-use type, the pillars from left to right stand for the change of the area of land-use in 10×10m, 20×20m, …, 200×200m respectively)

of CA, i.e. land-use categories. Urban land-use pattern occurs not just at certain scale, but also at certain land-use classification system. Characteristics of spatial scale effect on urban land-use pattern analysis may differ from land-use classification systems. The author tries to theoretically explore the problem through connecting land-use classification systems with spatial scale and land-use pattern analysis.

Although some scholars have proposed some land-use classification standardizations (Andersen *et al.*, 1976; Dickinson and Shaw, 1977), most literatures concerning spatial models of urban land-use change just choose their own urban land-use classification system in terms of their own purpose with no theoretical justification (Barredo *et al.*, 2003; White and Engelen, 1993; White *et al.*, 1997). Klosterman (2005) has pointed out that the number of land-use categories which can be projected and the scale at which they can be projected vary substantially for the different types of models (Klosterman, 2005). Little systematic investigation has been done as to how the relationship is between urban land-use classification system and spatial pattern of urban land-use. Actually, identification of urban land-use classification systems for modeling spatial process of urban growth is also closely linked to spatial scale in the model (Andersen *et al.*, 1976; Treitz and Rogan, 2004). Effect characteristics of different classification systems on the result of urban land-use pattern analysis is investigated at a range of scale using same experimental study area and data set in section 4.1.3 as well as the same methodology for this issue.

Three principles were set in order to identify appropriate land-use classification system for the model:

1) urban land-use pattern under the appropriate classification system should be relatively stable in certain range near the selected grid size of 100m×100m.

   This principle tries to keep the representation feature of urban land-use pattern in the grid size of 100m×100m.

2) urban land-use categories should be able to represent the essential individual activities in

urbanized area, and

3) loss of the area of land-use category should be kept as small as possible in the process of grid size conversion.

Land-use classification systems

Classifying land-use is one of manners to understand environment so as to provide important information to nation level or city level plans for overcoming the problems of haphazard, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, and loss of fish and wildlife habitat (Andersen *et al.*, 1976). Although land-use relates to physical form, land-use classifications mostly come from social purposes. Bibby and Shepherd (2000) have discussed the complexity of social purposes in terms of possibility of specifying purposes at many levels of generality, interaction between form and function as well as multi-networks of purposes (Bibby and Shepherd, 2000). Classifying land-use, therefore, can not be deemed as a straightforward process. As this research does not identify how to classify urban land-use, two types of urban land-use classification system, systems A and B, were designed based on the land-use classification system in the data set of DDIMA10m (Table 4.2). It is obvious that this design would not affect the understanding of the characteristics of classification systems effect on urban land-use pattern analysis.

There are nine categories of land-use in system A, which is the same as in grid size study in section 4.1.3, and five in system B. In system B, the categories of vacant land, Industrial land and commercial land are the same as that in system A; two categories of low-storey residential land and high-storey residential land in system A were grouped into category of residential land in system B, and four categories of public land, park and woods, road and water into category of public land in system B. Through this kind of process, the author tried to investigate the effect characteristics of land-use classification systems on the land-use patter analysis.

Table 4.2 Two types of urban land-use classification system

Categories in system A	*Categories in system B*
1. Vacant land	1. Vacant land
2. Industrial land	2. Industrial land
3. Commercial land	3. Commercial land
4. Low-storey residential land	4. Residential land
5. High-storey residential land	
6. Public land	5. Public land
7. Park and woods	
8. Road	
9. Water	

Analysis

Figure 4.7 indicates land-use structure of the experimental study area in system B. The VMI of the land-use categories for system B at the series of grid size is shown in Figure 4.8. As the system is the same as in grid size study, corresponding results of system A are shown in section 4.1.3 (Figure 4.3 and 4.4).

Figure 4.8 illustrates that the spatial autocorrelations of urban land-use category in system B also show scale-dependent as the VMI decreases with increasing grid size. In order to explore the characteristics of land-use classification system effect on land-use pattern, the VMI of land-use category was compared between these two classification systems (Figure 4.9).

Figures 4.9a, b and c illustrate that scale-dependence characteristics of urban land-use pattern of vacant, industrial and commercial land does not change from system A to system B. However, Variogram of the VMI of each land-use category differs a little between these two classification systems. This phenomenon comes from the area change of land-use category in the procedure of cell aggregation.

Figure 4.9d shows the difference of grid size effect on land-use pattern of residential land in both classification systems. Residential land in system B was grouped from low-storey and high-storey residential land in system A (Table 4.2). While the variogram of the VMI of residential land is different from both the VMIs of low-storey and high-storey residential land, it is more alike that of low-storey residential land. Figure 4.7 illustrates that the proportion of low-storey residential land (23.7%) is more than that of high-storey (6.75%). This difference may indicates that the characteristics of grid size effect of one type M (e.g. residential land) of urban land-use in one classification system (e.g. system B) are mainly influenced by the type of urban land-use with higher proportion to the study area (here low-storey residential land) in all the types of land-use, which compose type M of land-use, in another classification system (e.g. system A). Moreover, Figure 4.9d also indicates that this kind of aggregation of land-use types enhances the spatial autocorrelation of the corresponding land-use pattern so as to reduce the

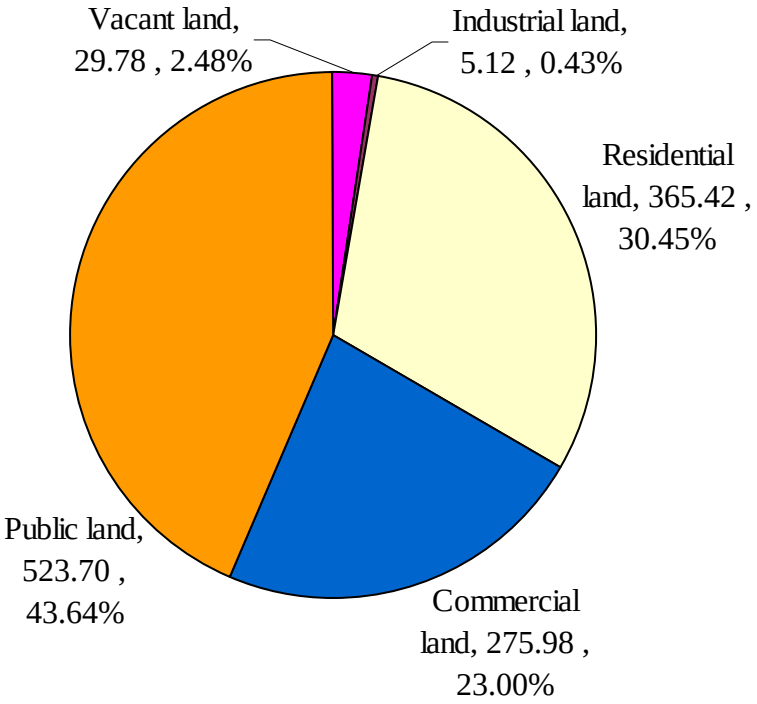


Figure 4.7 Land-use structure of the experimental study area in system B in 1994 (**Note:** The label stands for the category, area in ha. and proportion to the experimental area respectively)

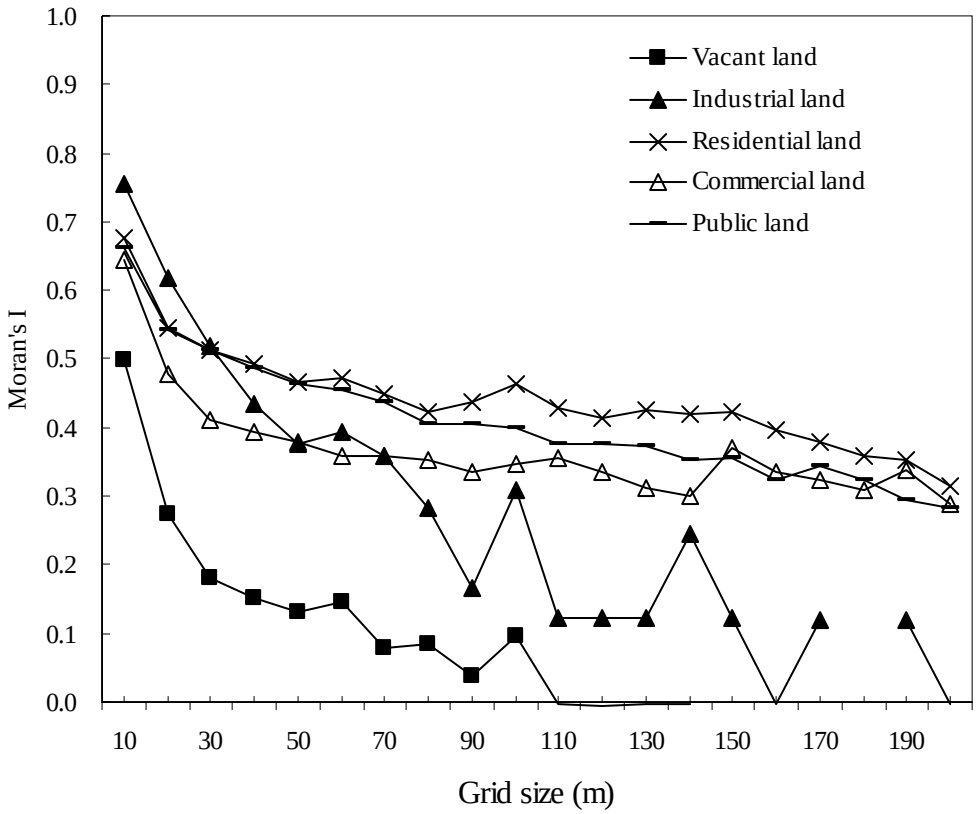


Figure 4.8 Variogram of the VMI of land-use category in system B across the series of grid size in 1994

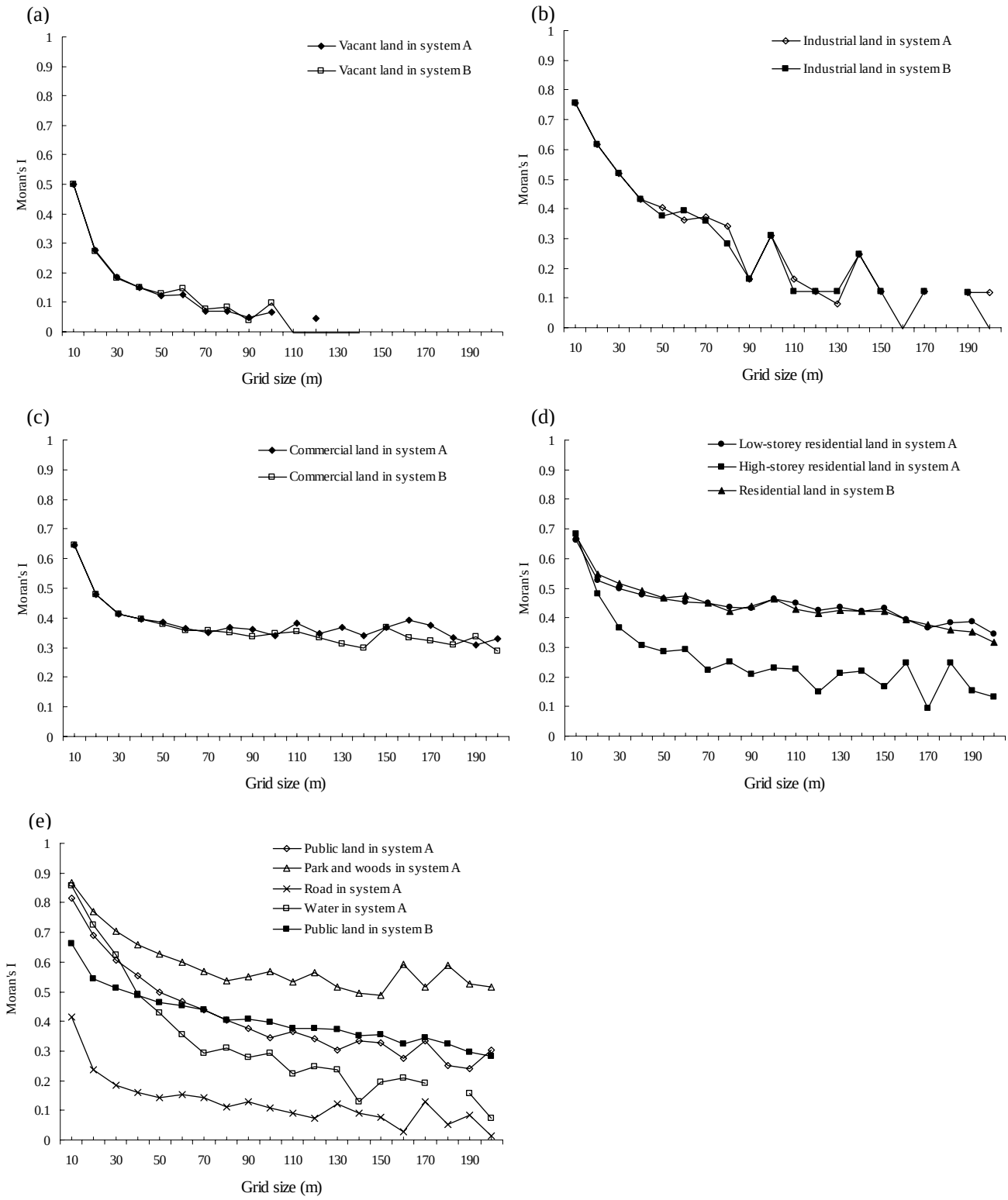


Figure 4.9 Comparison of the VMI of urban land-use category in two classification systems across a range of grid size. (a) Vacant land; (b) Industrial land; (c) Commercial land; (d) Residential land; (e) Public land

characteristic of random in land-use pattern.

Land-use of public land in system B was grouped from land-use of public land, water, road, park and woods in system A. Figures 4.9e illustrates the difference of urban land-use pattern of public land between these two classification systems. The VMI of land-use of public land in system B at BSU is located in the middle of that of system A which composes public of system B. Figure 4.3 indicates that the proportion of public land to the study area (16.63%) in system A nearly equal that of road (17.05%). All the VMI of road across the range of grid size are lower very much than that of others. So add of road to public land may influence the VMI of land-use of public land in system B at BSU. But grid size effect on public land in system B is not as notable as that of others. Since the proportion of land-use of water is small (0.86%) compared with that of other categories, it may does not greatly influence the public land. However, land-use of park and woods, the proportion of which is bigger (9.1%), may give more influence than water to the public land as their variograms parallel to each others.

Compared with Figure 4.6, Figure 4.10 illustrates that the amount of area change of land-use in different classification systems across the range of scale is different, and the amount in system B is less than that in system A across the range of grid size. It means that reducing number of urban land-use categories may diminish the loss of area of land-use categories across the range of grid size and the effect of grid size on urban land-use pattern analysis.

