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Urban Growth Modeling Based on Land-use Changes and Road Network Expansion

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To the memory of my grandfather
Huosheng Rui, 1937 - 2009

Abstract

A city is considered as a complex system. It consists of numerous interactive sub-systems and is affected by diverse factors including governmental land policies, population growth, transportation infrastructure, and market behavior. Land use and transportation systems are considered as the two most important subsystems determining urban form and structure in the long term. Meanwhile, urban growth is one of the most important topics in urban studies, and its main driving forces are population growth and transportation development. Modeling and simulation are believed to be powerful tools to explore the mechanisms of urban evolution and provide planning support in growth management.

The overall objective of the thesis is to analyze and model urban growth based on the simulation of land-use changes and the modeling of road network expansion. Since most previous urban growth models apply fixed transport networks, the evolution of road networks was particularly modeled. Besides, urban growth modeling is an interdisciplinary field, so this thesis made big efforts to integrate knowledge and methods from other scientific and technical areas to advance geographical information science, especially the aspects of network analysis and modeling.

A multi-agent system was applied to model urban growth in Toronto when population growth is considered as being the main driving factor of urban growth. Agents were adopted to simulate different types of interactive individuals who promote urban expansion. The multi-agent model with spatio-temporal allocation criterions was shown effectiveness in simulation. Then, an urban growth model for long-term simulation was developed by integrating land-use development with procedural road network modeling. The dynamic idealized traffic flow estimated by the space syntax metric was not only used for selecting major roads, but also for calculating accessibility in land-use simulation. The model was applied in the city centre of Stockholm and confirmed the reciprocal influence between land use and street network during the long-term growth.

To further study network growth modeling, a novel weighted network model, involving nonlinear growth and neighboring connections, was built from the perspective of promising complex networks. Both mathematical analysis and numerical simulation were examined in the evolution process, and the effects of neighboring connections were particular investigated to study the preferential attachment mechanisms in the evolution. Since road network is a weighted planar graph, the growth model for urban street networks was subsequently modeled. It succeeded in reproducing diverse patterns and each pattern was examined by a series of measures. The similarity between the properties of

derived patterns and empirical studies implies that there is a universal growth mechanism in the evolution of urban morphology.

To better understand the complicated relationship between land use and road network, centrality indices from different aspects were fully analyzed in a case study over Stockholm. The correlation coefficients between different land-use types and road network centralities suggest that various centrality indices, reflecting human activities in different ways, can capture land development and consequently influence urban structure.

The strength of this thesis lies in its interdisciplinary approaches to analyze and model urban growth. The integration of 'bottom-up' land-use simulation and road network growth model in urban growth simulation is the major contribution. The road network growth model in terms of complex network science is another contribution to advance spatial network modeling within the field of GIScience. The works in this thesis vary from a novel theoretical weighted network model to the particular models of land use, urban street network and hybrid urban growth, and to the specific applications and statistical analysis in real cases. These models help to improve our understanding of urban growth phenomena and urban morphological evolution through long-term simulations. The simulation results can further support urban planning and growth management. The study of hybrid models integrating methods and techniques from multidisciplinary fields has attracted a lot attention and still needs constant efforts in near future.

Keywords: urban growth / sprawl, land-use simulation, multi-agent system, road network pattern, space syntax, complex networks, evolving weighted networks, nonlinear growth, local world, hierarchy, self-organized, local optimization, morphological changes, street centrality, adaptive kernel density estimation, dual representation.

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Stockholm, April 2013
Yikang Rui

Contents

List of abbreviations

LUCC	- Land-use / land-cover change
CM	- Cellular model
CA	- Cellular automata
ABM	- Agent-based model
MAS	- Multi agent systems
GIS	- Geographical information system / science
ICN	- Intersection continuity negotiation principle
MST	- Minimum spanning tree
OTT	- Optimal traffic tree
BBV	- Barrat, Barthélemy and Vespignani model
LC	- Local world model
PA	- Preferential attachment
NPA	- Neighborhood Preferential attachment model
KDE	- Kernel density estimation

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I. **Yikang Rui** and Yifang Ban, 2010. Multi-agent Simulation for Modeling Urban Sprawl In the Greater Toronto Area. *13th AGILE International Conference on Geographic Information Science*, Guimarães, Portugal.
(Author contributions: YR: developed the method, performed the experiments, analyzed the data and wrote the papers. YB: initiated the idea and helped to improve the analysis.)

II. **Yikang Rui** and Yifang Ban, 2011, Urban growth modeling with road network expansion and land use development. *Advances in Cartography and GIScience, Volume 2*. Springer Berlin Heidelberg, 399-412.
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(Author contributions: YR: conceived the idea, performed the experiments, analyzed the data and wrote the papers. YB: edited the paper.)

IV. **Yikang Rui**, Yifang Ban and Jiechen Wang. The effects of neighboring connections on weighted network evolution. Submitted to *the journal of PLOS ONE*.
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(Author contributions: YR: conceived the idea, performed the experiments, analyzed the data and wrote the papers. YB: helped to improve the conception. JW: helped to improve the analysis. JH: helped to run some experiments and proofread the paper.)

VI. **Yikang Rui** and Yifang Ban. The influence of street centrality on urban structure in Stockholm. Submitted to *the International Journal of Geographical Information Science*.
(Author contributions: YR: conceived the idea, performed the experiments, analyzed the data and wrote the papers. YB: helped to improve the conception and analysis.)

1. Introduction

1.1 Background

In the last two centuries, particularly in the last decades, mankind has witnessed drastic population changes from rural to urban areas. According to the 2011 Revision of World Urbanization Prospects (United Nations, 2012), the world's urban population increased from 0.75 billion (29.4 percent of the world's population) in 1950 to 3.63 billion (52.1 percent) in 2011 and is expected to reach 6.25 billion (67.2 percent) in 2050. More strikingly, during 2011-2030, urban population in developing regions is expected to increase on average annually by 2.02 percent, from 2.67 billion to 3.92 billion. In contrast, the urban population in developed regions is expected to increase modestly from 0.96 billion to 1.06 billion.

Two outcomes from this rapid urbanization are the number of megacities and unprecedented size of the largest cities. By 1970, the world had only two megacities (with populations more than 10 million). Today, there are 23 megacities and the number is estimated to be 37 in 2025. Most new megacities have arisen or will appear in Asia. This indicates a clear trend of rapid urban concentration in developing countries.

Population growth is one of the most important driving forces of change in any urban system. If urban population swells, the city must expand upward or outward. Along with economic development and technologies (mainly transport and communication) revolution, rapid urban growth can be characterized by the development of suburban expansion and redevelopment in the city centre. Sprawl is a form of urban growth that happens through rapid suburbanization, especially in North America, with a fragmented form and low density in development (Gordon and Richardson 1997, Duany et al. 2001, Carruthers 2003).

Urban growth benefits human civilization in terms of society, economy and culture. Nowadays, cities control the world's economy and political decision power, manage the flows of financial, man-made and natural resources, and concentrate the knowledge of science, art and technology. However, rapid urban growth/sprawl also causes social, physical and environmental problems. Nuissl et al. (2008) pointed out that urbanization leads to an unnatural or spoiled landscape in spatial planning. Agricultural land or forest at the urban fringe is converted to residential and industrial areas. Such conversion weakens ecosystem services and landscape functions in different ways (de Groot et al. 2002, Curran and de Sherbinin 2004). Meanwhile, the increasing use of cars and increased energy consumption cause concentrate pollution, which both damages people’s health and the natural environment. Urban sprawl in suburban requires more costs in terms of travel, and increases the inefficient investment of infrastructure and services (i.e. road, water supply, electricity, sewerage and drainage) in low density urban areas (Batty, 2008). In developing regions, rapid urban growth has led to enormous environmental loads and a growing problem of poverty.

1.1.1 Modeling and simulation

As an essential way to learn the urban growth/sprawl phenomena, modeling and simulation is regarded as a efficient way to understand the mechanisms of urban dynamics, to evaluate current urban systems, and to provide planning support in urban growth management, e.g. land-use models may help to build future growth scenarios and to assess possible environmental impacts (Lambin et al. 2006).

Modeling can either be conceptual, symbolic or mathematical. This depends on the purposes of the specific application. Before carrying on the modeling, one has to figure out the driving forces behind urban growth phenomenon. It is well known that a city is a complex system. It contains various interactive sub-systems and is thus affected by a variety of variables or factors. Bürgi et al. (2004) distinguished between five major types of driving forces: socioeconomic, political, technological, natural and cultural factors. They also classified these into the primary, secondary and tertiary driving forces, although many times it is not easy to differentiate between impacts and driving factors in reality (Verburg 2006). According to Miller et al. (2004), an integrated urban system model with a focus on transportation should include socio-demographic components, demographics, location choices of households and firms, economic variables, transportation and effects on land use and environment.

Urban models have a long history. During the last few decades, the development of urban models has grown rapidly. The variety of models makes the classifications rather diverse. Therefore, several researchers have proposed many classification rules based on different benchmarks. Recently, Silva and Wu (2012) gave a very comprehensive review with several model classification schemes.

From the perspective of modeling approaches, models evolve from macro-simulations to micro-simulations. Nowadays, cellular automata, agent-based models and fractals are main approaches used to understand cities (Batty 2007). They are all promising methodologies in a new generation of urban models.

1.1.2 Scientific relevance

Urban growth modeling is an interdisciplinary field involving numerous scientific and technical research areas, e.g. geographical information science (GIS), remote sensing, urban geography, transport science, complexity theory, and computer science. A new generation of aggregated models should integrate methods and techniques from these multi-disciplinary fields.