It is clear from above discussions that number of land-use categories should be as small as possible in order to satisfy the first and third principle set for identifying land-use classification system as pattern of grouped land-use category is relatively stable and the loss of area is small. However, in order to satisfy the second principle, identified land-use classification system should includes elementary urban activities. Based on these considerations, land-use classification system used in this research was designed as shown in Table 4.3. This land-use classification system was divided into two levels. Level two was used for discussing the interactions of urban activities in spatial process of urban growth. Level one was used for analyzing general

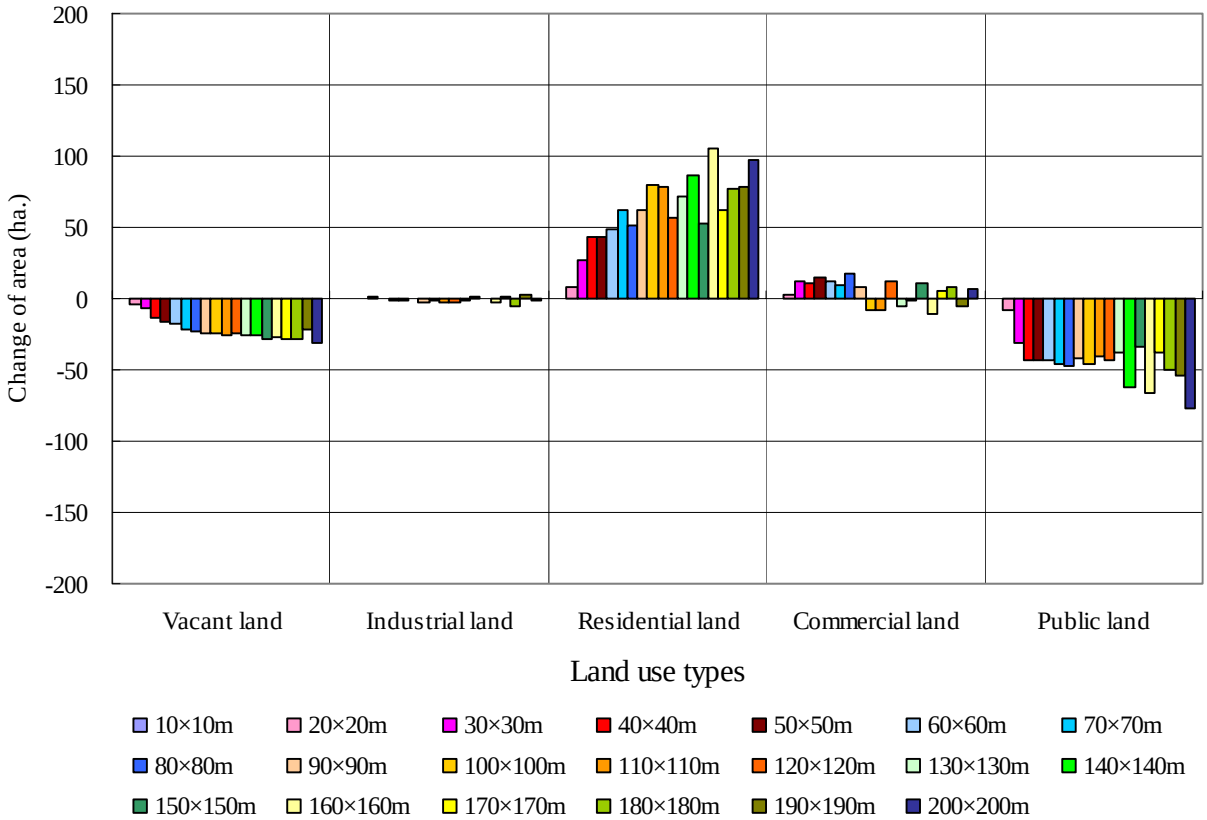


Figure 4.10 Change histogram of the area of land-use type across a range of grid size in system B

(**Note:** For every land-use type, the pillars from left to right stand for the change of the area of land-use in 10×10m, 20×20m, …, 200×200m respectively)

Table 4.3 Land-use classification system in this research

Land-use classification system in original data set	**Land-use classification system in this research**		**Characteristics**
	Level two	**Level one**	
Land under construction	Vacant land	Urbanized area	Active
Vacant land			
Industrial land	Industrial land		
Low-storey residential land	Residential land		
Densely developed low-storey residential land			
Medium and high-storey residential land			
Commercial land	Commercial land		
Road	Road		Active passively
Public facility	Public land		
Park			
The others	Special land		
Forest & wasteland	Forest & wasteland	Non-urbanized area	Passive
Paddy field	Cropland		
Dry field & other farmlands			
Water	Water	Water	Fixed

characteristics of the spatial process when urbanized area is dealt as one category.

In level two, vacant land and land under construction was grouped into vacant land as both of them possess the potential of being transformed to other kind of built-up area in the future. Industrial land, commercial land, road, were retained as they stand for elementary activities of urbanized area. Land-use category of the others also was kept because of its special characteristics in urbanized area. Low-storey residential land, densely developed low-storey residential land, Medium and high-storey residential land were grouped into one category of residential land as they have the same characteristics of providing habitation for people. Public facility and park aim to provide people open space for leisure or other public activities. Therefore, both of them were aggregated into one category of public land. In non-urbanized area, forest & wasteland was kept. Dry field & other farmlands and paddy field were grouped into one category of cropland.

As for characteristics of land-use categories, water represents fixed features in the model, that is, this feature are assumed not to change and which therefore do not participate in the dynamics in order to protect the life environment. Forest & wasteland and cropland are passive features that participate in the land-use dynamics, but the dynamics are not driven by an exogenous demand for land; they appear or disappear in response to land being taken or abandoned by the active functions. The active functions are the four land-use categories which are forced by demands for land generated exogenously to the cellular automata in response to the growth of the urban area: vacant, industrial, residential, and commercial land. Road, public land, and special land are active passively features which are dynamics in the model (Table 4.3).

4.2 Calibration

The process of experimentation connected with the design of the model is usually called calibration. The chief purpose of calibrating the model is to estimate the values of parameters

which control the model's locational simulation and the repercussions of activity through time. In other words, purpose of calibration is to establish the relationship between land-use change and the factors that affect probability of land conversion. The regression can be seen as a process to extract the coefficient of the empirical relationships from observations, which is critical step towards the development of more procedural and realistic urban CA simulation (Wu, 2002). Calibration of CA transition rules is complex due to the many interacting coefficients that do not necessarily yield unique solutions: different processes (rule sets) may lead to identical patterns (Verburg *et al.*, 2004). Calibration, therefore, does not always lead to new understandings of the relative importance of the different coefficients and is inappropriate for testing hypothesis concerning the underlying factors of urban development. The same argument holds for other methods that calibrate the transition rule set without explicating the relations used. Li and Yeh (2001, 2002) propose a method that overcomes the definition problem of the transition rules of a CA model by training artificial neural networks (Li and Yeh, 2001; Li and Yeh, 2002). However, neural networks do not give insight in the relations actually used in modeling, leaving the user uninformed about the possible lack of causality in the relations that are used in the model. Also the method of Yang and Billings (2000) that solves this inverse problem of cellular automata based on genetic algorithms has a number of drawbacks (Yang and Billings, 2000b; Yang and Billings, 2000a). This method is, at present, only operational for simple, binary patterns. Spatial process of urban growth at multiple land-use types are much more difficult to unravel. The main drawback of all these calibration techniques forms the huge set of parameters to be calibrated and consequently, the large amount of computing time. A good initial set of transition rules would be of great help to get these procedures on their way. Here, new methods, especially for neighborhood effect calibration, are proposed to calibrate the model.

Data set of DDIMA10m in 1984 and 1989 was used to calibrate the model. Then the land-use pattern of 1994 was simulated under the calibration for assessment of the model as well as analysis the spatial process of urban growth of the Tokyo metropolitan area.

4.2.1 Neighborhood effect

4.2.1.1 A new model of neighborhood interactions

As discussed above, in CA–based model the state of each cell in an array depends on the previous state of the cells within a neighborhood according to a set of transition rules. Although the approaches of CA were improved greatly in the application on the geosimulation of urban growth, the neighborhood effect still is the key point in this kind of models. Especially in the context of spatial process of urban growth, neighborhood interactions are often addressed based on the notion that urban development can be conceived as a self-organizing system in which natural constraints and institutional controls (land-use policies) temper the way in which local decision-making processes produce macroscopic urban form. Different processes can explain the importance of neighborhood interactions. At large scale, simple mechanisms for economic interaction between locations were provided by the central place theory (Christaller, 1933) that describes the uniform pattern of towns and cities in space as a function of the distance that consumers in the surrounding region travel to the nearest facilities. Spatial interaction between the location of facilities, residential areas and industries has been given more attention in the work of Krugman (Fujita *et al.*, 1999; Krugman, 1999). The spatial interactions are explained by a number of factors that either cause concentration of urban functions (centripetal forces: economies of scale, localized knowledge spill-overs, thick labor markets) and others that lead to a spatial spread of urban functions (centrifugal forces: congestion, land rents, factor immobility etc.).

In keeping with the spirit of simplicity, neighborhood interactions in the applications of CA on urban growth simulation most often adopt either the Von Neumann neighborhood or the Moore neighborhood as shown in Figure 2.3 (Batty, 1998; Wu, 1998a; Yeh and Xia, 2001). For most physical systems, these are clearly the most appropriate definitions, since such systems typically have only local causation (e.g. groundwater must first flow through adjacent cells

before it can reach more distant ones). In the case of human systems like cities, the idea of locality may be much larger, since people and institutions are aware of their surroundings in a wider space (White and Engelen, 2000). Thus it is desirable to define a neighborhood large enough to capture the operational range of the local processes being modeled by CA. White and Engelen (1993) firstly proposed this kind of configuration of neighborhood for exploring the relationship of CA-based model with urban form evolution (White and Engelen, 1993). They divided the neighborhood area into 19 zones according to the distance to the centre, and empirically gave the effect weights of different land-use types for different distance zones. In 1997, White et al. calibrated the neighborhood effect by means of a trial and error approach for geosimulation of Cincinnati city (White *et al.*, 1997). In 2004, this research group proposed automatic calibration procedure for this kind of neighborhood effect (Straatman *et al.*, 2004). However, this approach is also a method of trial and error. Here, this kind of neighborhood definition by White and Engelen was adopted, which can stands for the local interactions of urban activities in human social systems, and a new theoretical model for capturing the neighborhood interactions was proposed.

Tobler's first law of geography, "Everything is related to everything else, but near things are more related than distant things", is the fundamental theory in this model. The first law of geography was firstly proposed by Tobler in August 1969, at the International Geographical Union Commission on Quantitative Methods Conference held in Ann Arbor, Michigan. Tobler presented a paper entitled "A computer movie simulating urban growth in the Detroit Region". In next year, this paper was published in Geographical Analysis (Tobler, 1970).

As Tobler named the sentence "the first law of geography", this law brought strong controversy in geography domain. In 2003, a panel on this law was organized in AAG meeting in New Orleans. Five famous geographers in the world presented their comments in this panel and these comments were published in a forum of Annals of the Association of American Geographers in 2004. Some professors agreed with Tobler, others not. However, all of them

accepted the actual geography phenomena illustrated by the first law of geography. The divarication existed on the word “law”. Goodchild discussed the validity and usefulness of this first law of geography in GIScience and geography (Goodchild, 2004). Here, the controversy of whether phenomena can be expressed as “law” was discarded, and the local knowledge expressed in Tobler’s first law of geography was accepted. It is assumed that the effect of the cell states in the neighborhood area of developable cell accord with the rule of distance decay described by the first law of geography.

The expression of Tobler’s first law of geography is very qualitative. A distance decay function is needed for representing the law. Here, the idea of Reilly’s law of retail gravitation (Reilly, 1931) was adopted. In 1931, using Newton’s gravity principles, Reilly proposed two simple rules that would help to describe the flow of retail trade between towns and cities. The first rule was that the larger the city the more retail trade it would draw from towns in the surrounding region. From his empirical work he discovered that retail trade increased at about the same rate as the population of another city would draw about twice as much retail trade from the surrounding region. The second rule was that a city draws more trade from nearby towns than it does from more distant ones. Again from his empirical word he found that retail trade decreased approximately in inverse proportion to the square of the distance from the city. Combing these two rules, Reilly’s law stated that ‘A city will attract retail trade from a town in its surrounding territory, in direct proportion to the population size of the city and in inverse proportion to the square of the distance from the city’. In algebraic terms the attraction of the shopping centre of city i, R_i, with population P_i, to individuals living in a town k, distance d_{ki} from city i, will be

$$R_i = \frac{P_i}{d_{ki}^2} . \qquad (4\text{-}5)$$

This is a typical power function which can be used to express the distance decay. Here, the function was adopted and modified for expressing Tobler’s first law of geography in this

research.

Figure 4.11 shows one of the extended neighborhood configurations of one developable cell *i* in this research, which is defined as all cells within a radius of eight cells, an area containing 196 cells. It is assumed that in cellular environment all the cells in the neighborhood contribute to the conversion of developable cell *i*. The contribution of one cell is associated with the state of it and the distance to the developable cell *i* based on Tobler's first law of geography. It can be express as follows:

$$f_{kh} = G_{kh} \frac{A_j}{d_{ji}^2} \qquad (j \neq i). \qquad (4\text{-}6)$$

Where,

f_{kh}: constribution of one cell *j* with land-use *k* in the neighborhood to the conversion of the developable cell *i* to land-use *h* for next stage,

A_j: area of the cell *j* (here in square meters),

d_{ji}: the Euclidean distance between the cell *j* in the neighborhood area and the developable cell *i*, and

G_{kh}: constant of the effect of land-use *k* on the transition to land-use *h*. + stands for positive, – repulsive.

Figure 4.12 indicates the scheme of the impact gradient using this function. It should be noted that this is a modificatory Reilly's gravity function and in this function no unit problem exists.

Then the aggregated effect of the cells in the neighborhood can be expressed as:

$$F_{kh} = G_{kh} \sum_{j=1}^{m} \frac{A_j}{d_{ji}^2} I_{kj} \qquad (j \neq i). \qquad (4\text{-}7)$$

Where,

m: number of the cells in the neighborhood, and

I_{kj}: index of cells. I_{kj}=1, if the state of cell *j* is equal to *k*; I_{kj}=0, otherwise.

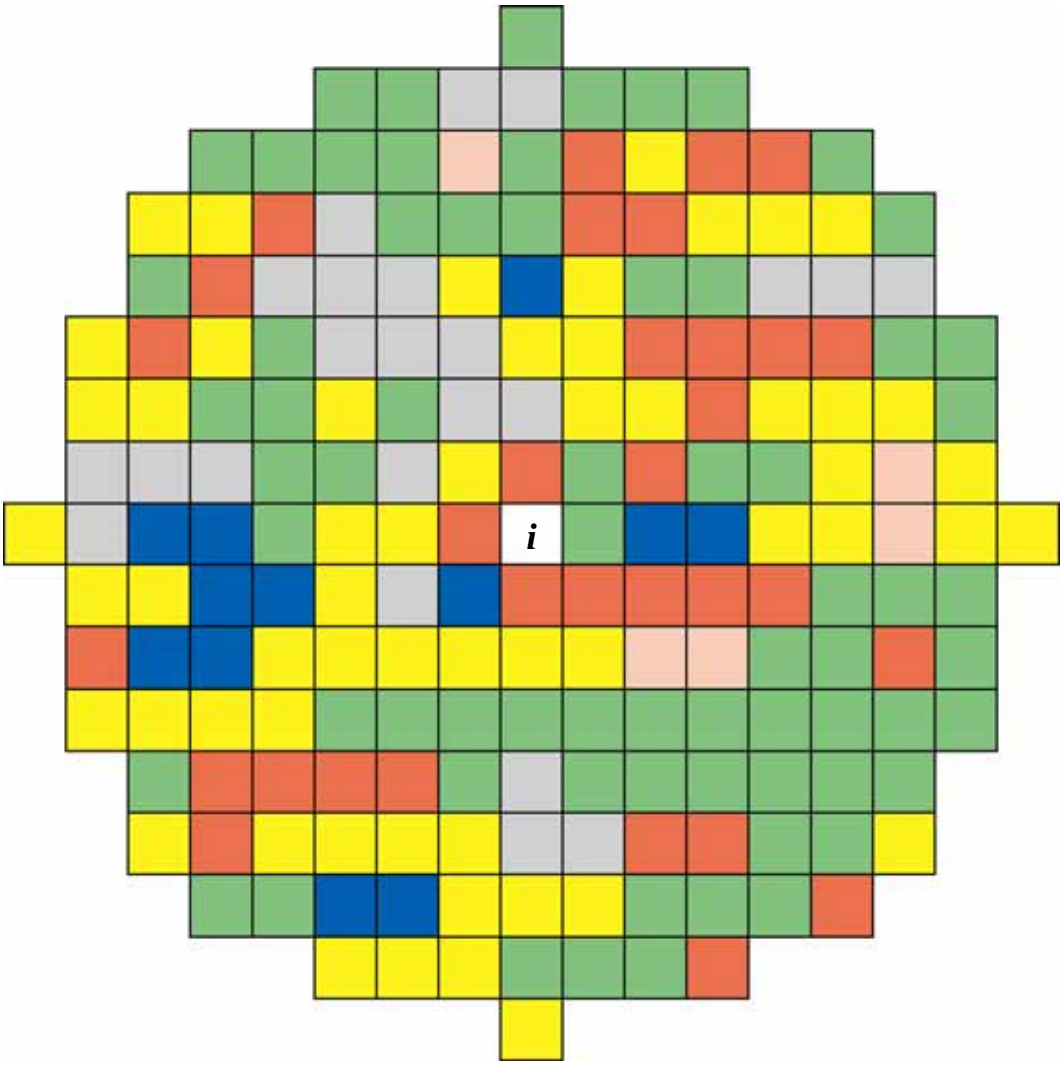


Figure 4.11 An extended neighborhood configuration

(**Note**: The different color of the cells stand for different land-use types)

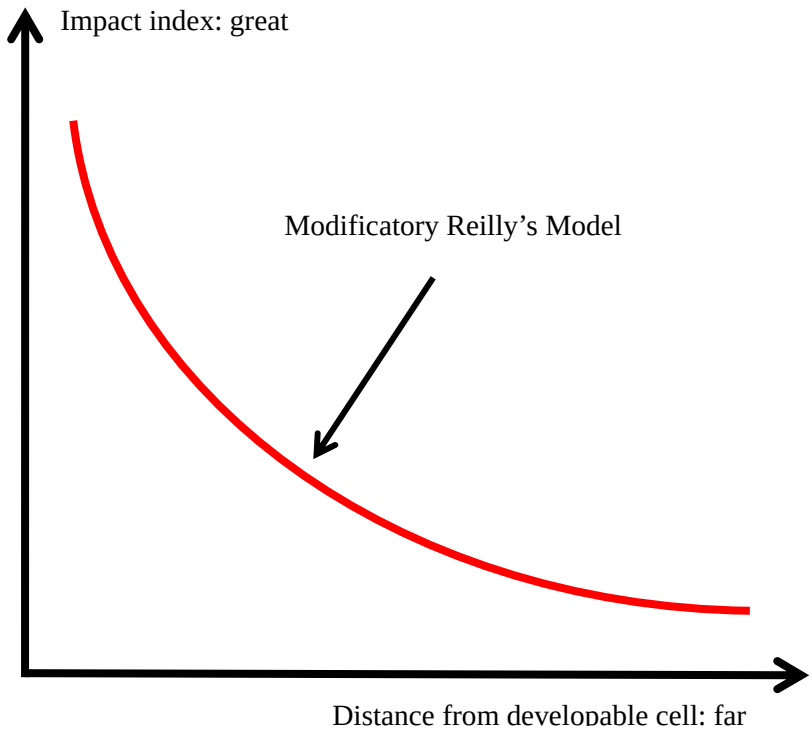


Figure 4.12 Scheme of the impact gradient

For one cell one land-use type, there are just two results of transition: change or no change. Therefore, logical regression approach was selected to calculate the probabilities of the transition of cell *i* under neighborhood effect. The general form of logistic regression is described as follows:

$$y = \ln(\frac{P}{1-P}) = a + b_1 x_1 + b_2 x_2 + \cdots + b_m x_m \qquad (4\text{-}8)$$

$$P = \frac{e^y}{1+e^y} . \qquad (4\text{-}9)$$

Where x_1, x_2, x_3, …, x_m are explanatory variables, y a linear combination function of the explanatory variables representing a linear relationship. The parameter b_1, b_2, …, b_m are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 (z = 1) means the occurrence of new unit such as transition from non-urbanized area to urbanized area, and value 0 (z = 0) indicates no change. The P means the probability of occurrence of a new unit, i.e. z = 1. Function y represents the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1. In logistic regression, the probability value can be a non-linear function of the explanatory variables. This is a strictly increasing function, probability P will increase with value y. Regression coefficients $b_1 – b_m$ imply the contribution of each explanatory variable on 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).

Based on the consideration of logistic regression approach, the neighborhood effect contribution to the probability of conversion to land-use h of a cell (P_i) is described as a function of a set of aggregated effect of different land-use types:

$$Log(\frac{P_{ih}}{1-P_{ih}}) = \beta_{oi} + \sum_k \beta_{ikh} F_{ikh} = \beta_{oi} + \sum_k \beta_{ikh} G_{kh} \sum_m \frac{A_m}{d_{mi}^2} I_{mk} . \qquad (4\text{-}10)$$

As G_{kh} is a constant, let:

$$\beta_{0i}^{'} = \beta_{0i}, \qquad \beta_{ikh}^{'} = \beta_{ikh} G_{kh}$$

Then:

$$Log(\frac{P_{ih}}{1-P_{ih}}) = \beta_{0i}^{'} + \sum_{k} \beta_{ikh}^{'} \sum_{m} \frac{A_m}{d_{mi}^2} I_{mk} . \qquad (4\text{-}11)$$

Where, β'_{oi} and β'_{ikh} are the coefficients to be calibrated with maximum likelihood estimation.

4.2.1.2 Calibration of neighborhood effect

As discussed in section 4.1.3, urban land-use pattern take the characteristics of spatial autocorrelation. Therefore, as one of statistical analysis techniques, logistic regression has to consider the problem of spatial statistics like spatial dependence and spatial sampling in this calibration procedure. Ignoring these issues will lead to unreliable parameter estimation or inefficient estimate and false conclusions regarding hypothesis tests (Irwin and Geoghegan, 2001).

Traditional logistic regression does not take spatial dependence into account (Wu, 2000; Wu and Yeh, 1997). There are few selective alternatives to consider 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 sampled sites. The latter results in a much smaller size of sample and will lose certain information. However, the maximum likelihood method, upon which logistic regression is based, relies on a large-sample of asymptotic normality. It 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 large size of sample. A reasonable design of spatial sampling scheme is becoming a crucial point of spatial statistics. Frequently adopted schemes in logistic regression modeling are either stratified random sampling (Dhakal *et al.*, 2000; Gobin *et al.*, 2001) or systematic sampling (Sikder, 2000). Spatial sampling aims to reduce the size of samples and

remove spatial autocorrelation. Systematic sampling is effective to better reduce spatial dependence but may lose some important information like relatively isolated sites when land-use is not spatially homogeneous. Conversely, random sampling is efficient in representing land-use pattern but low in efficiency in reducing spatial dependence especially local spatial dependence. Following the idea, the integration of both systematic and random sampling is better able to balance sample size and spatial dependence (Cheng and Masser, 2003).

Firstly, land-use changes were detected from 1984 to 1989. In order to eliminate the effect of boundary, the changes in the area with distance less than 600m to the boundary of study area were deleted. Then a systematic sampling was implemented and approximately half cells of the changes for every one of four active land-use types: vacant, industrial, residential, and commercial land, were remained. After the systematic sampling, in order to gain unbiased parameter estimation, the author continued to systematically select one of four cells from developable cell in 1984, and then randomly select appropriate sample numbers to create nearly 1:1 ratio for changed cells and not changed cells. Its total size was 27, 070 cells. Systematic and random sampling was implemented under the environment of ArcGIS 9.0 coupled with VC++ programming.

The calibration was implemented according to the model proposed in section 4.2.1.1. The results of the coefficients and test of the calibration are shown in Table 4.4. Table 4.4 indicates that all the factors contribute to the transition of land-use to other three active land-use types except industrial land. Land-use type of residential land, road and public land do not statistically contribute to industrial land. All the values of PCP (Percentage Correctly Predicted) of four active land-use types are more than 80%, and all of the values of ROC (Relative Operating Characteristic) more than 0.9, showing goodness of fit of this neighborhood effect model. The ROC is based on a curve relating the true-positive proportion and the false-positive proportion for the complete range of cut-off values in classifying the probability (Pontius and Schneider, 2001; Verburg *et al.*, 2004). The ROC statistic measures the area beneath the curve and varies

Table 4.4 Result of the calibration of neighborhood effect

factors and test	Active land-use types			
	Vacant land	Industrial land	Residential land	Commercial land
Total size (cells) of sampling	11034	1732	11596	2708
$\beta'_{Vacant\ land,\ h}$	**1.147**	*0.091	0.190	0.158
$\beta'_{Industrial\ land,\ h}$	0.334	**1.446**	0.262	0.457
$\beta'_{Residential\ land,\ h}$	0.103	**	**0.562**	0.209
$\beta'_{Commercial\ land,\ h}$	0.348	0.727	0.181	**1.821**
$\beta'_{Road,\ h}$	0.199	**	0.421	0.561
$\beta'_{Public\ land,\ h}$	0.198	**	0.199	0.224
Constant β'_0	-2.428	-1.988	-2.830	-2.763
Test				
PCP (%)	84.3	87.6	83.6	86.3
ROC	0.924	0.937	0.905	0.937

PCP: Percentage Correctly Predicted.

ROC: Relative Operating Characteristic.

*: significant at $p<0.05$;

**: non-statistically significant;

others significant at $p<0.01$.

between 0.5 (completely random) and 1 (perfect discrimination). The high values of ROC of four active land-use types indicates that it is possible to predict new area locations reasonably well based on the neighborhood characteristics.

It should be noted that in Table 4.4 the regressed coefficient of land-use type to itself is higher than that of other factors. This illustrates the characteristics of spatial autocorrelation in urban land-use pattern.

4.2.2 Accessibility

Empirically, White et al. (1997) have shown that the transportation network is one of the determinant factors of the "visual urban form". Here, railway station network was used to present the transportation. And exploratory spatial data analysis (ESDA) technique was utilized to detect the spatial relationship of spatial process of urban growth with railway station network.

In urban theories, a widely accepted assumption is the negative exponential decrease of density of development units such as building, people and resources illustrated as:

$$f(x) = \beta e^{-\lambda x}. \qquad (4\text{-}12)$$

Where, x is the radial distance from the CBD situated at the core, and λ is the density gradient. 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 maximization (Wilson, 1970) have made widespread use of the negative exponential function. In 1971, Batty has published his urban dynamic model based on the negative exponential function (Batty, 1971). Cheng and Masser (2003) have used this theory to explore the spatial patterns in data set (Cheng and Masser, 2003). Here, the CBD was extended to railway stations, and also density was extended to probability of change (it is defined as the possibility of land-use transited from developable land to urbanized area at any cell). It is assumed that probability of change is characterized with exponential increase or decrease in

relation to each development factor. In this case, function *f(x)* could be transferred to *p(x)* (probability) through the procedure:

$$f(x) = \lim_{\Delta x \to \infty} \frac{\Delta p}{\Delta x} \approx \Delta p = \frac{CH_{\Delta x}}{D_{\Delta x}} = \beta e^{\lambda x} = p(x) . \qquad (4\text{-}13)$$

Where *p(x)* is the change probability function, *Δp* the probability of change in the scope (*x*, *x* + *Δx*). When *Δx* is very small, *p(x)* could be approximately equal to *Δp*. *Δx* is a radial distance interval, which should be as small as possible. $CH_{\Delta x}$ counts the total amount of land-use change located in the scope (*x*, *x* + *Δx*), $D_{\Delta x}$ is the total amount of developable cells in the same scope. *Δx* is actually the buffering distance interval.

Equation 4-13 also can be:

$$\log(p(x)) = \log(\beta) + \lambda x . \qquad (4\text{-}14)$$

The slope λ indicates the degree of spatial influences; $\lambda > 0$ 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* represents probability value of the event of land-use change in the scope (*x*, *x* + *Δx*).

Data set of railway station (Figure 4.13) comes from Digital Land Information (DLI) of Japan in 1989. According to equation (4-13) and (4-14), the relationship between urban growths in four active land-use types with railway stations was regressed as shown in Table 4.5. It shows that the railway stations obviously influence the land-use changes on vacant, residential, and commercial land, but not on industrial land.

4.2.3 Suitability

Land-use suitability is always associated with land slope (Chen *et al.*, 2001). As digital land condition map of Japan was released in 2006, in this research land condition map was added to evaluate the land-use suitability for urban growth.

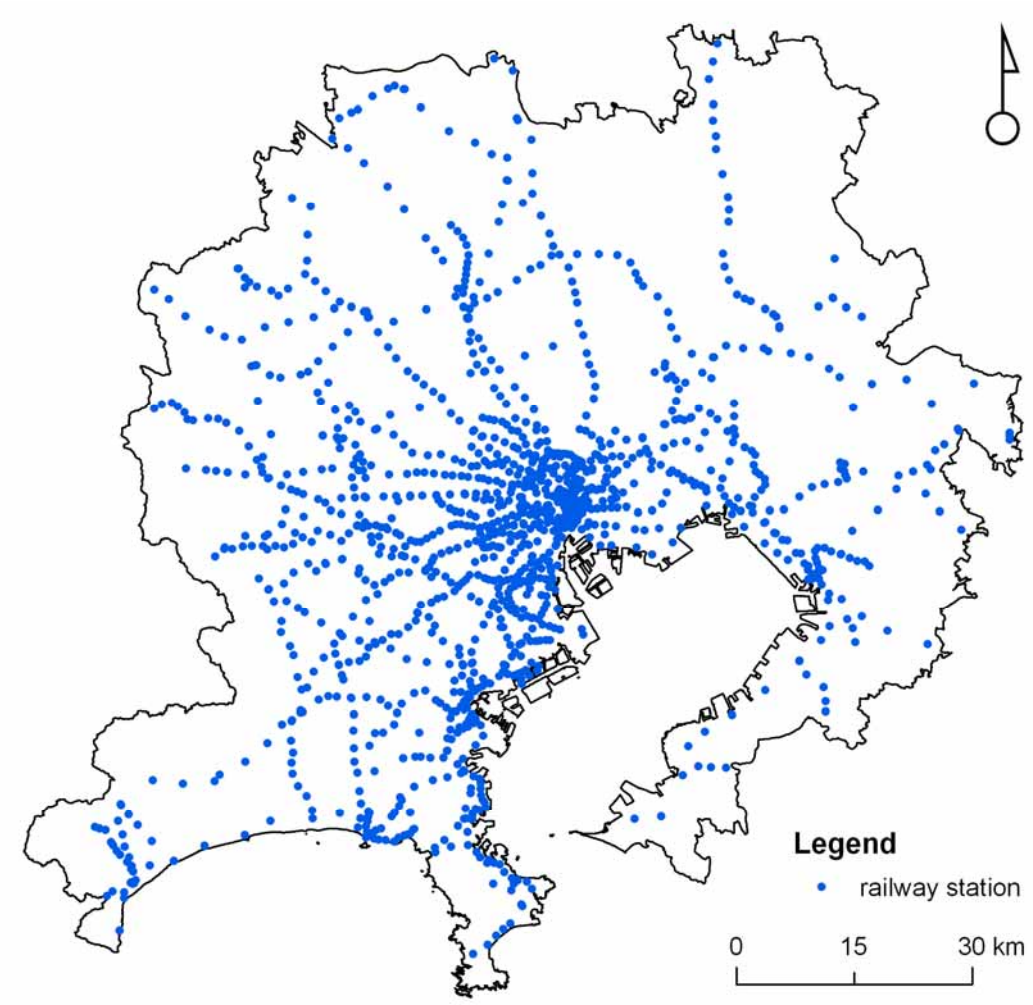


Figure 4.13 Railway stations in the Tokyo metropolitan area in 1989

Table 4.5 Result of the regression for exploring the relationship of urban growth with railway stations

Land-use type	Coefficient		
	β	**λ**	**R^2**
Vacant land	0.069	-0.351	0.868
Industrial land	**	**	**
Residential land	0.102	-0.680	0.936
Commercial land	0.018	-0.375	0.643

**: $p>0.05$

Others: $p<0.01$

Land condition investigation in Japan was carried out from 1960 in order to provide important land-use suitability information for land-use planning and disaster prevention. The digital information in raster structure with high resolution of 100m grid was released from April 1st of 2006. As no more information of slope is included in this data set, data set of altitude with 50m mesh (Figure 4.14) was used to generate degree of slope for the study area. Slope degree was divided into six classes: 0º ~ 5 º, 5 º ~ 10 º, 10 º ~ 15 º, 15 º ~ 20 º, 20 º ~ 35 º, and more than 35 º. The slope information was integrated into digital land condition map under the support of spatial module of ArcGIS 9.0. Table 4.6a and b show the classification and proposed code system of the integrated digital land condition map, and Figure 4.15 illustrates the integrated land condition map.

Evaluation of land-use suitability is a complicated process (Malczewski, 2006). As this research focuses on the spatial modeling approach for geosimulation of spatial process of urban growth, in order to simplify the evaluation of land-use suitability, concept of relative land-use suitability (Chen *et al.*, 2001) is adopted:

$$R_{sk} = \frac{A_{sk}}{N_k} . \qquad (4\text{-}15)$$

Where, R_{sk} stands for the suitability of the integrated land condition class s for land-use type k; A_{sk} the area of land-use type k in the integrated land condition class s; N_k total area of land-use type k. It was assumed that for so long time, the land-use types selected the land-use suitability underlying integrated land condition. In certain period, the relative land-use suitability keeps stable to a certain extent. The author checked the relative land-use suitability for four active land-use types in 1984 and 1989 respectively (Figure 4.16) and verified the assumption.