Geographic information science: Remote sensing and geographic information system (GIS) are two efficient ways to monitor, evaluate and model urban growth by gathering, processing and analyzing spatial information. In the last two decades, GIS has gradually shifted its emphasis from a tool to a science. The term geographic information science (GIScience) was first introduced to encompass the set of fundamental research surrounding GIS. Mark (2003) defined it as: “The development and use of theories, methods, technology, and data for understanding geographic processes, relationships, and patterns.” GIScience has produced a series of accomplishments and expanding literature reviews of current research. Goodchild (2010) listed five research topics that may be tackled by GIScience in the coming decade: knowing where everything is at all times; the role of the citizen as a consumer and producer of geographic information; a technology of dynamics; the third fourth and fifth dimensions; and the challenge of education.

Complexity science: Complexity theory has become a hot topic across almost all research fields concerned with understanding systems characterized by nonlinear behavior, self-organization, irreducibility, and emergent properties (Anderson 1972, Johnson 2001, Miller and Page 2007). Durlauf (2005) identified four key features of complex systems, including non-ergodicity, phase transition, emergence, and universality. Cities are considered as being complex systems (Batty and Longley 1994) because there are comprehensive entities coping with infinite variety. Urban evolution is bottom-up (partly in top-down fashion) and urban development is temporally dynamic (Batty 2007), i.e. urban growth involves multiple individuals with various behavior patterns at both spatial and temporal scales, and reflects dynamic interactions between socio-economic and environmental impacts. Agent-based models in cellular environments are therefore suitable to model complex urban systems.

1.2 Research motivation and objectives

1.2.1 Research motivation

Cities consist of many interactive subsystems. Among major types of urban subsystems, land use and transportation networks change very slowly (Wegener 2004). However, when considering the changes of urban morphology in long term, land use and transportation systems are perhaps the two most important subsystems and they are supposed to influence each other over time. Apparently, the expansion of one road network would affect the location choice of firm/household and land development. Meanwhile land-use changes in turn affect the travel demand and accessibility. This feedback relationship is emphasized as a link or cycle (Kelly 1994, Iacono et al. 2008).

Involving complex processes, urban systems are generally difficult to simulate well through traditional 'top-down' models. In recent years, some 'bottom-up' approaches, such as cellular automata (CA) and agent-based model (ABM) have been adopted (Couclelis 1997, Torrens 2006). CA models focus on landscapes and transitions while ABM models represent behaviors and decisions of individuals who play important roles in urban systems. A multi-agent system (MAS) is supposed to consist of components from these two approaches.

The specific motivation behind this thesis includes the following issues:

- Urban growth models should consider land-use simulation, road network expansion and their interactions, since they determine urban structure in the long term. However, seldom existing urban growth models involve road network growth and its dynamic interactions with land-use changes.

- Transport networks in current urban models are usually held fixed or handled as variables. However the growth of transport networks greatly influences urban dynamics, and should be modeled.

- Road networks are skeletons of cities. Urban growth models in terms of morphological changes therefore can be built through modeling the evolution of road networks. This is a new direction to model urban growth.

- Advanced urban models demand the integration of interdisciplinary knowledge and approaches. For instance, 'bottom-up' approaches in land-use simulation, and theories of complex networks in evolving network modeling. These new approaches from different research branches have not been integrated in one framework in existing urban models.

Urban growth models help to understand the mechanisms of urban evolution, to examine the existing urban theories (especially about the dynamic relationship between land use and road network), and to provide planning support in urban growth management by developing future growth scenarios.

1.2.1 Research objectives

The overall objective of this research is to understand the urban growth/sprawl phenomena through modeling and simulation. After the study of the complicated urban system and driving forces behind urban dynamics, urban growth models are built based on the modeling of land-use change and road network growth.

Based on the research motivation, an evolving model for road networks is particularly built as an important component of urban growth modeling. This thesis endeavors to address modeling issues by integrating knowledge and methods in GIScience with numerous other scientific and technical areas. The science of promising complex networks is particularly brought to advance network analysis and network modeling in GIScience.

To achieve the main objective, there are three basic research issues to be addressed:

- How to model land-use changes with ‘bottom-up’ approaches?
- How to model network growth of urban streets?
- How to integrate land-use and road network to build an urban growth model?

According to the research issues, the specific research objectives are:

- To simulate urban land-use development by using the MAS approach and examine the influence of different types of entities on urban growth/sprawl.
- To propose a long-term urban growth model by integrating road network expansion with land-use simulation.
- To explore the preferential attachment mechanisms in evolving weighted networks and then build a growth model for self-organized urban street networks to study urban morphological changes.

- To investigate the relationship between land use and road network for future hybrid modeling. Road network can be measured by major centralities from different perspectives.

1.3 Thesis organization

This thesis is based on the following papers:

I. Yikang Rui and Yifang Ban (2010). Multi-agent Simulation for Modeling Urban Sprawl In the Greater Toronto Area. 13th AGILE International Conference on Geographic Information Science, Guimarães, Portugal.

II. Yikang Rui and Yifang Ban (2011). Urban growth modeling with road network expansion and land use development. Advances in Cartography and GIScience, Volume 2. Springer Berlin Heidelberg, 399-412.

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V. Yikang Rui, Yifang Ban, Jiechen Wang and Jan Haas (2013). Exploring the patterns and evolution of self-organized urban street networks through modeling. The European Physical Journal B, 86: 74.

VI. Yikang Rui and Yifang Ban. The influence of street centrality on urban structure in Stockholm. Submitted to the International Journal of Geographical Information Science.

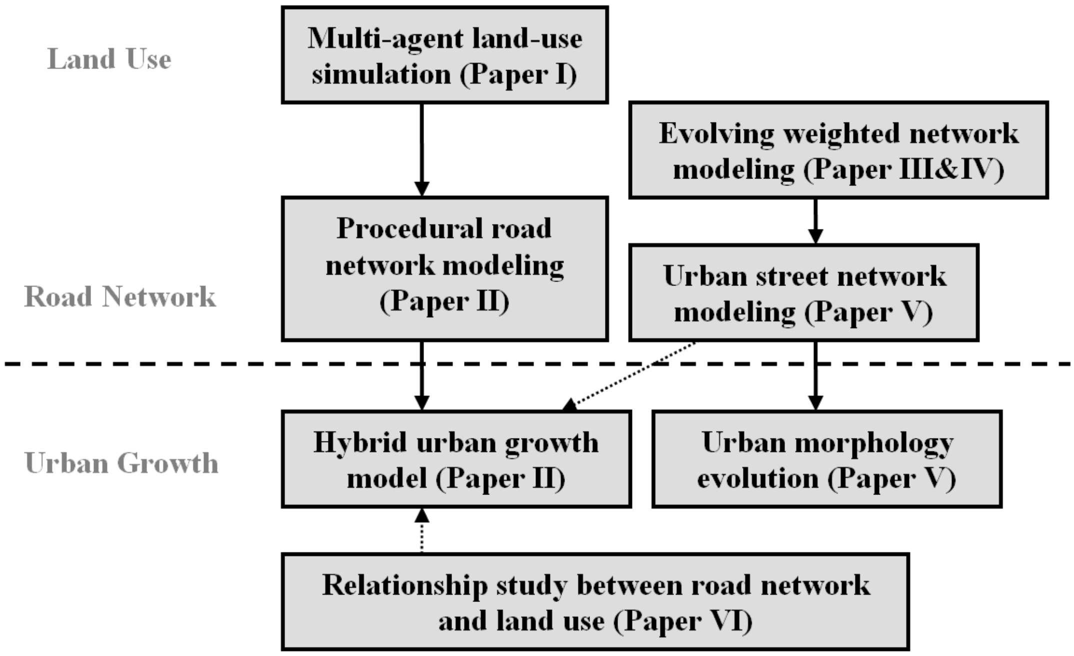

Figure 1.1: Organization of the selected papers in the thesis.

Figure 1.1 shows the organization of the selected papers in the thesis. The urban growth modeling is based on urban land-use change simulation and road network growth modeling.

Paper I simulates the land-use change in the Greater Toronto Area (GTA) from 1985 to 2005 using MAS to represent different types of individuals in a urban system. **Paper II** presents a hybrid urban growth model integrating land-use change with road network expansion, since they are the two most important subsystems in the long-term urban simulation.

A lot of effects have been made to improve road network growth modeling. First of all, it is essential to study the growth mechanisms for weighted networks because road networks are weighted. **Paper III & IV** proposed a novel theoretical model to study the influence of nonlinear weight growth and neighboring connections on network evolution. Then, a growth model for self-organized urban street networks is presented in **paper V**. This model succeeds in reproducing a large diversity of road network patterns of real-world cities and shows the evolution of urban morphology.

Finally, because analyzing the relationship between land use and road network is necessary for modeling, paper **VI** examines the static correlation between different land-use types and street centralities in Stockholm. Centralities are crucial indices to measure the properties of street networks from different perspectives. This analysis can be further extended to investigate the dynamic correlation between the changes of land use and road network over time.

Note that currently the hybrid urban growth model in **paper II** is still preliminary. However, many later works show the potentials to advance this integrated model. For instance, both road network model in **paper V** and relationship analysis between land use and road network in **paper VI** (pointed out by dotted arrows) can be introduced into the building of a new hybrid urban growth model in future research and studies.

The thesis is structured as follows:

- Chapter 1 gives an overview of the research, including the background, motivation, objectives and organization of the thesis.

- Chapter 2 reviews current urban land-use models (urban growth models as well) and particularly introduces the MAS approach, which is used in **paper I**. Chapter 3 reviews growth models of spatial networks, especially urban street networks. The procedural road network generation in section 3.1 is used in **paper II** while the spatial networks modeling from the field of complex networks in section 3.2 is used in **paper III, IV & V**.

- Each model in every selected paper is well designed and developed. Chapter 4 introduces the methodologies of analysis and modeling, which are listed according to the order how the organization of selected papers is described in Figure 1.1.

- Each model is evaluated by the comparison between simulation results and real cases. Chapter 5 summarizes the results of each paper and discusses the contributions.

- Finally, chapter 6 presents the conclusions of the thesis and describes challenges and opportunities for future research.