4.2.4 Land-use zoning

Land-use zoning map expresses the urban and regional land-use planning policy of city government. Through land-use zoning plans the city is regulated to be occupied by land-uses in

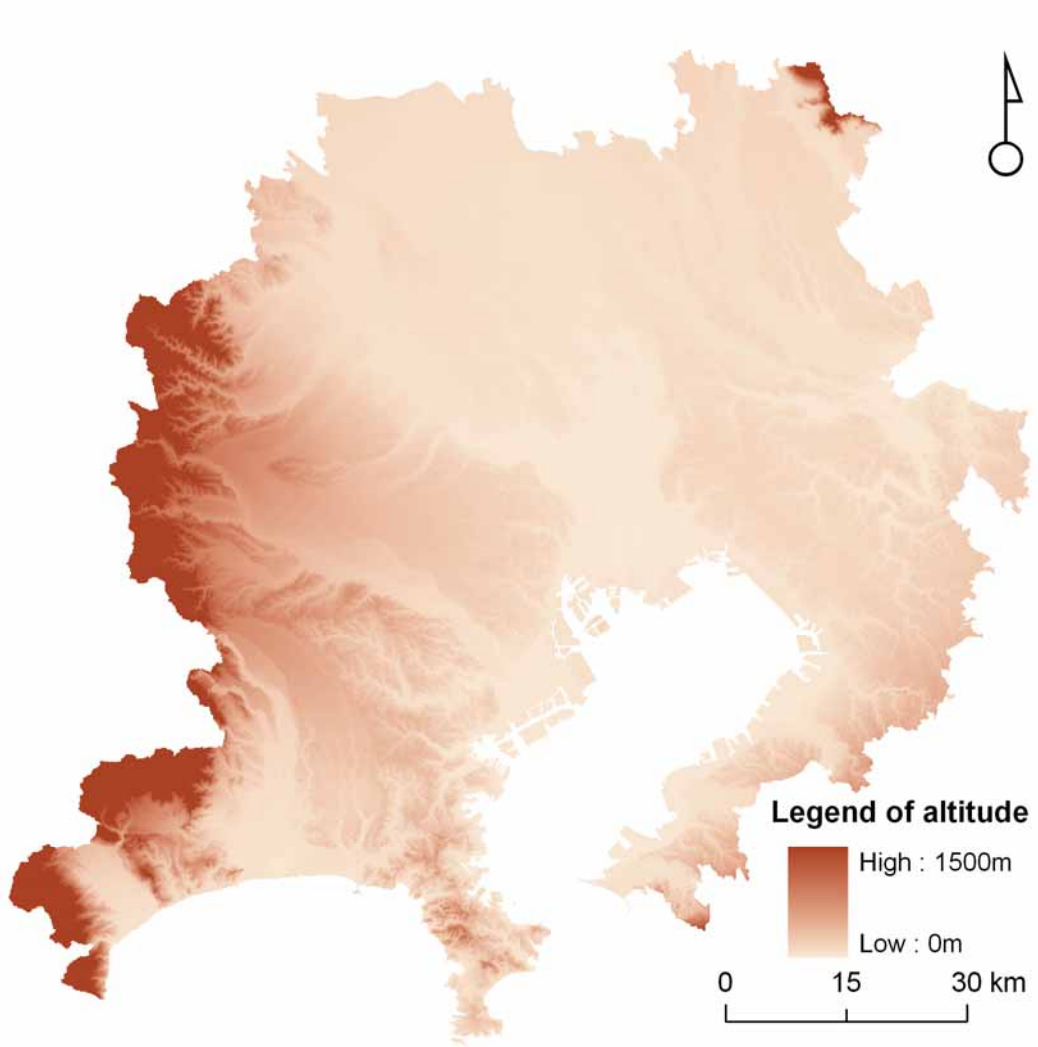


Figure 4.14 Altitude map of the Tokyo metropolitan area

(*Source:* Geographical Survey Institute, released in 1997)

Table 4.6a Classification and code system of the land condition map

First class	Second class	Code
A, Cant	Cant with slope of 0 º ~ 5 º	0101
	Cant with slope of 5 º ~ 10 º	0102
	Cant with slope of 10 º ~15 º	0103
	Cant with slope of 15 º ~ 20 º	0104
	Cant with slope of 20 º ~ 55 º	0105
	Cant with slope of more than 35 º	0106
B, Metamorphism area	Wall rock	0202
	Bald ground	0204
	Landslide (landslip area)	0205
	Landslide (accumulated area)	0206
C, Terrace	Higher-ranking bevel	0301
	High-ranking bevel	0302
	Medium-ranking bevel	0303
	Low-ranking bevel	0304
	Lower-ranking bevel	0305
D, Piedmont	Rubbish area	0401
	Talus cone	0402
	Mud flow heap	0403
	Mud flow terrace	0404
E, Minute highland of depression	Alluvial fan	0501
	Gently alluvial fan	0502
	Natural levee	0503
	Dune	0504
	Sandbar	0505
	Minute highland along ceiling river	0506

Table 4.6b Classification and code system of the land condition map

First class	Second class	Code
F, Valley	Valley	0601
G, General aspect of depression	Ravine plain	0701
	Coastal plain	0702
	Rear depression	0703
	Old river channel	0704
H, Near water terrain	Flood bed	0802
	Low water flow bed	0803
	Swamp land	0804
	Falling moat	0805
	Tidal ground	0806
I, Water	Water	0901
J, Artificial area	Leveling area	1001
	Leveling area for agriculture	1002
	Cut slope	1003
	Laid slope	1004
	High laid area	1005
	laid area	1006
	Filling area	1007
	Polder	1008
	Concave falling area	1009
	Under construction	1010
K, Volcano area	Lapillus hill	1201
	Scoriae hill	1202
	Craterwall	1203
	Scoriae area	1204

Source: Geographical Survey Institute, released in 2006

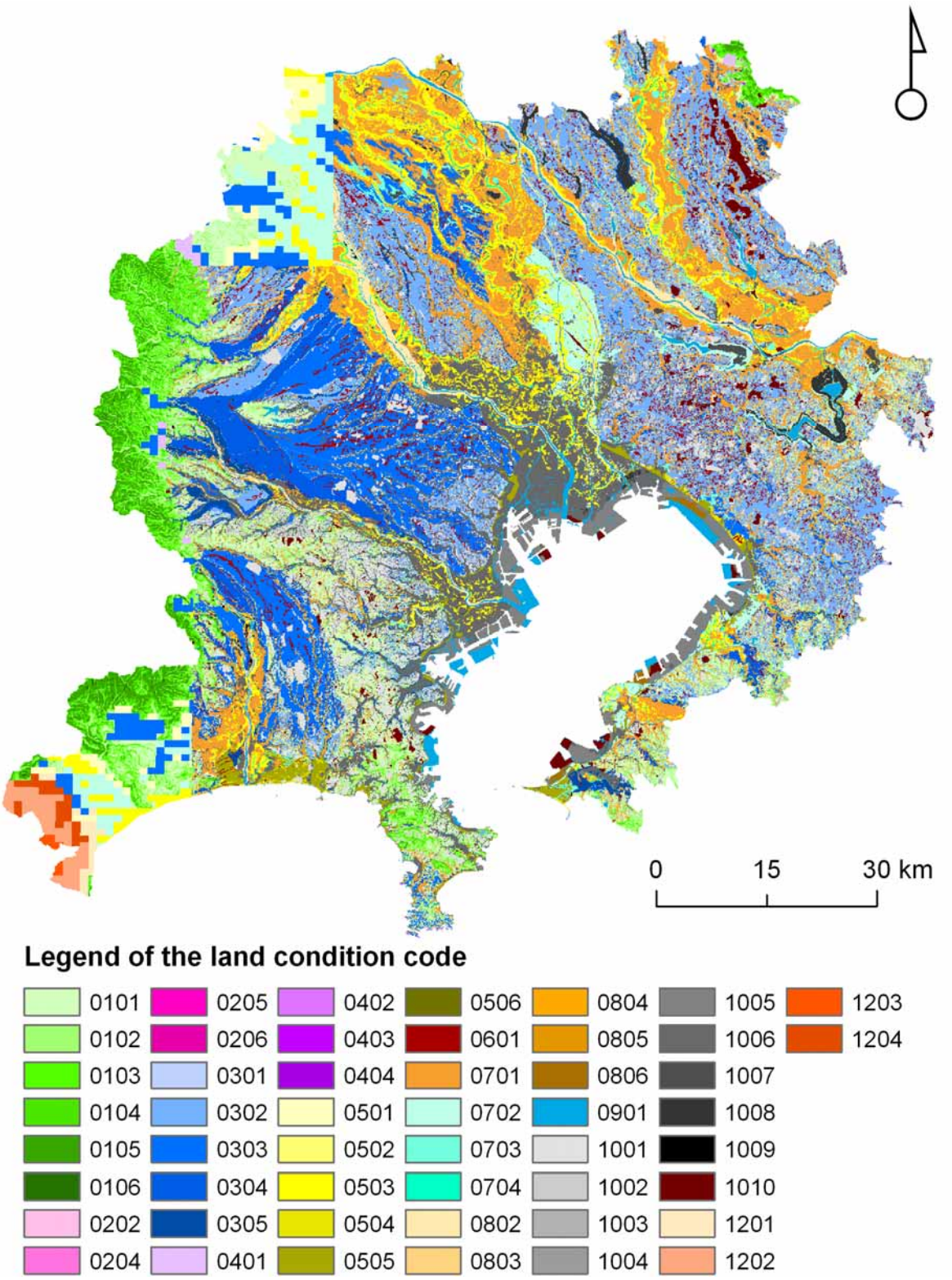


Figure 4.15 Land condition map of the Tokyo metropolitan area

(*Source:* Geographical Survey Institute, released in 2006)

(**Note**: See the Tables 4.6a and b for the definition of code)

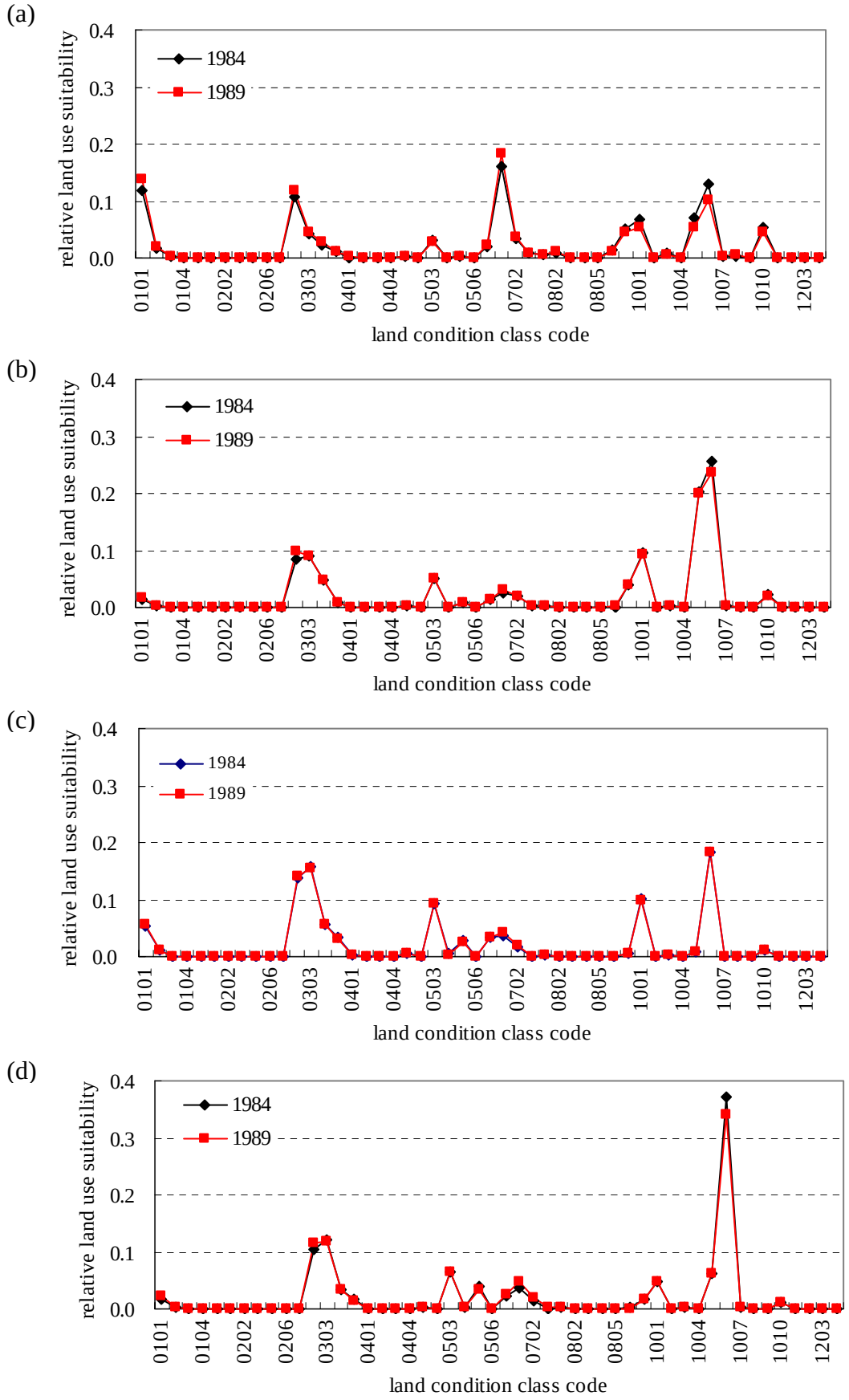


Figure 4.16 Relative land-use suitability for active land-use types in 1984 and 1989. (a) vacant land; (b) industrial land; (c) residential land; (d) commercial land

space and time. White and Engelen (2000) have argued the importance of land sue zoning in urban and regional modeling. Saizen et al. (2006) have analyzed the relationship between land-use plans with urban land-use changes.

As Japan experienced extremely high economic growth from 1950s to 1970s, and faced urgent issues of urbanization and industrialization especially in metropolitan areas (Takahashi and Taniuchi, 1994), the City Planning Act was enacted in 1968 (Saizen *et al.*, 2006). It established a system to divide land into two types of urban planning zones, urbanization promotion zone and urbanization control zone, based on the "Policy on the Preparation, Development or Preservation of Urbanization Promotion Zones and Urbanization Control Zones" (Miyazawa, 1978). An urbanization promotion zone is either an already urbanized area or an area which policy-makers consider should be urbanized within the next 10 years or more long time. Main land-use types promoted also are regulated in these zones. Urbanization control zones consist of areas where urbanization must be constrained. In principle, they are designed as areas without urban facilities or anything else for promoting urbanization. There are specific standards and restrictions on development activities. Urbanization control zones are mainly designated for two purposes. First is to protect natural resources, such as forest and farmland, while the second is to reserve land for urban development in the future. However, some urbanization control zones in city fringes are often converted to urbanization promotion zones chiefly due to increasing demand for housing development and a lack of affordable land pricing in city centers (Saizen *et al.*, 2006).

Digital land-use zoning map with 100m grid in 1989 was derived from high-resolution digital land information which was released by Geographical Survey Institute of Japan. Tokyo metropolitan area was divided into three kinds of planning: urbanization promotion area, urbanization control area, and non planning area. In urbanization promotion area, main land-use types of residential, industrial, commercial land were regulated. The map is shown in Figure 4.17.

The relationship of land-use changes with land-use zoning was analyzed to catch the effect of land-use zoning on land-use changes. The result is shown in Figure 4.18. This figure indicates the area percentage of increment of four active land-use types to different land-use zones. It is obvious that the percentage of residential land to residential urbanization promotion area is more than that to other zones and the percentage of industrial land to industrial urbanization promotion area is more than that to other zones. However, land-use change of commercial land did not show predominance in commercial urbanization promotion area. All of the land-use changes of four active land-use types took place in urbanization control area as the same as discussed by Saizen et al. (2006). In order to simplify this aspect of this calibration, relative land-use zoning effect index was adopted in this model from the concept of relative land-use suitability in section 4.2.3. And the index was assumed to be relatively stable in a certain short period of several years.

4.2.5 Random perturbation

The random perturbation parameter produces non-continuous (i.e. “leap-frog”) growth of urban land-uses based on a stochastic function. If the perturbation is increased, then the stochasticity of the simulation increases too. In this case, the value has to be fine-tuned to generate a sufficient number of new “seed” cells of various land-uses in new locations, which will subsequently develop into, for example, new industrial, commercial or residential land. Under this consideration, α was set 0.6 following a “trial and error” approach by comparing the NP metrics of simulated land-use map with reality in 1989. The value is same as the random perturbation parameter set in the geosimuliation for Berlin (Barredo *et al.*, 2003).

4.3 Implementation

GIS has provided a important platform for implementation of spatial modeling, especially

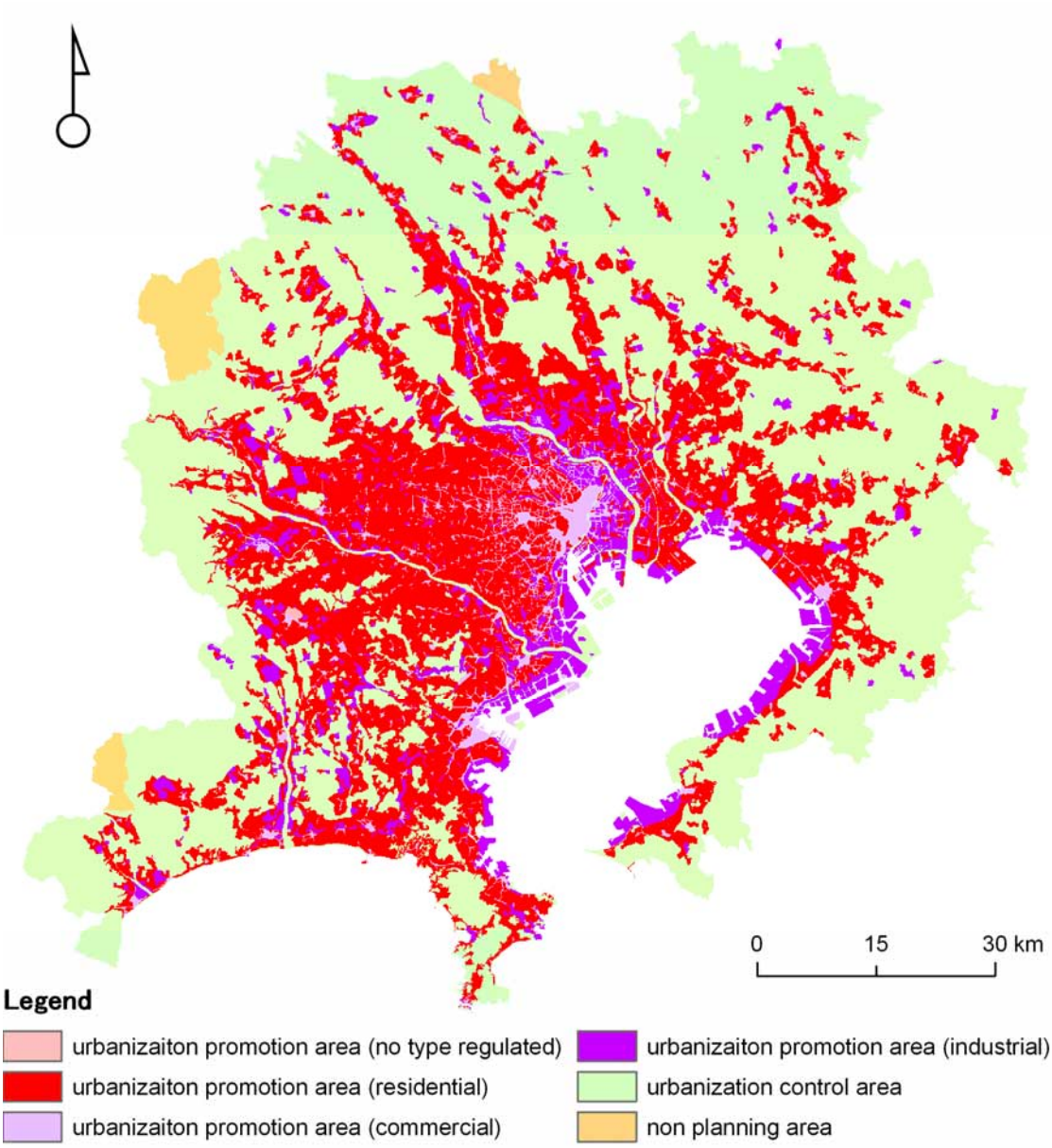


Figure 4.17 Land-use zoning map of the Tokyo metropolitan area in 1989

(*Source*: Geographical Survey Institute)

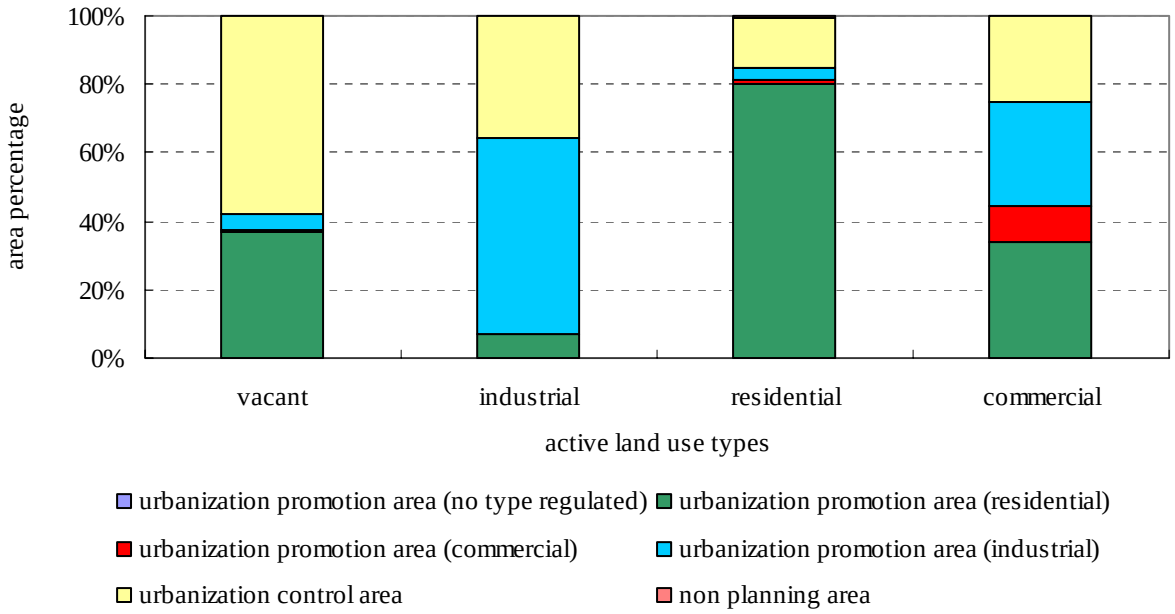


Figure 4.18 Relationship of land-use change (from 1984 to 1989) with land-use zoning

for environmental issues (Clarke and Gaydos, 1998; Goodchild *et al.*, 1996; Wagner, 1997). However, how to well integrate GIS with spatial modeling keeps a challenging yet (Clarke and Gaydos, 1998). Some current GIS applications provide a set of operators enough to develop spatial modeling: user defined filters, dynamic operations, overlay, reclassification, and a scripting language to put the operations in a logical order. Some other researchers have recently proposed ways of building CA functionality into GIS, or conversely, GIS functionality into CA. The second approach can be called loose coupling (Clarke and Gaydos, 1998). This research follows this approach to implement the proposed model of spatial process of urban growth by programming under VC++ environment and coupled with ArcGIS 9.0 software.

In the context of this CA-based model, GIS served as two important roles. The first was as data integrator. All the spatial data were processed in ArcGIS 9.0 software in either GRID file or SHAPE file. Further modeling and analysis depended on this essential first step, what Chrisman has called a 'Universal requirement' for GIS (Chrisman, 1997). Secondly, GIS allowed the results of simulation to be reintroduced into the GIS data sets available for visualization and further application. By broadening the definition of GIS, such as that of GIScience, the model coding can even viewed as part of the science, if not part of the system (Goodchild, 1992). Obviously, within this loose coupling approach, the possibility of delivering the model to end-users as a stand-alone software is a clear advantage.

4.4 Results and discussions

Spatial process of urban growth in the Tokyo metropolitan area from 1989 to 1994 was simulated using the CA-based urban geosimulation model according to the results of model calibration in the period of 1984 to 1989. This simulation also represents the prediction of spatial process of urban growth in the study area. Result of the simulation was tested by comparison with actual land-use datasets to assess the model proposed in this research and discuss the spatial

process of urban growth in the Tokyo metropolitan area. The comparison was implemented in two levels according to the land-use classification system in Table 4.3: level one and level two. In level one (macro classification scale), urbanized area in 1994 was emphasized in order to discuss the general characteristics of urban growth in the study area when considering city as one object like an “organism” (Batty and Xie, 1994; Batty *et al.*, 1999). As this research divided urbanized area into more detailed land-use categories and assumed that the result of urban growth was derided from the emergence, interaction, and competition of these land-use categories, the result of the simulation of detailed land-use categories in level two (micro classification scale) also was discussed towards cognizing the characteristics of spatial process of these land-use categories.

Although more research is needed in order to generate new appropriate testing methods for CA-based urban models (White *et al.*, 1999), several approaches are feasible. The simulation was discussed in four ways for both classification scales (macro classification scale and micro classification scale):

1) a quantitative comparison through cell-by-cell;

2) comparison of spatial form of urbanized area through fractal dimension;

3) comparison of urban landscape through spatial metrics;

4) regional characteristics.

4.4.1 Land-use of the Tokyo metropolitan area in 1994 at macro classification scale

1) A quantitative comparison through cell-by-cell

The result of simulated land-use pattern in 1994 is shown in Figure 4.19. This figure also indicates the good visual comparison of land-use pattern between simulation and reality.

The precision was evaluated through comparing the simulated land-use pattern with actual

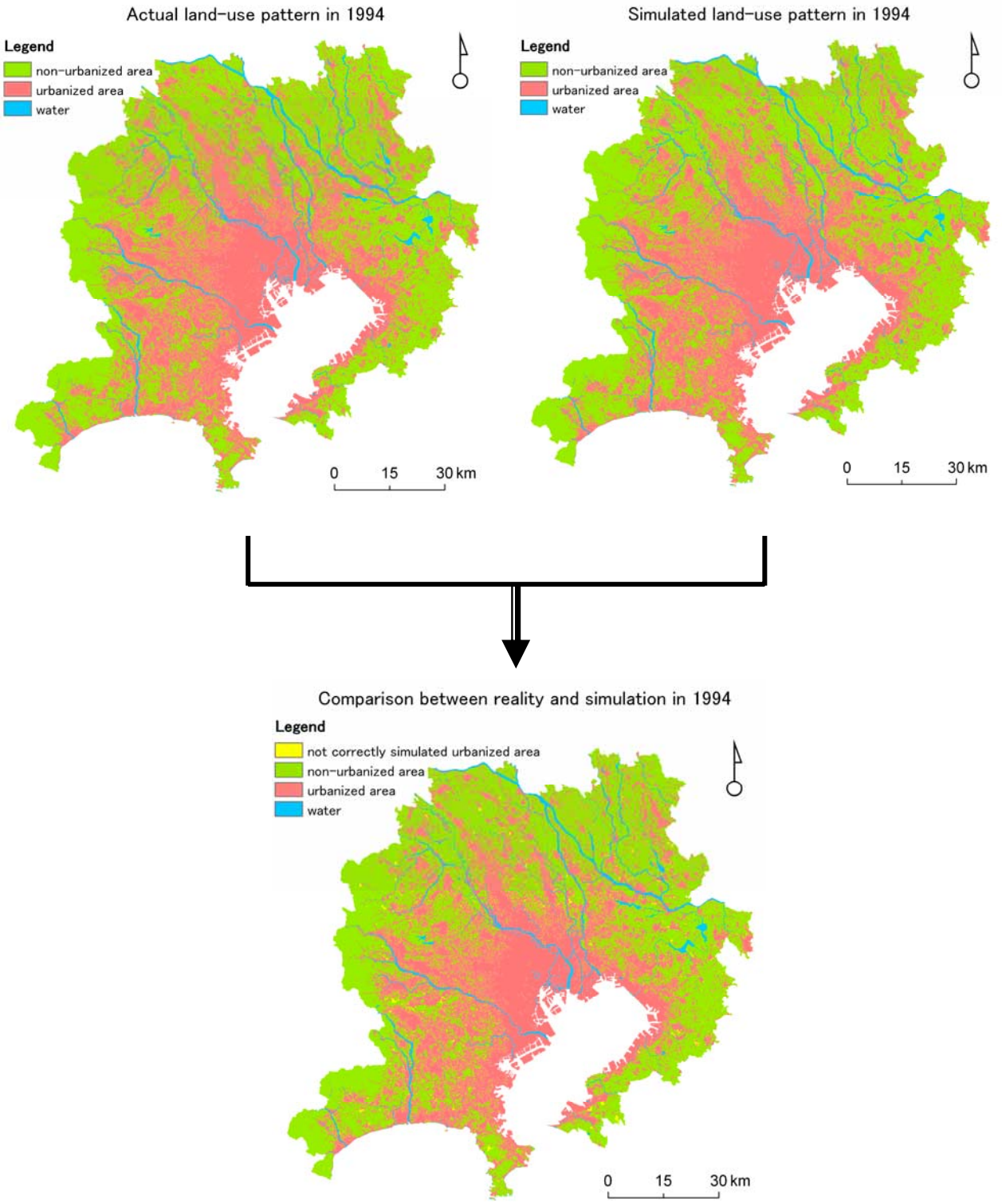


Figure 4.19 Visual comparison of the land-use pattern between reality and simulation in 1994

one through cell-by-cell. This approach is useful for identifying the cells that are identical in both maps of simulation and reality. Although this approach generates quantitative measures of coincidence for the two maps, there are some weaknesses in their implementation in CA-based urban models (Torrens and David, 2001; White *et al.*, 1997; Wu, 1996). This procedure is not able to evaluate patterns and structure, since the procedure is based on independent comparisons between pairs of cells, and therefore is unable to take account of patterns or distributions in nature. This means that small displacements are identified as discordances, and the same discordance will be stated if the displacement is of 100 cells instead of 1 (Barredo *et al.*, 2003). On the other hand, in land-uses with a low number of cells, the *kappa* coefficient value will not yield a useful statistical indicator. Regardless of these drawbacks the technique was applied for testing the simulations in this research.

Table 4.7 shows the result of accuracy assessment of the simulation using approach of cell-by-cell comparison. Where, producer's accuracy is a measure of the precision of a particular classification scheme. It shows what percentage of a particular ground class was correctly simulated. User's accuracy is a measure of the reliability of an output map generated from a classification scheme. It is a statistic that can tell the user of the map what percentage of a class corresponds to the ground-truth class. Overall accuracy reflects the percentage of correctly simulated cells. Table 4.7 indicates that all the values of producer's accuracy and user's accuracy as well as the overall accuracy exceed the high level of more than 95%. Value of *Kappa* coefficient even reaches 0.94. These results testified the high accuracy, so that the function, of the prediction for spatial process of urban growth of the Tokyo metropolitan area in 1994 using this model.

2) Spatial form of urbanized area in terms of fractal dimension

As cities are complex emergent systems, urban geosimulation model should catch the characteristics of spatial form (White and Engelen, 1993; Wu, 2002). Chapter three analyzed the characteristics of urban growth in the Tokyo metropolitan area in terms of fractal dimension.

Table 4.7 Accuracy assessment of the simulation through cell-by-cell for 1994 at macro classification scale

Class name	**Producer's accuracy**	**User's accuracy**
Urbanized area	96.7%	96.7%
Non-urbanized area	97.1%	97.1%
Overall accuracy	96.9%	
Kappa coefficient	0.94	

Here, the fractal dimension was used to check whether the simulation grasps the characteristics of the form of urban growth in the Tokyo metropolitan area or not. Area-radius plots for simulated urbanized area and reality in 1994 is shown in Figure 4.20. Considering the boundary effect, urbanized areas which are far more than 50km from Tokyo station were omitted because cell counts for these areas are dominated by boundary effects. It is obvious that actual urbanized area in 1994 has the bifractal form: inner zone of radius with 0-16km and outer zone of radius with 16-50km. In Figure 4.20, simulated urbanized area shows the same characteristics of bigractal form as actual urbanized area. Table 4.8 illustrates the comparison of fractal dimension of the urbanized area for both zones of radius with 0-16km and 16-50km between simulation and reality. The value of fractal dimension of the urbanized area in simulation is same as that in reality for both zones of inner and outer part. This testifies the capability of this model for predicting and presenting the spatial form of urban growth in the Tokyo metropolitan area in 1994.

The value of fractal dimension of actual urbanized area in 1984 and 1989 also were calculated in order to discuss the characteristics of spatial form of urban growth in the Tokyo metropolitan area so as to further understand the validity of this model (Table 4.9). By comparing Table 4.8 and Table 4.9 it shows that the fractal dimension of the urbanized area did not change in the inner zone of 0-16km from 1984 to 1989, meaning stably complete urbanization process in the zone. The value of fractal dimension in this zone in 1994 grew just a little. The value of fractal dimension of the urbanized area in outer zone of 16-50km had grown 0.05 from 1984 to 1989, and 0.03 from 1989 to 1994. This indicates the sustained urbanization process under stochastic effects in this zone. While the speed of urban growth had declined from 1989 to 1994, the fractal characteristics had not changed. It could be forecasted that the spatial process would keep until the fractal dimension of outer zone reaches its biggest value as that of inner zone, which means that urbanization process even in outer zone would be complete by that time. The constrained CA model constructed in this research catches the characteristics of urban