2. Models of urban land-use changes

2.1 City and urban growth

2.1.1 Definition of city

Approximately 5000 years ago, a small number of Neolithic villages developed into small towns and cities. Increase agricultural productivity sustained a variety of specialized labor forces. Consequently, more complex social organizations and advanced civilizations arose.

Nowadays, there is still no general agreement among nations on how to define “a town” or “a city” (Hardoy et al. 2001). Governments usually define urban centers by the number of inhabitants (for example settlements with 2000 or more inhabitants), the proportion of the population that are dealing with non-agricultural activities, administrative or political status. The term “city” and “urban center” are often used interchangeably. However, there exist definitions of “city” in urban studies and related fields. Cities are the places for the association of individuals to enable more efficient production means. In ecological theory, cities are considered as being man-made ecosystems with their own energy periods and species (Watt 1973).

2.1.2 Characteristics of urban growth and sprawl

From the early 20th century, cities began to grow upward quickly. Especially in American cities (e.g. Chicago, New York), skyscrapers came to change urban landscapes with numerous tall commercial buildings. However, in the latter part of the 20th century, urban structure has become less compact. Unending miles of shopping malls, offices and houses are now commonly dominating the urban structure. Early on, citizens may live in sprawling suburbs but continued to work in city centers. Then jobs may however follow the people, and this trend in turn leads to decentralization of homes and jobs.

As a relatively new form of urbanization, sprawl is a natural expansion of metropolitan areas when population expands (Sinclair 1967, Lowry 1988) and equates to haphazard or unplanned growth (Peiser 1984, Koenig 1989). Sprawl is also defined according to undesirable land-use patterns, i.e. continuous low-density, strip/ribbon, scattered, and leapfrog development (McKee and Smith 1972, Popenoe 1977, Heikkila and Peiser 1992, Ewing 2008).

Several suggestions have been offered to explain the causes of sprawl:

- Population growth is one of the most important driving factors behind the urban sprawl. It contributes to sprawl through absolute growth, increased urbanization (the percentage of the population living in urban areas is growing), and the restructuring of household demography (household sizes decrease and housing units increase) (Torrens 2006).

- The increased use of cars is considered as a root cause of urban sprawl. At the same time, highways and other transportation systems have grown quickly. Due to these two reasons, people can choose to live in suburbs. In order to follow labor forces and pursue cheap land, industry and business move from the city to suburbs by accessing an expanding highway network. Intersections of suburban highways have become sub-centers of new urbanization.

- Internet and communications technologies may encourage sprawl trends. Nowadays, disparate parts of a city may be separated spatially but linked functionally through the advances in communication technologies.

- Other causes may include subsidies for suburban development in terms of owner-occupied housing and infrastructure, external benefits related to open space, and encouragement in low-density development by suburban land-use regulation (Ewing 2008).

Urban sprawl has been conceptualized as a multi-dimensional phenomenon that requires a set of measures for each dimension (Torrens and Alberti 2000, Ewing et al. 2002).

- Growth rate (sprawl index). It is defined as the ratio between the growth rate of built-up areas and the population (Hadly 2000).

- Density. Normally it is defined as the ratio between the amount of a certain urban activity and the area where it takes place (Burton 2000, Chin 2002). Density decreases during a certain time period and is relatively low in a sprawl area.

- Spatial geometry. There are numerous spatial geometric measures, most of which have been adopted within ecology (McGarigal and Marks 1995; Turner 1989) or in fractal geometry (Batty and Kim 1992, Torrens and Alberti 2000). Spatial geometric measures quantify the configuration and composition of an urban landscape. Configuration describes the geometry of an urban built-up area while composition depicts the level of heterogeneity. In a sprawling urban area, geometric configuration is scattered, irregular and fragmented. Land-use composition is segregated and homogenous.

- Accessibility. It can be quantified by measuring fractal dimensions of road networks (Benguigui 1995), road lengths, road areas and traveling times (Hadly 2000) or by using complex transportation models (Torrens and Alberti 2000). A sprawling urban area generally shows a worse accessibility (Ewing et al. 2002).

Sprawl is understood to be problematic for several reasons. These are as follows:

- Extra travel and congestion. Low densities generate more vehicle miles of travel (VMT) per capita. Besides, when density decreases, trips become longer and people will walk less (Levinson and Wynn 1963, Newman and Kenworthy 1989, Dunphy and Fisher, 1994). The level of traffic congestion not only depends on how much occurs, but also where travel occurs, so extra travel can increase congestion in some key road segments.

- Energy inefficiency and pollution. Comparison between centralized and low-density development shows that the former is more energy-efficient (Newman and Kenworthy 1989). Air and noise pollution are mainly governed by the amount of motor vehicles. Sprawl cities obviously produce more pollution because of the increased use of vehicles.

- More infrastructure and public service costs. Sprawl in suburban areas is followed by new infrastructure. Extra costs of public service are needed in low-density residential areas. These public services include police, fire, schools, sanitation, water supply, etc. (Downing and Gustely 1977).

- Loss of farmlands and open spaces. The loss of farmlands and open spaces is a consequence of urbanization. Particularly low-density sprawled suburban areas need more land to develop residential, industrial and commercial areas.

To solve the problems brought by urban growth and sprawl, smart growth strategies have been introduced to build a compact and sustainable city in the field of urban planning and transportation (Punter 2003, Berelowitz 2005, Lewis et al. 2009, Dempsey 2010). Smart Growth BC (2012) defines smart growth as a collection of land development principles to improve the life quality and protect the natural environment. The following principles are implemented in smart growth:

- Merge land uses.
- Build well-designed compact neighborhoods.
- Foster a unique neighborhood identity.
- Create diverse housing opportunities.
- Support growth in existing communities.
- Supply diverse transportation choices.
- Utilize smarter infrastructure and green buildings.
- Protect open spaces and environmentally sensitive areas.
- Protect and improve agricultural lands.
- Train engaged citizens.

2.2 Land use modeling approaches

Some related terms need to be clarified before the introduction of modeling. There are various definitions for the term "land", "land use" and "land use change" according to the context of the use and purpose of the application (Briassoulis 2000).

In natural science, the term "land" refers to a wide range of natural resources from the atmosphere above the land surface down to some meters below the surface (Stewart 1968, Wolman 1987). "Land use" indicates the human employment of land (Turner and Meyer 1994, Skole 1994). FAO/IIASA (1993) states that "land use concerns the function or purpose for which the land is used by the local human population and can be defined as the human activities which are directly related to land, making use if its resources or having an impact on them". "Land-use change", therefore, indicates quantitative increases or decreases in the area of a given type of land use (Briassoulis 2000).

The term "model" is the representation of a system through mathematical, logical, physical, and iconic methods. Popper (1972) reasoned that science is a process of conjecture and refutation of problems, followed by tentative solutions, error elimination and the redefinition of the problems. This concept is applied in urban studies (Batty 1976). Models can be generally classified into four types: descriptive, explorative, predictive and operational models (Echenique 1972).

Classifications of urban land-use change models have been proposed by many scientists. Merlin (1973) divided urban models into three types: urban development, transportation and urban resources. Briassoulis (2000) classified land-use change models based on their functional and methodological aspects: statistical and econometric, spatial interaction models, optimization models, integrated models, natural sciences-based models, GIS-based models and Markov chain-based models. More model classification schemes can be obtained in the following papers (Batty 1976, Issaev et al. 1982, Stahl 1987, Verburg et al. 2004). Recently, Silva and Wu (2012) presented a list of comprehensive classification schemes according to different characteristics, methodologies, application areas and modeling approaches:

- Modeling approaches: mathematical/statistical models, GIS-based models, cellular automata-based models, agent-based models, rule-based models, and integrated models.

- Levels of analysis: micro level, macro level, and cross level models.

- Spatial scales: regional scale, metropolitan scale, local scale, and multi scale models.

- Temporal scales: long term, medium term, and short term models.

- Spatial emphasis: spatial oriented, aspatial oriented, and integrated models.

- Planning tasks emphasis: land-use/land-cover change, urban growth, transportation land use, impact assessment, and comprehensive projection models.

In the following sections, urban land use models will be discussed in greater detail according to applied approaches.

2.2.1 Spatial interaction models

The earliest class of land-use models was based on the principle of spatial interaction. In the fields of regional science and quantitative geography, spatial interaction denotes that every movement in space is a consequence of a human process (Haynes and Fotheringham 1984). Adapted from Newton's first law, the gravity model was introduced to describe the spatial relations, which depend on the size of two objects and is in inverse proportion to the distance between them (Wilson 1970). The total interaction in a system equals the amount of all interactions between any pair of objects. Advanced formulations were derived later based on the ideas of "entropy maximization" or "information minimization" (Snickars and Weibull 1977).

The first operational urban land-use model is assumed to have been developed by Lowry (1964). One gravity sub-model distributes the residential population based on fixed employment locations. The other sub-model allocates retail businesses according to new demand. The interaction continues until a preset allocation difference occurs. Then, many models have been developed based on the basic Lowry's framework. For instance, the Time Oriented Metropolitan Model (TOMM) disaggregates the population into socioeconomic groups to enhance the representation and to incorporate inertia effects in activity allocation (Crecine 1964). The PLUM model allocates activities with an intervening opportunity model (Goldner 1971). The Integrated Transportation and Land Use Package (ITLUP) is widely accepted as the first fully operational transportation/land-use modeling software package (Putman 1974, 1983). It improved calibration techniques and incorporated traffic congestion effects in activity allocation. Another conventional travel model is the Leeds Integrated Land Use (LILT) model (Mackett 1983, Timmermans 2003).

2.2.2 Mathematical/statistical models

Almost all models involve a mathematical mechanism, but mathematical models especially lie on equations to reach a static or equilibrium status. The simple mathematical models are a set of equations describing population growth and redistribution to specify the land-use change over time (Sklar and Costanza 1991). Economic theories are usually involved in more complex models. The econometric framework normally consists of regional economic models and land market models.

One regional economic model is the MEPLAN model which has a zone-based structure (Echenique et al. 1969, 1990). It begins as a simple urban stock and activity model and then expands into a more comprehensive model. The activities in zones are decided by a spatial input-output model which estimates trade flows between zones in one region. Travel is processed as a derived demand. The TRANUS model (de la Barra 1989) is similar to MEPLAN in that a spatial input-output function decides the travel pattern. A relatively advanced trip-based model is introduced later to forecast more detailed travel information.

The economic analysis of land use often uses bid rent theory (Alonso, 1964), which focuses on the relationship between types and values of urban land use. Residents and firms estimate and decide the land consumption, land price and transportation costs. Another important concept is discrete choice theory (McFadden, 1978), which means that the probability that an individual chooses one alternative equals the ratio of the utility value of the particular alternative to the total utility value of all alternatives. Anas and colleagues (Anas 1982, 1998; Anas and Arnott 1994) developed a series of models to simulate how transportation improvements affect land markets and social welfare. The first developed model, called CATLAS, has a discrete choice framework to represent both the supply and demand of the housing market. CATLAS was later enhanced in the METROSIM model (Anas and Arnott 1994), which incorporates a dynamic model of metropolitan housing markets, as well as travel and traffic assignment.

Statistical techniques are commonly used to model land-use change. Various regression techniques are used to deal with decision making and social phenomena (Mertens and Lambin 1997). Many successful examples combining theories with statistics have been provided by spatial econometrics (Geoghegan et al. 1997, Leggett and Bockstael 2000, Munroe et al. 2001).

2.2.3 Expert models

Expert models integrate expert knowledge with Bayesian probability, Dempster-Schaefer theory (Eastman 1999) or artificial intelligence (such as logic-based and knowledge-based) approaches (Lee et al. 1992). These methods let users determine where each given land-use type is likely to occur (Klosterman and Pettit 2005). The rule-based models include the California Urban Futures (CUF) model (Landis 1994), the What-If? model (Klosterman 1999, Klosterman and Pettit 2005), and the UPLAN model (Walker et al. 2007). The CUF model simulates residential development scenarios by setting specified regulations based on governmental policy. The What-If? model can visualize alternatives of land use allocation once users define input data, development rules and parameters.

2.2.4 Cellular automata

Cellular models (CM), including cellular automata (CA) and Markov models, operate over a grid. The CA concept was first proposed by Ulam and von Neumann in the late 1940s (Silva and Clarke 2005). In the field of geography, CA was firstly introduced by Tobler (1979). Since then, CA theory has drawn a lot of attention in urban studies (Batty 1997, 2005).

CA models generally have four basic elements:

- A lattice of regular cells,
- A set of cell statuses,
- A neighborhood defined by the lattice,
- A set of transition rules for individual cells.

Many CA models also add time as the fifth element (Silva and Clarke 2005). CA models are basically deterministic and rule-based as they use logical statements to determine the transition rules. The improvement for CA models includes changes of the structure and dimension of grid, expanded neighborhood definitions, and changes of temporal element (Torrens and O'Sullivan 2001).

CA models for land-use change include simple state transition models and more complicated designs. The former use some probability for transition rules, while the latter determine one cell's status based on a function of status in its neighboring cells. The cell space of CA models is set up similar to the raster data structure in GIS. Thus, it can be combined with digital raster data from remote sensing systems and other sources. This grid-based structure is also convenient for programming and visualization. Neighborhoods are considered as one key element since they drive the interaction between land use and the dynamics of the systems (O'Sullivan and Torrens 2000, Verburg et al. 2004, Caruso et al. 2005). The Moore and von Neumann neighborhoods, shown in Figure 2.1, are the most widely used. The former includes eight neighboring cells while the latter includes four neighboring cells (Benenson and Torrens 2004).

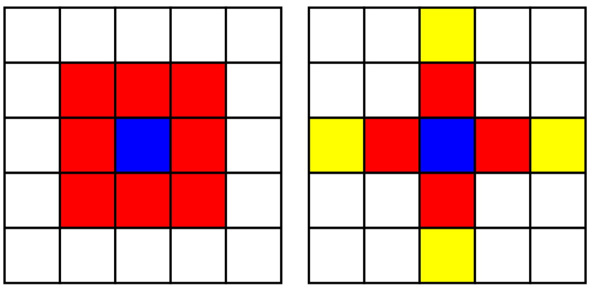

Figure 2.1: CA neighborhood. Left: The red cells are the Moore neighborhood for the blue cell. Right: Red cells are the von Neumann neighborhood for the blue cell, and yellow cells are the extended neighborhood.

CA has been widely applied to geography and related fields because of four main advantages: spatiality and affinity with GIS, dynamism, micro-simulation, and a bottom-up approach. There are lots of applications, such as: urban form modeling (Batty 1997, Yeh and Li 2001), urban growth (Clarke and Gaydos 1998, Torrens 2006, Zhang et al. 2011), urban and regional development and planning (White and Engelen 2000, Samat 2002, Hansen 2010). Yeh and Li (2002) incorporated a density gradient in the model to simulate different urban forms. The LUCI2 model (Ottensmann 2005) was built to estimate employment and land conversion by demonstrating how employment determines residential development and density. In recent years, more advanced artificial intelligence techniques are introduced such as genetic algorithms (Li et al. 2008, Shan et al. 2008), simulated annealing (Al-Ahmadi et al. 2009), and neural network (Almeida et al. 2008). A more detailed description of CA models for urban simulation can be found in the review by Sante et al. (2010).

2.2.5 Agent-based modeling

2.2.5.1 Definition and description

There are various definitions for the term “agent”. However, most of them share some common characteristics (Torrens 2004, Macal and North 2005, Castle and Crooks 2006):

- Autonomy. Agents are autonomous individuals without a centralized control. They can process and exchange information with other agents to make independent decisions.

- Heterogeneity. Agents can represent diverse individuals’ attributes such as age, sex, and education.

- Activity. Agents are active in a simulation. They can be pro-active (goal-directed), reactive (show awareness of their surroundings) and interactive (they communicate extensively). Agents also have mobility, which is particularly useful for spatial simulations. In complex adaptive systems, agents are designed to be adaptive, i.e. they have a learning ability.

An agent-based model (ABM) consists of multiple interacting agents within a simulated environment. Agents could represent a wide variety of entities in the real world, such as atoms, biological cells, people, organizations, buildings or land parcels (Conte et al. 1997, Epstein and Axtell 1996, Janssen and Jager 2000, Weiss 1999). Rules are defined for the agents’ actions and these rules affect their behaviors and relationships. These rules are usually derived from observation, expert knowledge and data analysis. All agents can share one rule or each agent can have its own unique rule. Rules are not always preset and they can evolve as agents having learning ability. Agents can interact with each other within the same type, between two agent types, or with the environment. Agents are spatially explicit, which means they have a geographical location in space, although some agents may not move in some special cases.

Agent-based models have been developed with wide applications such as archaeological reconstruction of ancient civilizations (Gumerman et al. 2003), the biological modeling of infectious diseases (Chen et al. 2006), studying the growth of bacterial colonies (Krzysztof et al. 2005), modeling economic processes (Topa 2001, Tesfatsion 2006), and investigating social networks of terrorist groups (North et al. 2004). In the land-use modeling community, five purposes have been identified by Matthews et al (2007): policy analysis and planning, participatory modeling, explaining spatial patterns of land use, examining social science concepts and demonstrating land-use functions.

2.2.5.2 Development tools

There are many tools available to develop ABM. These systems can be divided into three categories in terms of licensing policy (Castle and Crooks 2006):

- Open source (Swarm, MASON and Repast).
- Shareware/freeware (StarLogo, NetLogo and OBEUS).
- Proprietary systems (AgentSheets and AnyLogic).

There are many review papers that compare different ABM toolkits (Robertson 2005, Rand et al. 2005, Castle and Crooks 2006). In this work the software NetLogo was used. NetLogo is developed at the Centre for Connected Learning and Computer-Based Modelling at Northwestern University. The critical difference between NetLogo and StarLogo is that NetLogo is specifically designed for the deployment of models over the internet (NetLogo 2012). NetLogo is easy to operate. It has an extensive models library so that users can learn and improve their own models. It provides functionality to import image files, which is convenient to used as the simulation environment. Furthermore, NetLogo provides the ability to load GIS vector data. NetLogo has been applied to many applications in several disciplines varying from biology, mathematics, chemistry and physics to the social sciences and urban studies (Figure 2.2). Extensive tutorials and demonstration models are available and these models can be easily extended.

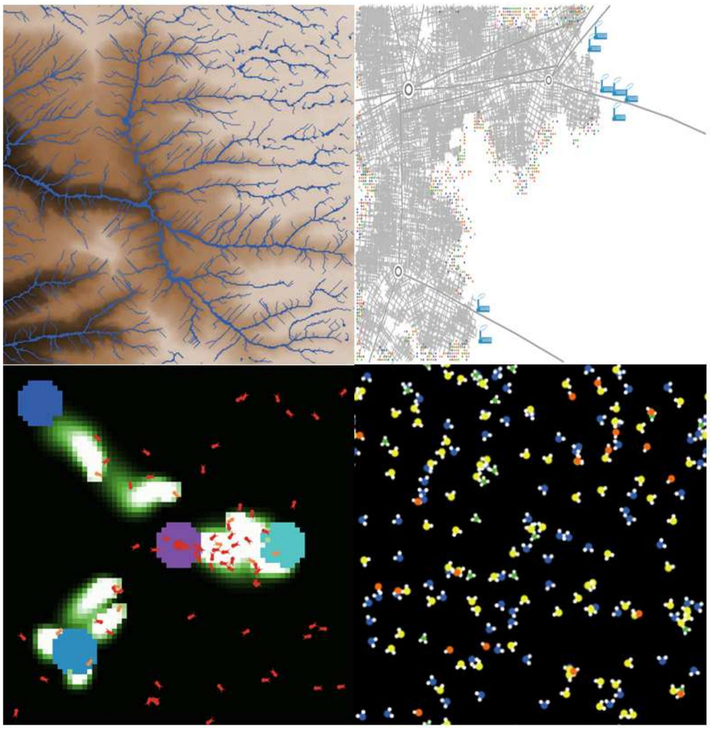

Figure 2.2: Model examples in NetLogo (2012). Grand canyon (top left), Tijuana bordertowns (top right), ants (bottom left), and weak acid (bottom right).