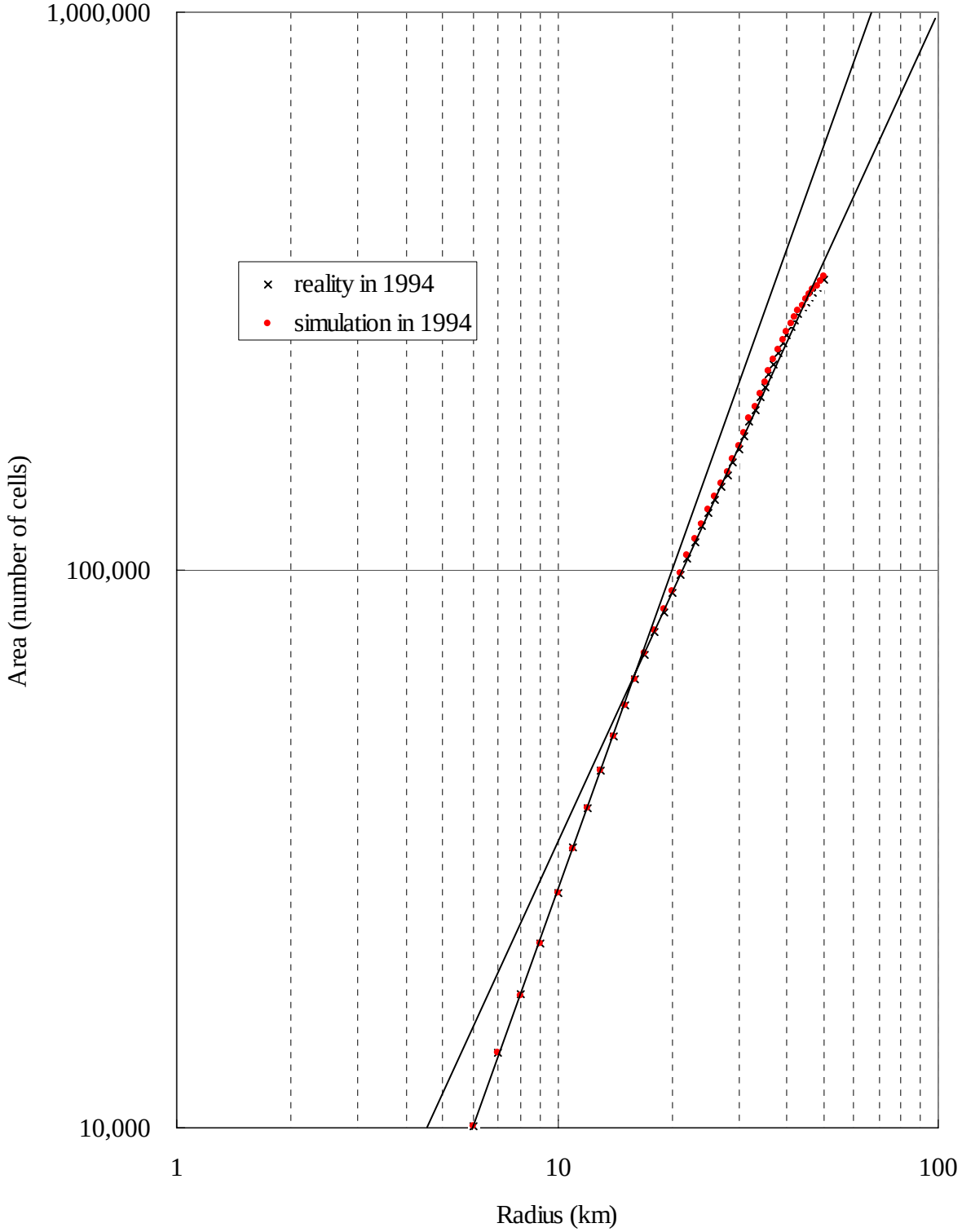


Figure 4.20 Area-radius plots for simulated urbanized area and reality in 1994

Table 4.8 Accuracy assessment of the simulation through fractal dimension for 1994 at macro classification scale

Fractal dimension in different radius zones	**Reality in 1994**	**Simulation in 1994**
In 0-16km radius	1.95	1.95
In 16-50km radius	1.48	1.48

Table 4.9 Fractal dimension of actual urbanized area in the Tokyo metropolitan area in 1984 and 1989

Fractal dimension in different radius zones	**Reality in 1984**	**Reality in 1989**
In 0-16km radius	1.94	1.94
In 16-50km radius	1.40	1.45

growth in the Tokyo metropolitan area and can be used to as a prototype which is moved closer to end-users such as urban planners. It will be possible to extend the richness of the modeling framework to provide better estimates of future conditions producing future scenarios.

3) Urban landscape in terms of spatial metrics

Spatial metrics were adopted to assess the ability of the model in simulating landscape of urban growth in the Tokyo metropolitan area. As discussed in chapter three, spatial metrics are different measure for analysis of characteristics of urban growth from fractal dimension. Fractal dimension can be used to catch the spatial structure of urban growth at the level of the whole metropolitan area, while spatial metrics can grasp the characteristics of fragmentation or conglomeration in urban growth. As the change of NP (number of patch) and PD (patch density) in spatial metrics can represent this kind of characteristics of urban growth (Zhao and Murayama, 2006b), both of them were selected in this assessment.

Figure 4.21 shows the comparison of urban growth significance of spatial metrics of urbanized area between reality and simulation in the Tokyo metropolitan area. In order to understand the change of spatial metrics in the spatial process of urban growth, values of NP and PD of urbanized area in 1989 also were calculated. It shows the same characteristics of urban landscape in the process of urban growth of the Tokyo metropolitan area as discussed in chapter three that with the process of urban growth, the values of NP had decreased from 9,909 to 9,609 and PD had decreased from 1.20 to 1.16 in reality within the period of 1989 to 1994. This phenomenon indicates the characteristic of the compact growth or conglomeration of the existing urbanized area in the Tokyo metropolitan area. Simulated urbanized area also shows the same characteristics in 1994. The value of NP of simulated urbanized area is 9,594, just a little difference from that in the reality. Therefore, it is clear that this model grasps the characteristic of landscape change in the process of urban growth of the Tokyo metropolitan area.

In fact, neighborhood interactions in CA-based urban geosimulation model contribute to this characteristic of urban growth. As this research proposes one new approach for modeling the

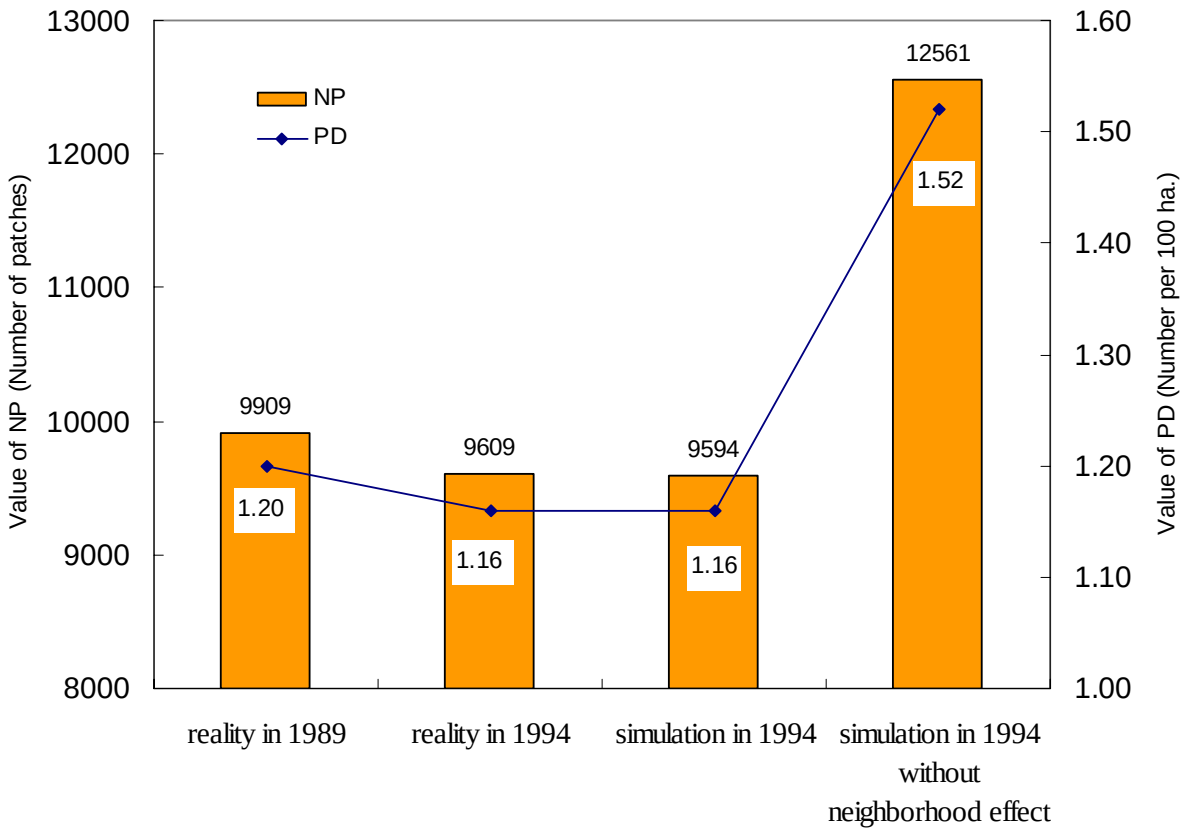


Figure 4.21 Comparison of urban growth significance of spatial metrics between reality and simulation in the Tokyo metropolitan area

neighborhood interactions, simulation of urban growth in the study area without the component of neighborhood effect in the model for 1994 was carried out in order to assess the function of the new method. The result also is shown in Figure 4.21. It shows that the value of NP of urbanized area without neighborhood effect reaches 12,561, and value of PD comes to 1.52, both of which are much more than the values in the reality. This proves the validity of the neighborhood interactions method proposed in this research in modeling spatial process of urban growth of the Tokyo metropolitan area.

4) Regional characteristics

Although the assessments above show the goodness-of-fit of this model in simulating spatial process of urban growth in the whole Tokyo metropolitan area, in this large study area, different regions would take distinct characteristics of urban growth. It is necessary to check the goodness-of-fit of the model in presenting the spatial process of urban growth in different regions.

Considering the bifractal forms of urbanized area in the study area and orientations of urban growth (Batty *et al.*, 1999), the Tokyo metropolitan area was divided into 3 zones – 0-16km, 16-50km and more than 50km - according to the location in fractal parts and the distance to the center – Tokyo station. Four directions – Northeast (NE), Northwest (NW), Southwest (SW) and Southeast (SE) – were set for every zone. Therefore, 12 regions were generated in the study area. In every region, the proportion of urbanized area to total region area was calculated for the reality and simulation in 1994 respectively, and the difference was yielded through proportion of urbanized area in the reality minus that in the simulation. + means proportion of urbanized area in the reality is more than that in the simulation; otherwise, -. The result is shown in Figure 4.22.

Generally, Figure 4.22 shows that the differences are relatively small in the second fractal zone with radius of 16-50km and also in the south of first fractal zone with radius of 0-16km. This means that this model is relatively fitted to these regions in modeling the spatial process of urban growth. In other regions the differences are a little big. In all the directions of the third

fractal zone with radius of more than 50km, amount of the simulation of urban growth is a little less than that of the reality. The amount of the simulation, however, is more than that of the reality in the first and second fractal zone, especially in north of the first zone. This phenomenon expresses the effect of boundary of study area. Actually, the metropolitan area is an open system, which exchanges matters and information with outside every minute. As one study area, the links with outside should be simplified. This process diminishes the effect of borderlands, and enhances central areas. Accordingly, central areas show stronger charms to urban growth.

Based on discussions above, Figure 4.22 provides two inspirations to further research in urban geosimulation modeling: considering the characteristics of regional difference and open system of the study area.

4.4.2 Land-use of the Tokyo metropolitan area in 1994 at micro classification scale

There ten categories in level two of land-use classification system used in this research. In order to simplify the discussion, this research focuses on three active land-use categories in urbanized area: residential, commercial, and industrial lands as three of which stand for the elementary urban activities in urban growth at micro classification scale.

Figures 4.23, 4.24, and 4.25 respectively show the results of simulated land-use pattern of residential, commercial, industrial land in 1994. These figures also indicate the visual comparison of land-use pattern of these categories between simulation and reality.

Table 4.10 shows the accuracy assessment of simulated land-use through cell-by-cell approach at micro classification scale in the Tokyo metropolitan area in 1994. All the values of the producer’s accuracy and user’s accuracy of residential, commercial, and industrial land are more than 90%, showing accepted high precision. Kappa coefficient also reaches high level of 0.95 at the micro classification scale. Nevertheless, compared with the Table 4.7 at macro

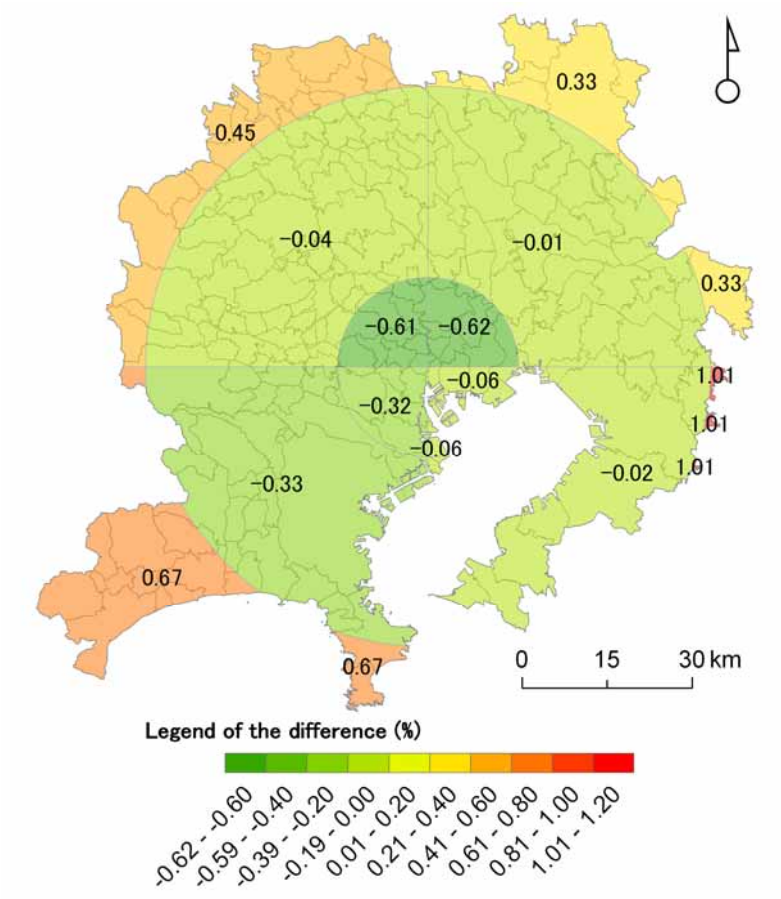


Figure 4.22 Distribution of the difference of the proportion of urbanized area to the region between reality and simulation in 1994

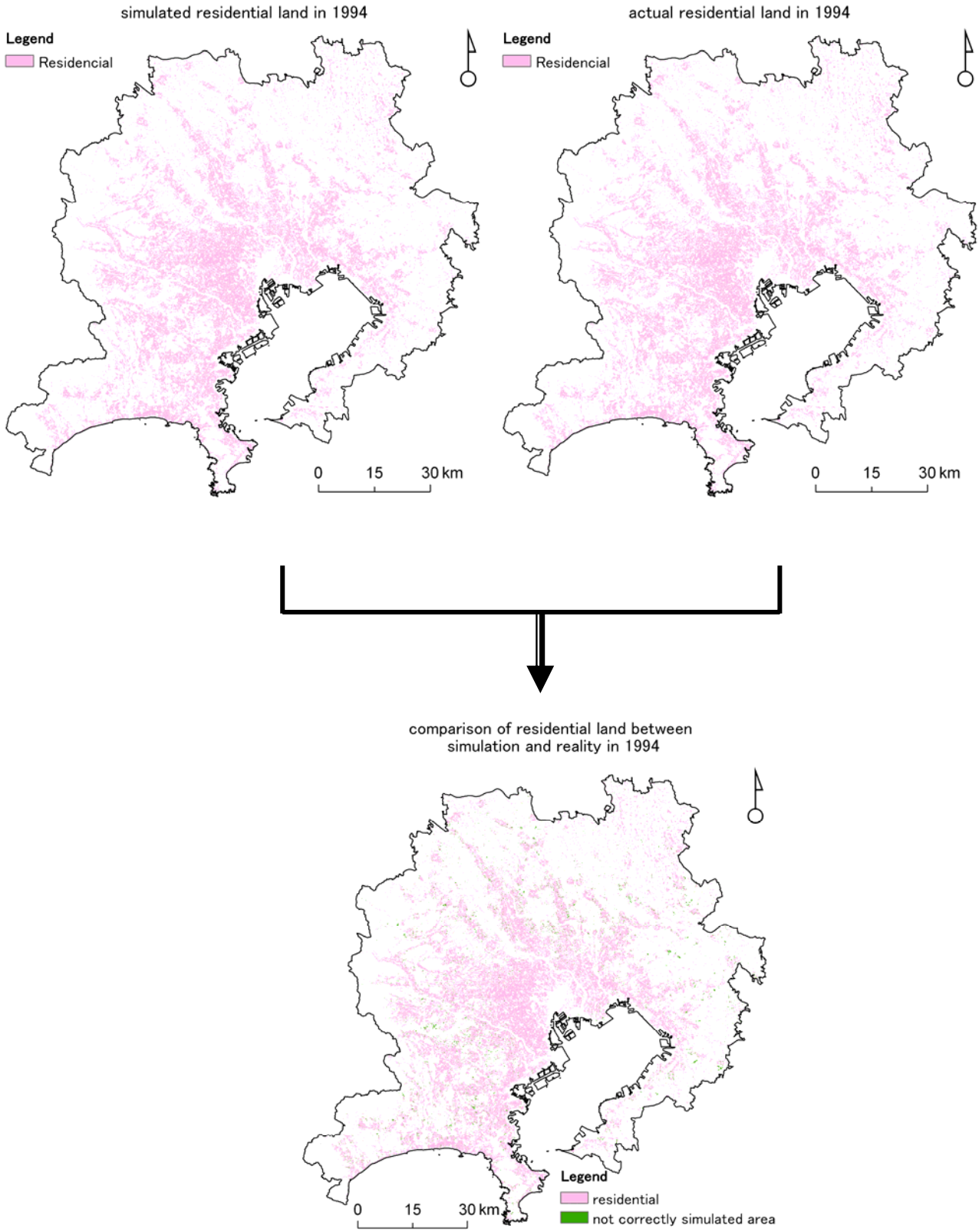


Figure 4.23 Visual comparison of land-use pattern of the residential land between reality and simulation in 1994