2.2.5.3 Verification and validation

Once an appropriate tool or software has been chosen, there are several other important issues that have to be considered in model development such as verification, calibration and validation (Batty and Torrens 2005, Crooks et al. 2008). Verification is the process of examining the logic of the model through the computer program. Verification can be easier if more models either use efficient communication of model design to others or adopt common modeling standards. Calibration is the process of identifying suitable values for model parameters in order to better fit the real world. There are many optimization methods available for calibration, such as the genetic algorithm (Fletcher 2000, Soman et al. 2008). Validation measures how well models represent real-world behaviors through the comparison between outputs and observations using the goodness-of-fit measurement for instance (Parker et al. 2003). Briefly speaking, verification implies building the systems right and validation means building the right systems. Recently, Ngo and See (2012) discussed verification, calibration and validation issues in the field of ABM.

2.2.5.4 Advantages

The bottom-up ABM approach claims some advantages over traditional top-down methods (Castle and Crooks 2006, Crooks and Heppenstall 2012):

- It captures emergent phenomena from the bottom up by describing the behavior and interactions of agents in the simulated urban system.

- It can directly incorporate with dynamics. The time step can be small enough to approximate how real world changes.

- It is a natural method to describe and simulate a system since it inherently simulates people and objects in a very realistic way.

- It is flexible, since agents can physically move in a geographical space in different directions and at different speeds in a spatial model.

2.2.5.5 Limitations and challenges

Agent-based modeling has some limitation in simulating urban dynamics. Cities are very complicated. Thus, the problem is that how much the amount of details is used to serve the purpose. If the abstraction for the model is too simple, the key variables are missed. Too many details make the model over complicated to build. Suggestions on building an ABM have been given by Abdou et al. (2012). The second problem is how one uses an agent to simulate human behavior, as human beings are irrational and make subjective choices. These properties are very difficult to quantify and calibrate. Thirdly, time consuming for modeling large systems is a big challenge. Finally, ABM for urban simulation can be very data demanding, and there is a lack of personal statistical data because of privacy issues. With regards to the development of ABM, Crooks et al. (2008) proposed the following seven challenges: the purpose of the model, independent theory of the model, replication and experiment, verification and validation, model dynamics in terms of interactions, operational modeling, sharing and dissemination of the model.

2.2.6 Multi-agent simulation

ABM is later extended to a Multi-agent system (MAS), which not only contains an ABM representing disaggregated decision making, but also includes a CA. The CA part describes the land-use changes, while the agents represent human behaviors and perform in the simulated environment (Figure 2.3). Thus the complicated interactions among agents or between agents and environment are simulated.

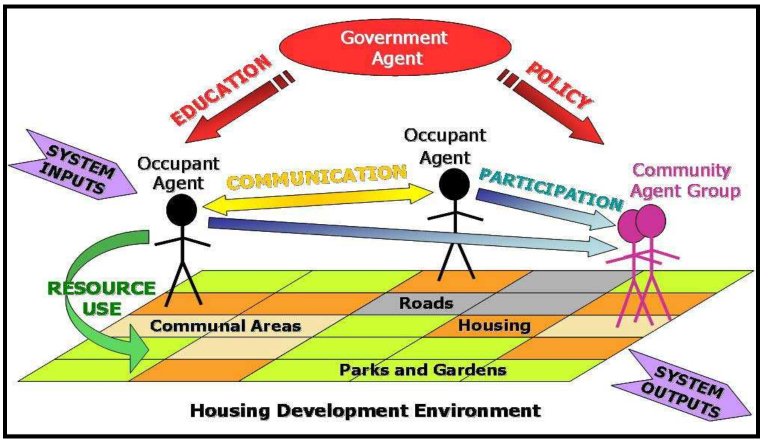

Figure 2.3: Multi-agent representation of a residential development (Source: Daniell et al. 2006).

Current Applications of MAS for land-use modeling include: natural resource management (Rouchier et al. 2001), agricultural economics (Berger 2001), archaeology (Dean et al. 2000), and urban simulation. In urban studies it was only until the past decade MAS started to be used for urban land-use modeling (Parker et al. 2003, Bousquet and Le Page 2004). In urban modeling, MAS was introduced to micro-simulate land-use changes, incorporating environment, transport, and other economic models in order to build complicated urban systems, such as Ramblas (Veldhuisen et al. 2000), UrbanSim (Waddell 2000, 2002, Waddell et al. 2003), ILUTE (Miller et al. 2004), PUMA (Ettema et al. 2005), ILUMASS (Moeckel et al. 2003, Wagner and Wegener 2007). Some other models with simple use of road network include ABLOoM (Otter et al. 2001), CityDev (Semboloni 2005) and Kou's artificial urban (Kou et al. 2008).

MAS can be applied to simulate how individuals interact with environment to analyze the influence of urban sprawl (Li 2005, Monticino et al. 2007, Kou et al. 2008). Various development scenarios are developed for policy makers to make decision in a spatial planning process (Li 2005, Ligmann-Zielinska and Jankowski 2007). As population growth is the main engine of urban sprawl (Torrens 2006), many studies have focused on residential preference and location choice (e.g. Benenson 1998, Eliasson and Mattsson 2000, Otter et al. 2001, Semboloni 2005, Brown and Robinson 2006, Filatova et al. 2007, Li and Liu 2008, Eliasson 2010).

Specifying the diversity and behavior of realistic agents is always challenging (Verburg 2006). However, there is no doubt that MAS is a useful tool to explore existing theories and verify assumptions when complex phenomena greatly affect model outcomes. When agents and their environment are interdependent or heterogeneous, adaptive behaviors are relevant, and decision making is assisted by individuals, MAS is especially appropriate to model the complexities in such cases.

2.3 Urban growth models

The previous section classifies the models based on modeling approaches. According to designed tasks, urban dynamic models can be divided into several groups: land-use/land-cover change, urban growth, transportation & land-use and impact assessment (Klosterman 2001, Silva and Wu 2012). (1) Land-use models mainly evaluate the transition of different land-use types to optimize land configurations or promote sustainable development (Pullar and Pettit 2003, Silva et al 2008). The IMREL model uses destination choice as a base for locating households in Stockholm (Anderstig and Mattsson 1991). The SLUCE model was built to understand the complexity in the generation of different land-use patterns and their ecological influences (Brown 2005). (2) Urban growth models focus on urban growth phenomena. The SLEUTH model simulates the transition from non-urban to urban areas (Silva and Clarke 2002). The Urbansim model implements a perspective on urban development via urban market dynamics (Waddell et al. 2003, 2007). The UPLAN model is based on the attractiveness of landscape features and growth constraints (Walker et al. 2007). (3) Transportation & land-use models concentrate on the interpretation of the relationship between transportation and land use (Anderstig and Mattsson 1998, Jonsson 2008). The ILUTE model includes four main modules: land development, location choice, activity/travel, and auto ownership (Miller and Salvini 2001, Miller et al. 2010). It models eight scenarios by combining land use, economic and transportation policy factors. In transport module, activity-based model is widely used as a micro-simulation approach (Algers et al. 2006). Travel demand model is therefore an important component (Flötteröd and Bierlaire 2011, Flötteröd 2012). (4) Impact assessment models aim to measure and evaluate the influence of simulated future status (Kwartler and Bernard 2001, Klosterman and Pettit 2005).

Actually, there is no clear distinction between the classifications of urban models above. For example, most urban growth models contain land-use modules or vice versa. The SLEUTH model is counted as an urban growth model. It however can simulate land-use transitions. The LEAM model (Deal 2001, Deal and Pallathucheril 2007) computes the growth potential of different land-use types. Meanwhile it is also used to study urban growth and consequent environmental impacts. The SLEUTH and the LEAM model share very similar functions except for the main purpose. Therefore, the urban growth model mentioned in this thesis has the same meaning as urban land-use model.

3. Models of road network growth

There is a long history of studying the temporal development of transportation systems and sustained effects have been made to analyze and model the network growth. The studies involve technical, topological, morphological, economic, social, or political aspects in broad research fields, such as transportation engineering, geography, physics, computer science, economics and urban planning (Xie and Levinson 2009).

Geographers in the 1960s studied network growth as topological transformation with heuristic and intuitive connection rules (Garrison and Marble 1962, Taaffe et al. 1963, Harggett and Chorley 1969, Lowe and Moryadas 1975). From the 1970s, transportation planners applied travel demand modeling to predict traffic flow in order to model the optimal changes for the network (Newell 1980, Vaughan 1987, Yang and Bell 1998, Zhang and Levinson 2005). Thanks to the availability of sufficient data and processing capacity of massive data, researchers can now study the temporal changes of transportation through statistical analyses of historical data (Taylor and Miller 2003, Levinson 2007, Levinson and Chen 2007). Transportation economists focus on various economic dimensions of network growth ranging from network pricing, ownership structures to capacity investment (Gomez-Ibanez et al. 1999, Knight 2002, Verhoef and Rouwendal 2004, Kopp 2006, Xie and Levinson 2007a). In later 1990s, a new network science of complex networks emerged. The growth of transportation networks are interpreted with the concepts of preferential attachment and self-organization mechanisms. Recently, a growing interest of agent-based modeling is to simulate the initiatives and behaviors of independent individuals in order to investigate the dynamics of transportation networks.

Transport systems can be waterways, canals, roads, rails and airlines. The main interest in this thesis lies in the road network. The following sections will fully review growth modeling methods from the perspective of procedural urban modeling and spatial network modeling.

3.1 Road network generation in procedural city modeling

In procedural modeling of cities, it is critical to generate a road network. Road networks are divided into different levels, including highways, major roads and minor roads. Highways are usually generated by linking centers with the shortest path algorithm (Teoh 2007) or population density map (Parish and Müller 2001, Sun et al. 2002). The first step to generate major roads is selecting nodes. The selection principle can be based on where users position the nodes (Kelly and McCabe 2007), the highest transition possibility (Jiang 2007, Weber et al. 2009), jobs distribution and highways location (Vanegas et al. 2009), or the difficulty of diffusing in an existing transport structure (Yamins et al. 2003). Then nodes are linked into road segments after considering elevation difference strategies (Kelly and McCabe 2007, Jiang 2007), or least-cost choice (Yamins et al. 2003). Minor roads can be generated using the same procedure as for major roads (Weber et al. 2009, Vanegas et al. 2009) or more commonly by using road pattern templates (Parish and Müller 2001, Sun et al. 2002, Teoh 2007). Legality tests are used in the expansion process, i.e. proposed streets are checked for intersection, extension, snapping, avoidance and slope adaptation. Esch et al. (2007) and Chen et al. (2008) used user-guided tensor fields to generate streets. Lechner et al. (2004, 2006, 2007) and Watson (2006, 2007) applied extender and connector agents to generate tertiary and primary roads. The following sections will describe road pattern templates and agent-based behavior model in greater detail.

3.1.1 Road pattern templates

According to Mackaness and Edwards (2002) patterns can be defined as a property within an object or between objects that is repeated with sufficient regularity, referring to shape, orientation, connectedness, density or distribution. Marshall (2005) introduced a taxonomy of main general road patterns and distinguished between the following types: linear, treelike, radial, cellular and hybrid. On the basis of this taxonomy, Heinzle et al. (2005) introduced some basic patterns that can be detected in urban road networks such as strokes, grids, stars and ring roads. Zhang (2004) argued that patterns can be recognized as complex objects: Star-like patterns consist of a hub junction with radial roads and optional rings around the hub. Grid-like patterns have two sets of roads intersect perpendicularly.

In the field of procedural modeling, road pattern templates are widely applied. A template consists of two parts: rules and parameters. Rules decide the overall road structure while parameters provide inputs. Parish and Müller (2001) applied a group of road patterns in the CityEngine system (Table 1 and Figure 3.1). Similar frequent road patterns have been listed by Sun et al. (2002): population-based, raster, radial and mixed. Kelly and McCabe (2007) used a set of parameters to construct different road patterns: regular raster, industrial and organic in their Citygen system. In polycentric cities, regular raster patterns dominate, whereas in monocentric cities radial patterns prevail. As for different road levels, highways can be represented with raster and radial patterns whereas minor streets usually have raster patterns.

Table 1. Typical road patterns.

Pattern name	Pattern
Basic	No superimposed
Paris	Radial to center
New York	Rectangular Raster
San Francisco	Elevation min or max

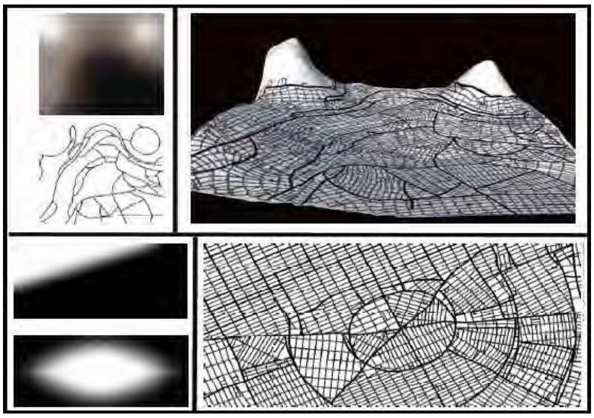

Figure 3.1: Road patterns and generated streets. Streets created with an elevation map as input data (Top). A streets map controlled by two different patterns (Bottom) (Source: Parish and Müller 2001).

3.1.2 Agent-based behavior simulation

A very different approach to generate roads is using agents for modeling. Lechner et al. (2004, 2006, 2007) and Watson (2006, 2007) used an agent-based simulation to generate a street network. They used three types of agents and implemented two road levels in a road hierarchy:

- Tertiary extenders, navigate through a distance-from-existing-roads landscape and ensure undeveloped land is accessible.

- Tertiary connectors, make sure that tertiary roads are adequately interconnected, i.e. if a random destination is too long in an existing network, a new connecting segment is built.

- Primary developers, connect the city center to its surroundings and search new sites only for the primary road network.

Although these agents can produce satisfactory results, programming the agents realistically is still problematic.

3.2 Spatial networks

The scientific interests in complex networks have been steadily growing in many fields since the small-world phenomenon was introduced by Watts and Strogatz (1998) and the scale-free property was introduced by Barabási and Albert (1999). Many real-world networks such as the internet, social networks and metabolic networks have been found to exhibit properties of complex networks (Caldarelli 2007, Barrat et al. 2008, Cohen and Havlin 2010, Newman 2010).

Most previous works have focused on the study of topological properties while relatively little attention has been paid to the spatial structure of networks until recent years. Ignoring geographical factors may be reasonable for some network systems (e.g. social networks). However, spatial properties play an important role in some other networks, for instance transportation networks where the Euclidean coordinates of nodes and the physical lengths of edges are meaningful (Sienkiewicz and Holyst 2005, Erath et al. 2009, Ferber et al. 2009).

3.2.1 Planar graphs

Compared to social or biological networks, transportation networks are mostly spatial networks, i.e. vertices in the network are embedded in a Euclidian space and edges have geometrical length. For transportation networks, road networks differ from air networks as edges do not cross each other. In graph theory such a network is called a planar graph, i.e. the graph is drawn in the plane and its edges do not intersect (Clark and Holton 1991, Diestel 2005). There are many general properties to describe planar graphs, and Euler's formula is probably the most well-known.

$$N_V - N_E + N_F = 2, \tag{3-1}$$

where N_V is the number of vertices, N_E is the number of edges and N_F is the number of faces.

3.2.2 Primary and dual representations

A real-world urban road network can be represented with graph theory by assuming that vertices are road intersections and road ends (or culs-de-sacs), and edges are road segments connecting two vertices. This is the primary representation of a road network.

Another interesting representation is called the dual representation, where nodes represent individual roads and two nodes are linked if their represented roads intersect. The dual representation for an urban street network is unweighted and undirected. It describes the information content of the street network by representing the way a person navigates the city (Rosvall et al. 2005), i.e. when people move from one place to another, they think about how to choose the suitable and efficient individual roads to the destination instead of the shortest path with road segments in a primary representation.

The concept of dual graph originally comes from space syntax (Hillier and Hanson 1984). The “axial lines” are drawn to generate a primary “axial map” of a city. Then each axial line is turned into a node and each intersection of two axial lines becomes a link. Thus the derivate syntax “connectivity graph” is obtained and accessibility measures can be calculated (Figure 3.2, Row A). This is the first method that can be used to build a dual street network. A “named-street approach” (Jiang and Claramunt 2004) is considered later. Street segments with the same name belong to one individual road and then are turned into a node in the dual representation (Figure 3.2, Row B). However databases of street names are not easily available and process of inputting and updating street names into computation can be costly (Porta et al. 2006b).

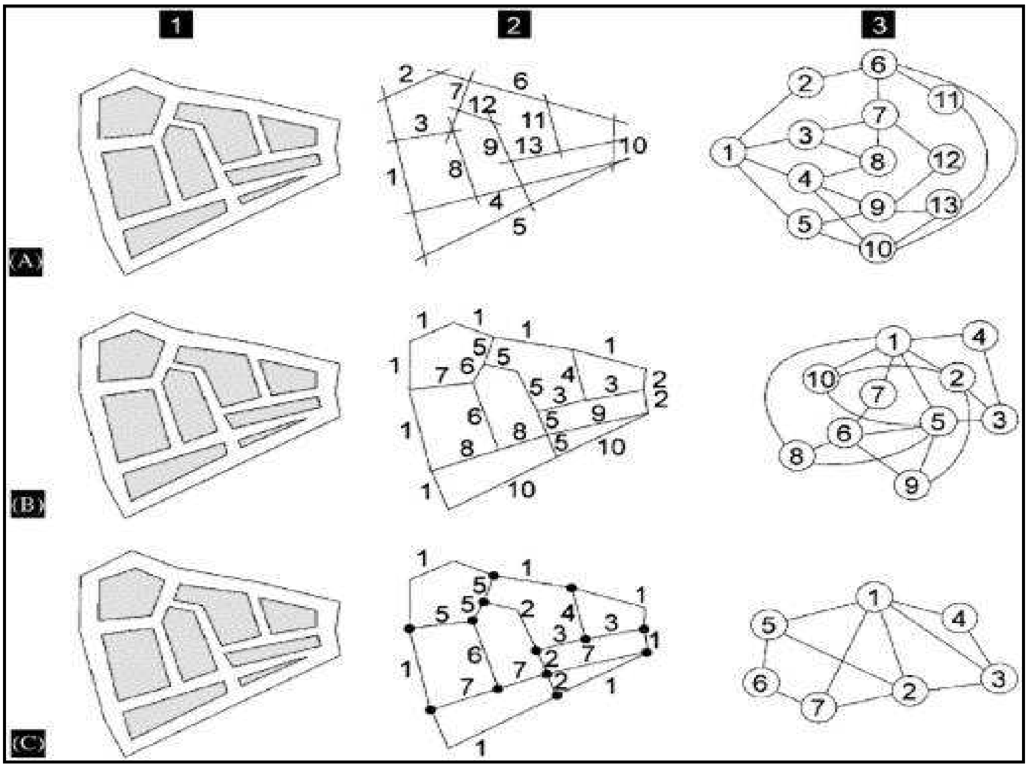

Figure 3.2: Representations of a road network. Row A: the Space Syntax method. Row B: the named street method. Row C: the Intersection Continuity Negotiation method. Column 1: a fictive street network. Column 2: the primary representation. Column 3: the dual representation (Source: Porta et al. 2006b).