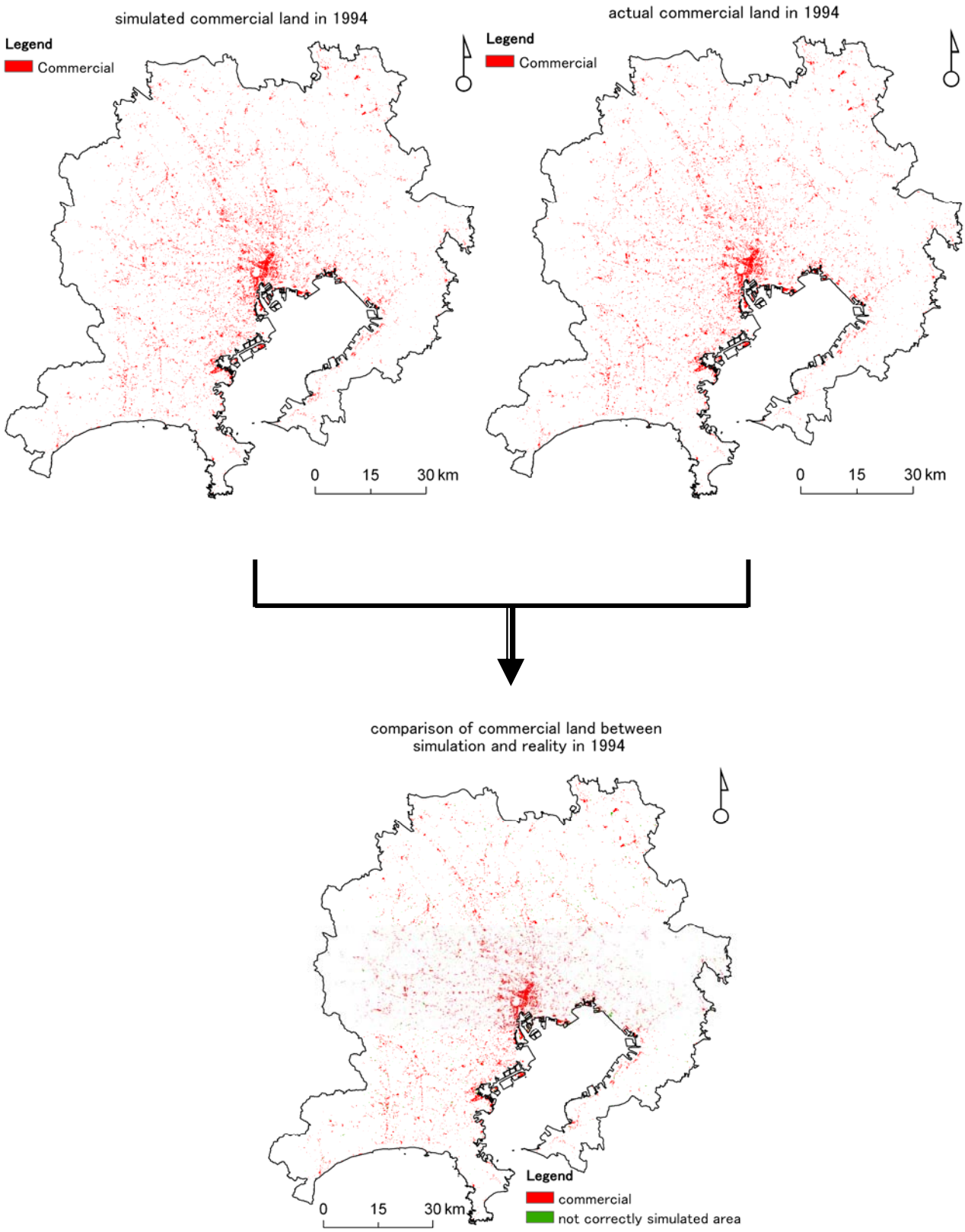


Figure 4.24 Visual comparison of land-use pattern of the commercial land between reality and simulation in 1994

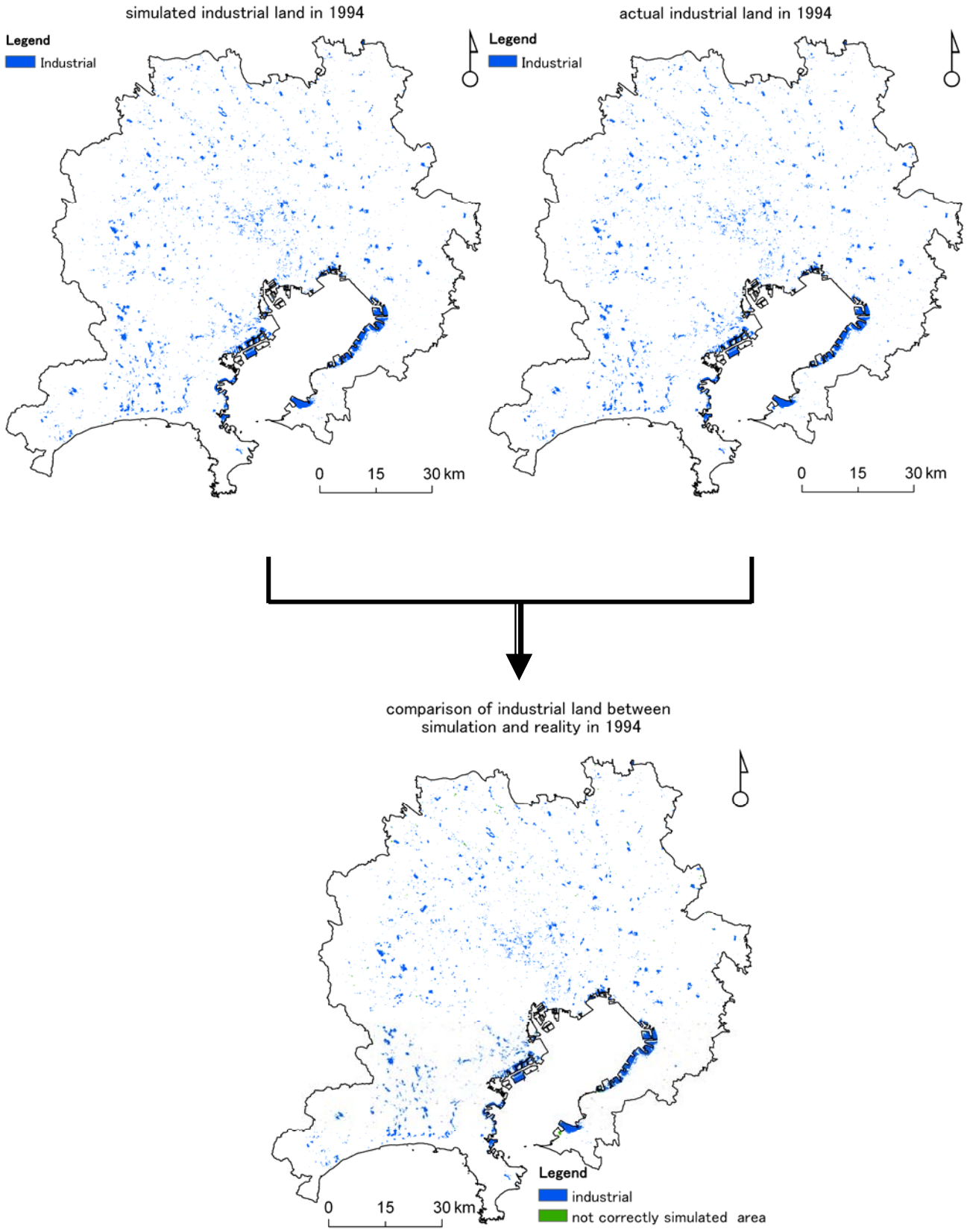


Figure 4.25 Visual comparison of land-use pattern of the industrial land between reality and simulation in 1994

classification scale, Figure 4.10 shows that accuracy of the detailed land-use types at micro classification scale is lower than that of aggregated type at macro classification scale. Moreover, the accuracy of distinct land-use types at micro classification scale is different. Residential and industrial lands take higher accuracy than commercial land.

As discussed in section 4.4.1, cell-by-cell approach can not grasp the characteristics of urban form change in the process of urban growth. Fractal dimension also was used to analyze the change of urban form at micro classification scale. Area-radius plots for detailed land-use types – residential, commercial and industrial land - between reality and simulation in 1994 are shown in Figure 4.26. Compared with Figure 4.20, fractal dimension of these detailed land-use types takes different characteristics from that of urbanized area in the study area. Figure 4.26a shows that in the zone of 0-2km from Tokyo station, area of residential land is very low. From 2km to 14km, fractal dimension becomes steep, and in the zone of 14-50km, the value of fractal dimension decreases. Fractal dimension of commercial land in the zone of 0-3km is higher than that in the zone of 3-50km where it does not shows obvious difference. This presents the compact development of commerce in the zone of 0-3km from Tokyo station. Industrial land takes multi-fractal dimension in the study area, meaning the characteristics of industrial development at the distance from Tokyo station. However, although fractal dimension of these detailed land-use types is different from each other, this model well simulated the fractal dimension of these land-use types as in Figure 4.26 the area-radius plots of simulation is same as that of the reality. This means that this model well catches not only the characteristics of urban form changes but also the characteristics of detailed land-use types in the process of urban growth of the Tokyo metropolitan area.

As for landscape change of detailed land-use types in the process of urban growth, Figure 4.27 shows the comparison of urban growth significance of spatial metrics at micro classification scale between reality and simulation in the Tokyo metropolitan area. Although the Tokyo metropolitan area took characteristics of compact growth or conglomeration of the existing

Table 4.10 Accuracy assessment of the simulation through cell-by-cell for 1994 at micro classification scale

Class name	**Producer's accuracy**	**User's accuracy**
Non-urbanized area	97.3%	97.3%
Industrial land	95.8%	95.8%
Residential land	95.5%	95.5%
Commercial land	90.2%	90.2%
Other urbanized area	92.6%	92.6%
Overall accuracy	95.8%	
Kappa coefficient	0.95	

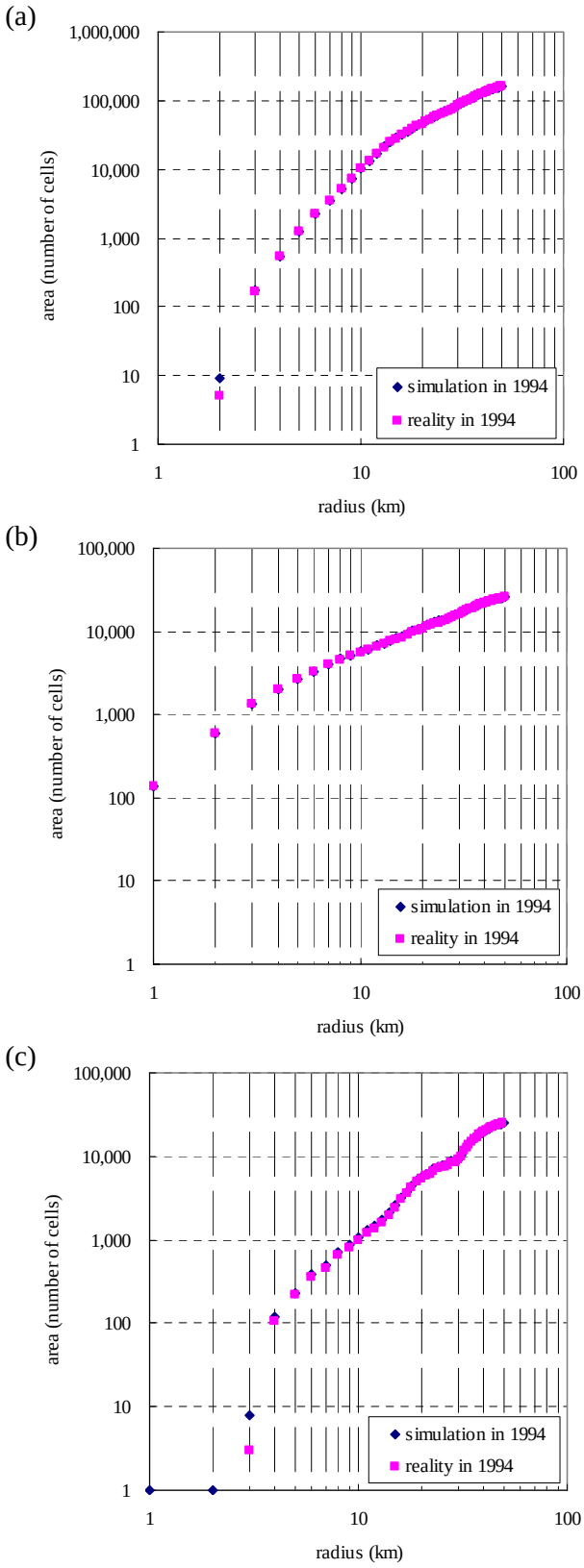


Figure 4.26 Area-radius plots for detailed land-use types between reality and simulation in 1994. (a) residential land; (b) commercial land; (c) industrial land

urbanized area as shown in Figure 4.21, the growth characteristics of detailed land-use types were different. Residential land took characteristic of compact growth or conglomeration, the same as urbanized area at macro classification scale, while commercial and industrial land showed characteristic of dispersive growth. Figure 4.27 indicates that this model also grasps the characteristics of landscape change of these detailed land-use types in the process of urban growth.

Figures 4.28, 4.29, and 4.30 respectively illustrate the distribution of difference of the proportion of residential, commercial, and industrial land to the region between reality and simulation in 1994 towards analyzing the regional characteristics of change of detailed land-use types. Although three detailed land-use types show the difference of land-use change in distinct region, boundary effect on these land-use types are same as discussed in section 4.4.1. These three figures present the goodness-of-fit of this model to simulate the spatial process of urban growth in the Tokyo metropolitan area at micro classification system.

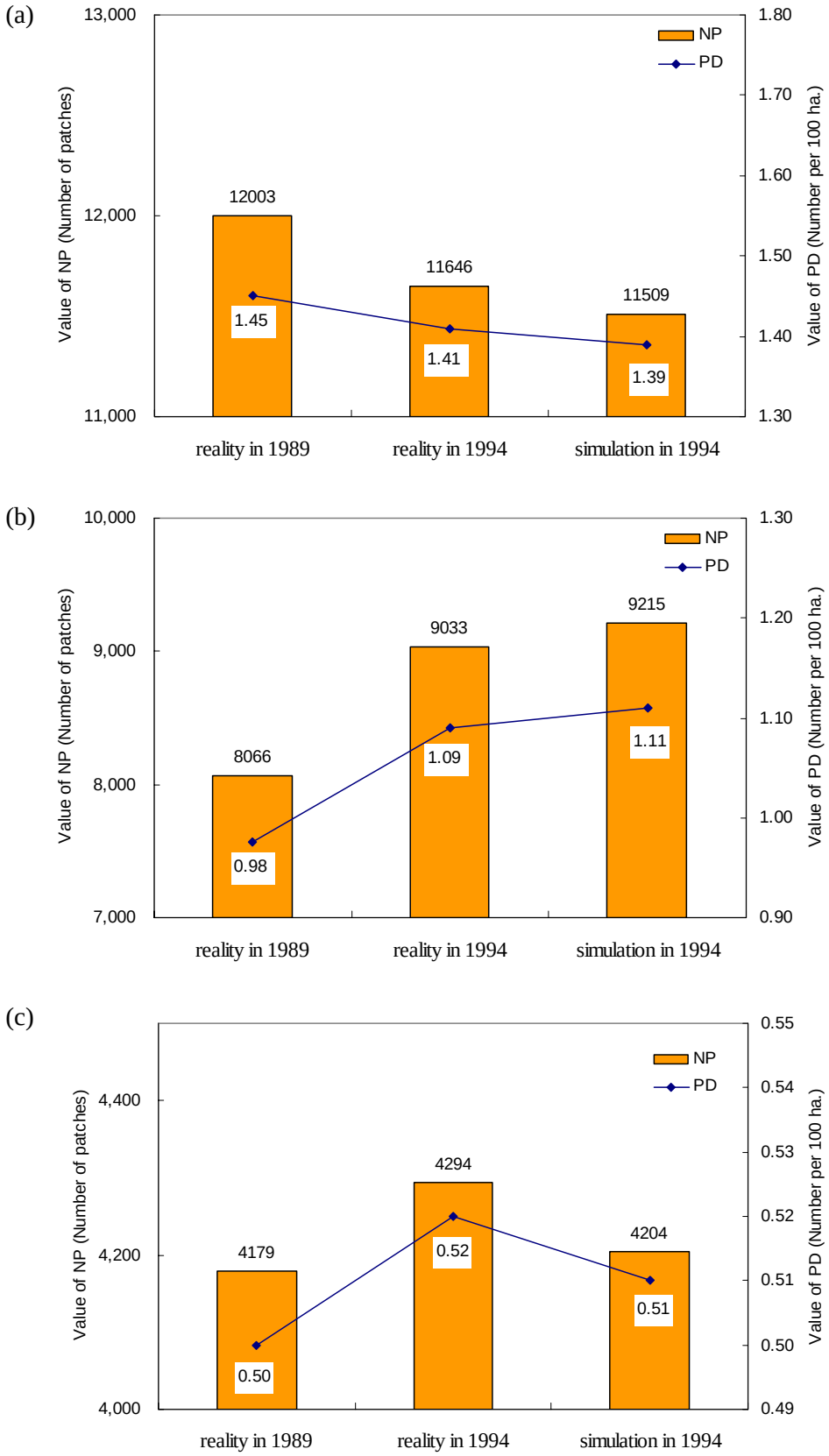


Figure 4.27 Comparison of urban growth significance of spatial metrics at micro classification scale between reality and simulation in the Tokyo metropolitan area. (a) residential land; (b) commercial land; (c) industrial land

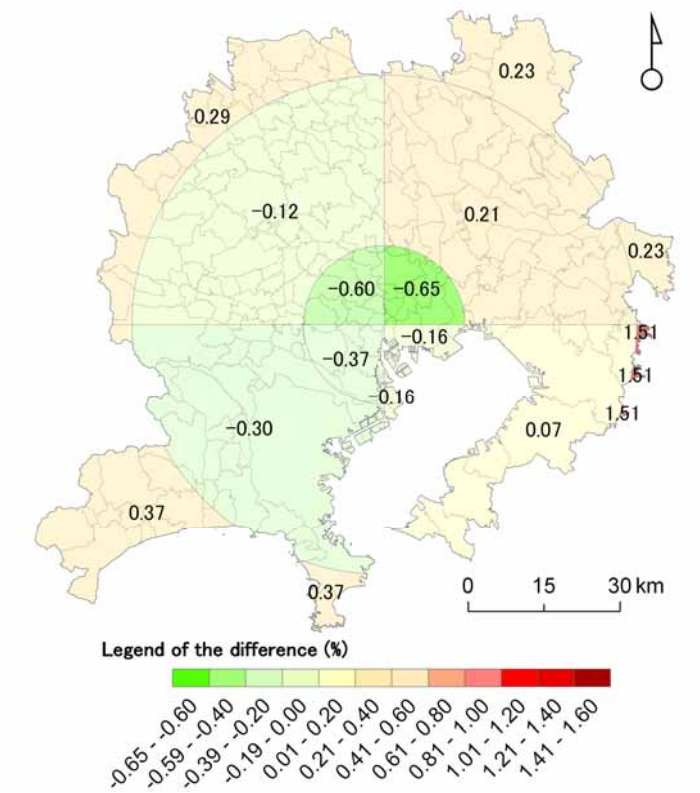


Figure 4.28 Distribution of the difference of the proportion of residential land to the region between reality and simulation in 1994

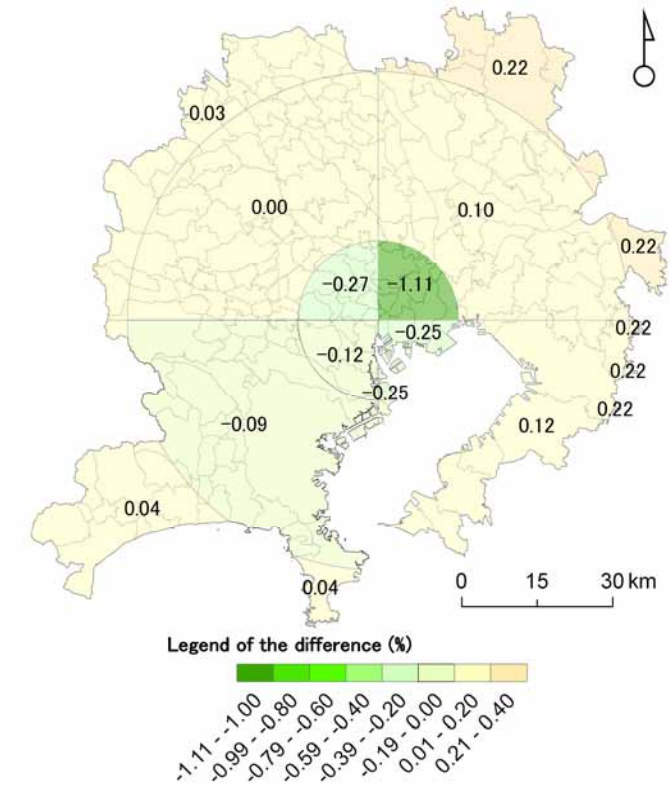


Figure 4.29 Distribution of the difference of the proportion of commercial land to the region between reality and simulation in 1994

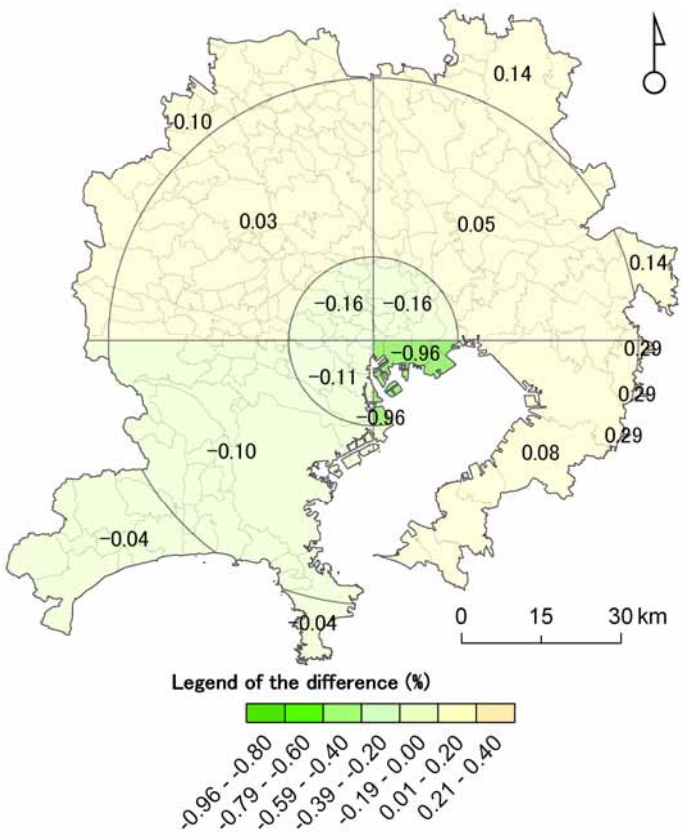


Figure 4.30 Distribution of the difference of proportion of industrial land to the region between the reality and simulation in 1994

Chapter Five

Conclusions

Cellular automata (CA) have been in popular use for urban simulation as CA have many advantages for modeling urban phenomena, including their decentralized approach, the link they provide to complexity theory, the connection of form with function and pattern with process, the relative ease with which model results can be visualized, their flexibility, their dynamic approach, and also their affinities with geographic information systems and remotely sensed data. Geosimulation of urban phenomena by modeling spatial processes of urban growth using CA coupled with GIS provides a visualized approach to well understand and predict the spatial process of urban growth in the future. However, CA modeling in urban geosimulation is still in its infancy and at a development phase, being faced with many challenges, such as grid size selection of CA, identification of cell state, neighborhood interactions modeling as well as appropriate calibration.

As one of top megacities in the world, urban land-use have greatly changed in last century in the Tokyo metropolitan area as the population have grown largely, and the trend would continue according to the population projection. This research aimed at gaining experience with the application of cellular automata to modeling spatial processes of urban growth for the Tokyo metropolitan area at high-resolution level so as to improve the methodology of application of CA. In particular, this research focused on three fundamental elements of the CA - the grid size, the cell states, and the neighborhood effect.

This research indicates that urban structure of the Tokyo metropolitan area took the bifractal structure in the period 1974 to 1994. In inner zone with 0-15km radius in the period, all the fractal dimensions were close to their ultimate value and kept relatively stable. This means that in this zone, the urbanization process was almost complete. In the outer zone with 15-50km radius, the fractal dimensions were very active. From 1974 to 1994, the fractal dimension in this zone had grown gradually. The process of urban growth in this zone still kept the characteristics of fractal dimension. It can be predicted that in the future, the trend would keep, and fractal dimension would increase to reach the high level as in inner zone. Meanwhile, the analysis of spatial metrics for this area illustrated the characteristic of compact growth or conglomeration of the existing urbanized area in the Tokyo metropolitan area. The model proposed in this research simulates the main characteristics in the process of urban growth.

Grid size of CA and urban land-use classification systems affect the understanding of the spatial process of urban growth. This research provides theoretical justification for selecting grid size and land-use classification system in CA-based urban models. Considering the confused status in selecting cell size for CA, theoretical analysis of characteristics of spatial scale effect on land-use pattern was carried out using spatial autocorrelation index in this research. The results show that all the land-use types take the characteristics of positive spatial autocorrelation, and at grid size of 100m×100m, the land-use patterns keep relatively table and representative. The effect of spatial scale comes from the procedure of aggregating small cells into big cells as this procedure generates the loss of information. The effect of land-use classification systems on the land-use pattern analysis also was theoretically explored. The results indicate that land-use classification systems affect the land-use pattern analysis. With aggregating multiple land-use categories into one category, land-use pattern becomes stable relatively across a large range of grid size. However this is a result of trade-off of decreasing land-use classification information. Cell size and cell states are most important elements in CA. Previously, few researches have theoretically explored the relationship of them with application of CA to urban geosimulation

models. This research exploringly focuses on these problems. The findings theoretically provide useful information for identifying cell size and cell states in the application of cellular automata.

Neighborhood interaction model proposed in this research provides a new method to calibrate the neighborhood effect in the spatial processes of urban growth instead of traditional "trial and error" approach. Neighborhood effect is one important component in urban dynamics and CA-based urban geosimulation models. Traditionally, neighborhood effect model was made empirically. Neighborhood effect model based on the integration of the theory of Tobler's First Law of Geography with Reilly's gravity model and coupled with logistical regression approach, proposed in this research, grasps the theoretical nature of the neighborhood interactions in urban dynamics. Simulation results validate the usefulness of the neighborhood effect model. More importantly, the neighborhood effect model not only can be used in raster structure, but also would be used in vector structure as it considers both area and distance. This is an important research theme for next step. In the fourth international conference on GIScience held in Germany, this model has been appraised as 'innovative' (Zhao and Murayama, 2006c).

Calibration is very important procedure in constructing spatial model. This research shows that using negative exponential decrease function of urban theory to explore the effect of transportation on urban dynamics stands for an alternative approach for calibration of urban geosimuation model. The exploration results indicate the effect of railway stations on the land-use changes of vacant, residential, and commercial land, but not on the land-use changes of industrial land. Detailed land condition map and land-use zoning map provide excellent data sets for calibrating the urban geosimulation model.

Urban geosimulation model proposed in this research can visually and well simulate spatial process of urban growth of the Tokyo metropolitan area, and can be used for predicting spatial processes of urban growth of the Tokyo metropolitan area by urban planners. This model was used to simulate spatial process of urban growth in the Tokyo metropolitan area in 1994. The results of simulation were discussed at both macro classification scale and micro classification

scale in four ways: quantitative comparison through cell-by-cell, comparison of spatial form of urbanized area through fractal dimension, comparison of urban landscape through spatial metrics, and regional characteristics analysis compared with actual land-use pattern in 1994. The results indicate that the constrained CA model constructed in this research catches the characteristics of spatial process of urban growth in the Tokyo metropolitan area and can be used to as a prototype which is moved closer to end-users such as urban planners. It will be possible to extend the richness of the modeling framework to provide better estimates of future conditions producing future scenarios.

CA modeling in urban geosimulation is still in its infancy and at a development phase. Seamlessly integrated models of urban dynamics based on socio-economics-biophysics interactions stands for the new research direction in CA modeling. Such a model could possibly be even a more effective tool for urban and regional planning.

Acknowledgements

I am indebted to all the people who have given me encouragements, supports, help and suggestions throughout my PhD study period.

I express my most sincere thanks to Professor Yuji MURAYAMA, my academic supervisor, for all the guidance, inspirations and supports. He is a wonderful mentor with thinking so internationally and openly that all the students can freely discuss scientific standpoints with him without fear. He led me walk into the sacred scientific palace of geographic information science. He was always kindly to support me to join in various activities, including six times of international conference, which provided me with much experience in scientific research. He supported all the data set needed in my research without any hesitation. I believe that this research would not have been possible without his guidance.

I am grateful to all supportive members of the faculty in this department for their invaluable guidance in my PhD study period. I give my special thanks to Dr. Takehiro MORIMOTO for his kind assistance. He always enthusiastically helped me with arranging experimental facilities and documents of research.

Special thanks also go to Professor Akira TABAYASHI, Professor Akira TEZUKA, Professor Kiyomi YAMASHITA, and Dr. Takehiro MORIMOTO for accepting to be my referees. Their helpful comments, suggestions and corrections during my presentations and on my dissertation helped me to improve the quality of my work.

I would like to thank Professor Gang DENG, Professor Yuanmin FANG, Professor Junsan ZHAO, Professor Lanyan ZHU at Kunming University of Science and Technology, and

Professor Xinzhou WANG at Wuhan University for their enthusiastic encouragement in my PhD study period.

I also thank all my friends and classmates at the division of Spatial Information Science, for their many contributions during the entire research period. I am grateful to Mr. Nobuhiko KOMAKI, Yumin ZHANG, Moses Murimi NGIGI, Tomohiko UEDU, Milimasa HARANO, Dr. Fatemeh AHMADI NEJAD MASOULEH and Kazuhisa OHBI for their kind assistances. As my tutor when I came to Japan, KOMAKI helped me accommodate to the new circumstances of study and life. Yumin was always kindly available to settle questions together with me when I was faced with technological challenges in my research. Special thanks to Dr. OHBI for his help in transferring data format used in my research.

Finally, I express my special gratitude to my parents for their prayers and encouragement. I am particularly very much thankful to my wife Fei DONG and daughter Qianqian for their enormous sacrifices, forbearance and support throughout the research period.

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Appendix

Fractal dimension of the cities

As geometrical objects, cities may be thought as Cantor dusts in two-dimensional space, or, more appropriately for cellular models, as Sierpinski carpets (Figure A.1), with, of course, a stochastic element in the pattern. For such objects it has been shown that

$$B^i = q^{-iD}, \tag{A-1}$$

where B is the number of cells occupied by the original object (B = 5 in Figure A.1), i is the step number, q is the scale reduction factor (in Figure A.1, for example, at each step the scale of the original figure is reduced by a factor of 1/3), and D is the fractal dimension. Solving this relationship for D, one obtains

$$D = (\lg B) / \lg(\frac{1}{q}), \tag{A-2}$$

which allows the dimension of the Sierpinski carpet to be calculated directly.

The fractal dimension, D (D < 2) reflects the fact, evident in Figure A.1, that as the object expands in cell space the number of cells composing it grows less rapidly than the number of cells in the square area necessary to contain it, so that the object becomes more sparse. In particular, the length L of a side of the figure is

$$L = \left(\frac{1}{q}\right)^i, \tag{A-3}$$

and the total number of occupied cells, B_T, by

$$B_T = B^i. \tag{A-4}$$

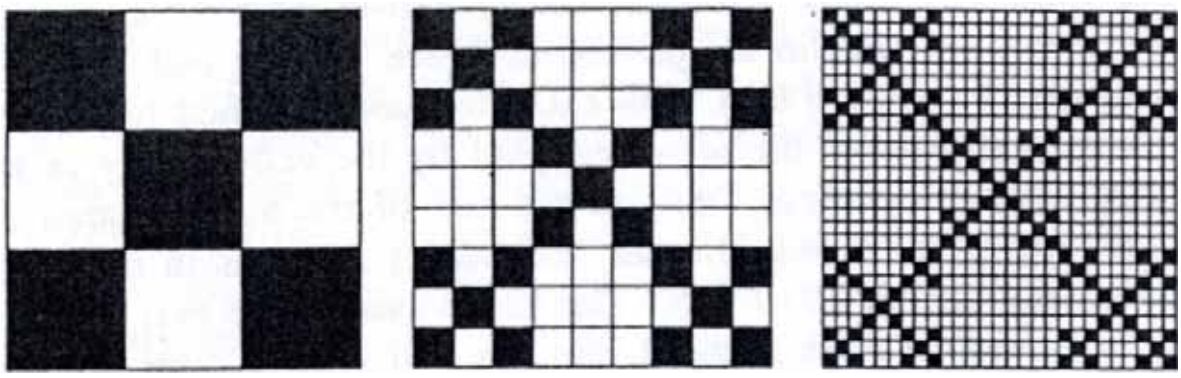
Thus the relationship between the size of the object, as measured by the number of cells composing it, and its diameter, is given by

$$B_T = L^D. \tag{A-5}$$

Then,

$$\lg B_T = c + D \lg r, \tag{A-6}$$

where, c is a constant and r is the radius of the object. D is the fractal dimension.



(a) (b) (c)

Figure A.1 Three stages in the construction of a Sierpinski carpet. (a) $S = 1$; (b) $S = 2$; (c) $S = 3$, where S is the step number