There are also some algorithms that are used to automatically extract the individual roads with join principles by negotiating the continuity among any pair of incident segments. The two segments with the largest convex angle are coupled together (i.e. segment *AB* and segment *AC* in Figure 3.3). In the Intersection Continuity Negotiation (ICN) algorithm (Porta et al. 2006b), the segment *AD* and segment *AE* with the second largest convex angle are coupled together, and continue if there are more edges. The same strategy is used in the self-organized process named every-best-fit join principle (Jiang et al. 2008). Besides, an ICN plus (ICNP) algorithm was proposed by Masucci et al. (2009) who argued that it is better not change the identities of segment *AD* and *AE* in order to better represent reality.

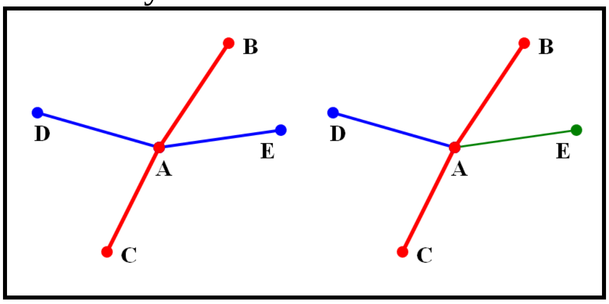

Figure 3.3: Extract individual roads from segments. In a generic crossroad with four segments, the same color segments are assigned to the same individual roads by the principle ICN (left) and principle ICNP (right).

3.2.3 Geometrical and topological measures

Complex networks measures are mainly used to explore social networks where there is no weight for links. When exploring transportation network, such as roads, it is necessary to define weights. Let V be the set of vertices and E be the set of edges, then the planar graph is $G = (V, E)$. For each edge e_{ij} in E (two end nodes i and j belong to V), the weight denotes the geometrical length in a primary representation of a road network. While in a dual representation, e_{ij} equals 1 since the dual graph is unweighted. Moreover, in an unweighted network, the shortest path length d_{ij} is the minimum number of edges from node i to j. In a road network, d_{ij} is the smallest sum of the edges lengths throughout all possible paths.

3.2.3.1 Degree and strength

In a topological aspect, the degree k_i of a node i is defined as the number of edges from/to the node i, or how many segments (or streets) intersect at this vertex. The average degree of the entire network is:

$$\langle k \rangle = \frac{2N_E}{N_V} . \tag{3-2}$$

A dual representation has a much broader degree distribution compared to a primary graph in real-world road network cases. In a weighted network, the correlation between the weight and the degree can be displayed by the study of the term “strength”. Particularly in a spatial network, the weight is represented with a Euclidean distance for each pair of two connected nodes. The strength s_i of the node i is defined as the sum of the lengths of edges intersecting at the node i (Yook et al. 2001).

$$s_i = \sum_{j \in V, j \neq i} e_{ij} \ . \tag{3-3}$$

e_{ij} = 0 if there is no direct connection between node i and j. It has been reported that the average strength as a function of the degree k is linear for uncorrelated random connections, and super linear for other cases.

3.2.3.2 Clustering coefficient and Assortativity

Clustering is an important property in many real-world networks. For one node i in a graph G, its first neighbors are obtained as the subgraph G_i. Suppose node i has k_i neighbors, the subgraph G_i will have at most k_i (k_i – 1)/2 edges but actually have k_i’ edges. Then the clustering coefficient C of the graph G is:

$$C(G) = \frac{1}{N} \sum_{i \in V} C_i = \frac{1}{N} \sum_{i \in V} \frac{k_i'}{k_i (k_i - 1)/2} , \tag{3-4}$$

where C_i gives some clustering information at local level. Apparently, the clustering coefficient depends on the number of triangles or cycles with 3 edges in the network. The clustering coefficient for a weighted network was rewritten by Barrat et al. (2004).

Another quantity used to describe the correlations of the degree of neighboring vertices is assortativity which measures the average nearest neighbor degree (Pastor-Satorras et al. 2001, Maslov and Sneppen 2002):

$$k_{nn,i} = \frac{1}{k_i} \sum_{j \in V(i)} k_j \ , \tag{3-5}$$

where j is one of the first neighbors of the node i. After computation of k_{nn} for all nodes, the nodes with the same degree k are averaged as the quantity $k_{nn}(k)$. If $k_{nn}(k)$ increases with k, the network is assortative, which means that large degree nodes prefer to link to other large degree nodes. On the contrary, a decreasing behavior of $k_{nn}(k)$ indicates a disassortative structure.

3.2.3.3 Efficiency

The global structural properties of a network are evaluated by analyzing the shortest paths between any pair of nodes in the network. Global efficiency E_{glob} was proposed by Latora and Marchiori (2001) and measures how well the nodes communicate in the network. It is defined as

$$E_{glob} = \frac{1}{N(N-1)} \sum_{i,j \in V, i \neq j} \frac{d_{ij}^{Eucl}}{d_{ij}}, \tag{3-6}$$

where d_{ij}^{Eucl} is the Euclidean distance between nodes i and j along a straight line, and d_{ij} is the shortest path between node i to j. As mentioned earlier, the length of each edge can be measured as a geometrical length or topological length. Thus it is easy to calculate two different measures of global efficiency, $E_{glob,T}$ and $E_{glob,G}$, using topological and geometrical distance respectively.

3.2.3.4 Indices α, γ, Gini and pattern measures

In a planar graph, let N_E be the number of edges (segments) and N_V be the number of vertices (nodes). The number of faces is: $f = N_E - N_V + 1$ according to Euler's formula. Because the maximum number of faces is $2 N_V - 5$, it is easy to compute the alpha index:

$$\alpha = \frac{N_E - N_V + 1}{2N_V - 5}. \tag{3-7}$$

Note that meshedness coefficient has the same definition (Buhl et al. 2006). The index α equals 0 if the network only consists of tree structures and it is 1 if the network is a complete planar graph.

The gamma index (γ) quantifies the interconnection of nodes in a network (Rodrigue et al. 2006). It compares the existing number of links to the number of all possible links in one network:

$$\gamma = \frac{e}{3(v-2)}. \tag{3-8}$$

The value of gamma is between 0 and 1, where 1 means a completely connected network.

The Gini index (G) was introduced to describe the distribution of idealized traffic flow in a network (Lämmer et al. 2006, Xie and Levinson 2009). A value of 0 expresses the total equality and a value of 1 represents the maximum inequality. It is based on the Lorenz curve and can be calculated according to:

$$G = 1 - \sum_{k=1}^{e} (X_k - X_{k-1})(Y_k - Y_{k-1}), \tag{3-9}$$

where X_k is the cumulative portion of links while Y_k represents the cumulative portion of total traffic flow.

The measure of connection patterns was developed by Xie and Levinson (2007b, 2009) including ringness, webness, treeness and circuitness. A tree structure is defined as a set of connected links with no complete circuit and forms a branching network. The treeness for a road network is then calculated as:

$$\Phi_{treeness} = L_t / L_A , \tag{3-10}$$

where L_t is the length of edges in the part of tree structure and L_A is the total length of all road segments in the network. The circuitness is then calculated as:

$$\Phi_{circuitness} = 1 - \Phi_{treeness} . \tag{3-11}$$

3.2.3.5 Centrality measures

Centrality measures are crucial for understanding the structure properties of complex networks by quantifying some nodes are more important or central than others. Common centrality measures include degree centrality, closeness centrality, betweenness centrality, straightness centrality and information centrality (Crucitti et al. 2006a). Among them, closeness and betweeness centrality measures are probably the mostly widely used.

Closeness centrality measures how a node v is near to all the other nodes by calculating the shortest paths, thus describing traveling convenience. It is defined as:

$$C_v = \frac{N-1}{\sum_{j \in V, j \neq v} d_{vj}}, \tag{3-12}$$

where d_{vj} is the shortest path length between the node v and j.

Betweenness centrality measures how a node v is traversed by many of the shortest paths between all pairs of nodes (Freeman 1977).

$$B_v = \frac{1}{(N-1)(N-2)} \sum_{i,j \in V, i \neq v \neq j} \frac{n_{ivj}}{n_{ij}}, \tag{3-13}$$

where n_{ij} is the number of shortest paths between node i and j, and n_{ivj} is the number of shortest paths between node i and j that contain the vertex v. The definition of edge betweenness centrality B_e for an edge e is quite similar and describes the fraction of all the shortest paths between any pair of nodes in the network that go through e. Edge betweenness centrality can identify the main traffic routes on the road network (Demšar et al. 2008, Barthélemy and Flammini 2009).

Some other centrality measures are listed below. Degree centrality describes that important nodes have more links in a network:

$$D_v = \frac{k_v}{N-1}. \tag{3-14}$$

Straightness centrality measures the efficiency in the communication between Euclidean distance and shortest path length:

$$S_v = \frac{1}{N-1} \sum_{j \in G, j \neq v} \frac{d_{vj}^{Eucl}}{d_{vj}}. \tag{3-15}$$

Information centrality measures the importance of a node by inactivating it in the network:

$$I_v = \frac{E[G] - E\left[G^{'}\right]}{E[G]}, \tag{3-16}$$

where $E[G]$ is the efficiency of a graph G and G' is a subgraph of G without node v and links from/to node v.

3.2.3.6 Cellular properties

A road network can be considered as a two-dimensional cellular system, if we assume that different small regions are enclosed by roads. For each cell c, surface area A_c is calculated. $P(A_c)$ is the frequency density distribution. Suppose D_c is the maximum distance between two points on the boundary of the cell c, we can compute the form factor F_c as the area ratio of the cell c to the circumscribed circle:

$F_c = (4\, A_c) / (\pi\, D_c^2)$. (3-17)

The cell is perfectly circular if F_c is 0 and infinitely narrow when F_c equals 1 (Lämmer et al. 2006).

3.2.4 Empirical observations

For the real-world spatial networks, there is a series of research objects: transportation networks, infrastructure networks, mobility networks, neural networks, etc. The main interests in this thesis are urban road (street) networks. The following empirical observations from other researchers are basic for the understanding and modeling of urban road networks.

In a planar graph, it is well known that the maximum degree for the road network of a real city is not high, for example nearly 60% vertices in London street network have the degree of three (Masucci et al. 2009), and the degree with the maximum proportion is four in the Hong Kong street network (Jiang and Liu 2008). Besides, the degree distribution is clearly peaked around its average $\langle k \rangle = 2E/N = 2e$. For a tree $\langle k \rangle = 2$, and for a two-dimensional lattice $\langle k \rangle = 4$. Empirical data has shown that real-world cities have a structure containing both trees and two-dimensional lattices. Empirical observation shows that average degree over all cities is $\langle k \rangle \approx 2.87$, and $1.05 \leq e_{emp} \leq 1.69$ (Buhl et al. 2006, Cardillo et al. 2006, Barthélemy and Flammini 2009). However values of the average degree for the 20 largest German cities (Lämmer et al. 2006) are from 2.01 to 2.37, which are obviously much smaller compared with the previous empirical data 2.87. The explanation is that the road networks of German cities probably contain many secondary roads which are more likely to have tree-like structures in topology compared with primary roads. It suggests that one should consider the level of detail when considering the average degree metric. The contrast between the initial and simplified road network in northern Sweden confirms this explanation (Jenelius et al. 2006).

The total length versus the number of nodes is a growth function as $L \sim$ SQR (N) (Barthélemy and Flammini 2009), while the length distribution for the street network of London is power-law (Masucci et al. 2009). The meshedness coefficient (M) is usually small because of the lack of triangles in real cities. For example, M ranges between 0.009 and 0.211 for street networks of self-organized urban settlements (Buhl et al. 2006). Cardillo et al. (2006) observed that both planned grid-like and organic self-organized patterns show high values of meshedness coefficient from 0.25 to 0.35 while some tree-like planned cities have a value lower than 0.1.

Cardillo et al (2006) reported that urban street networks of most world cities achieve 80% of the maximum value of the efficiency in a complete graph. Buhl et al. (2006) showed that the geometric global efficiency for street networks varies greatly from 0.4 to 0.837 with a majority of values lying between 0.7 and 0.8. They also found that the relative efficiency, both geometrical and topological, is positively correlated with network meshedness. Besides, the relation between robustness and geometric global efficiency appears to be linear.

Crucitti et al. (2006a, 2006b) studied centrality of street networks in 18 real world cities which could be divided into two main patterns: self-organized and planned. They found that closeness and straightness centrality follow similar distribution in all cases. Meanwhile betweenness centrality exhibits an exponential distribution for self-organized cities and a Gaussian distribution for planned cities. Information centrality distribution notably differentiates self-organized cities from planned cities where the former has a power law distribution and the latter has an exponential distribution (Figure 3.4). However, peaked distribution for betweenness centrality is not universal. Lämmer et al. (2006) found it very broad for German cities with a power-law exponent ranging from 1.279 to 1.486.

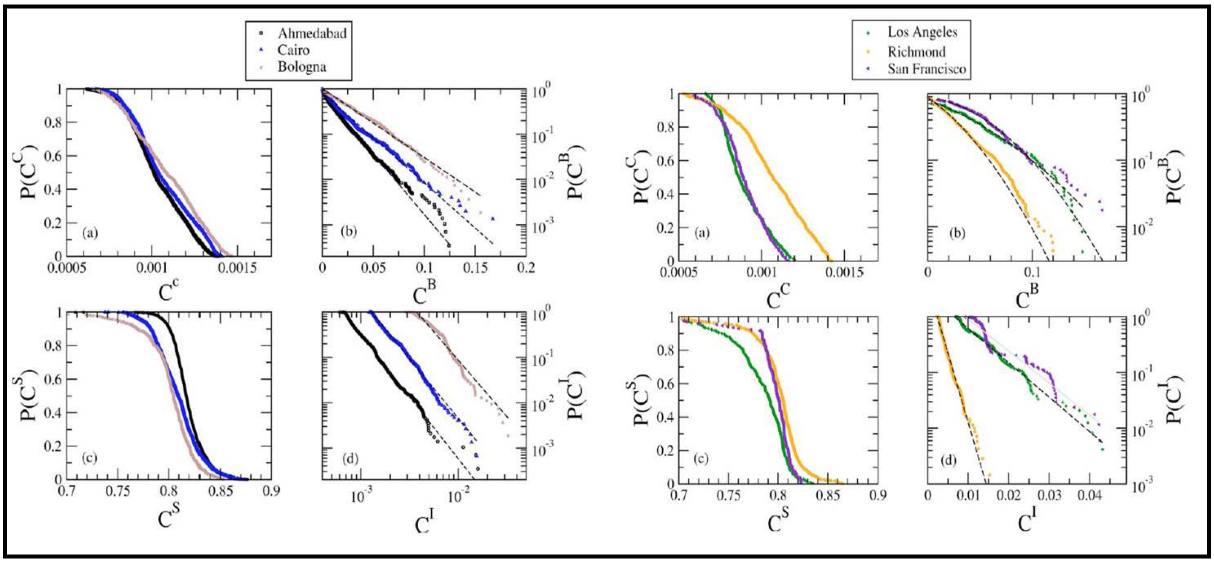

Figure 3.4: The cumulative distribution of centralities: (a) closeness, (b) betweenness, (c) straightness, (d) information centrality for three self-organized cities (left) and three planned cities (right). (Source: Crucitti et al. 2006b)

The frequency distribution $P(A_c)$ of the cell areas displays a power-law behavior of the form $P(A_c) \sim A^{-\alpha}$ with α near 1.9 according to Lämmer et al. (2006) which is totally different compared with an almost regular lattice. The authors also measured the distribution of the form factor F_c, and found most cells to have a form factor between 0.3 and 0.6. A similar power-law distribution of the cell areas with the slope -2 was found for the London street network by Masucci et al. (2009). Another interesting empirical study about road network evolution is presented by Strano et al. (2012). Over the last two centuries the Groane area in Italy changed from a polycentric region (29 urban centers) into a completely urbanized area. Meanwhile the distribution $P(A_c)$ in each year is power-law and the exponent changes over time from 1.2 in 1833 to 1.9 in 2007 due to the process of homogenization of the cells size.

Some other studies focus more on the dual representation of road networks. Connectivity in space syntax has the same meaning as the degree in the dual representation. Most streets have a small connectivity in many cities (Jiang and Claramunt 2004) while a minority of streets has a very high connectivity. This hierarchy further shows that 20 percent of these well connected streets contribute to the majority of traffic flow (Jiang 2009). Masucci et al. (2009) studied the dual analysis of the London street network and found that the degree distribution is power-law, average clustering coefficient displays a power law with exponent -0.89, average nearest neighbors degree $k_{nn}(k)$ shows a disassortative correlation, and betweenness centrality distribution displays a power-law behavior. Jiang et al. (2010) showed the cumulative degree distribution of an urban road network in Le Mans city in France is double power law with two exponents -3.35 and -0.017, respectively, in two power law regions. The average shortest path $L \approx L_{rand}$ and $C >> C_{rand}$ suggest that the dual graph has the small-world properties.

3.2.5 Models of spatial networks

There are many important models of spatial networks. Barthélemy (2011) divided them into five main classes: geometric graphs, Erdos-Renyi graph and its spatial generalization, spatial small worlds, spatial growth models and optimal networks. A random geometric graph can be obtained if nodes are positioned in a plane and are linked with some given geometric principles, one of which is the proximity rule. Extensive research has been carried out on geometric graphs (Quantanilla et al. 2000, Dall and Christensen 2002, Andrade et al. 2005, Krioukov et al. 2010). The Erdos-Renyi model is the paradigm for the random graph (Erdos and Renyi 1959). A simple way for the generation is to run through any pair of nodes and link them based on one probability. There are some extended planar models including planar Barabási-Albert model (Barabási and Albert 1999), the Waxman model for internet (Waxman 1988). The Watts-Strogatz model is a simple but powerful spatial small-world network that implements a spatial component and long-range links (Watts and Strogatz 1998). This model starts from a regular lattice and rewires the links with a probability p. Both clustering coefficient and the average shortest path rely on the probability p. Research on spatial growth models and optimal networks will be discussed in the following sections.

3.2.5.1 Growth and optimization

The basic connection probability in spatial growth models is related to node degree k_i, which means nodes with high degrees are more important and are thus connected. Since distance is crucial in spatial networks, many extended models were thus proposed with the connection probability: $k_i f(d)$, where f is a Euclidean distance function. The decreasing distance function could be an exponential function: $f(d) = e^{-d/r_c}$ (Barthélemy 2003), or a power-law function: $f(d) = d^{\alpha}$ (Xulvi-Brunet and Sokolov 2002).

The optimization problem has a long tradition in mathematics and physics. It is also involved in many research fields, such as: mammalians circulatory system, transportation networks, metabolic rates, gas pipelines, river networks, and neural networks. All these studies are related to spatial networks since nodes are embedded in a Euclidean space. The optimal networks without spatial constraints have been widely studied in recent years, especially after the rise of the study of complex networks.

There are many models using a global optimal principle, i.e. N nodes randomly located in a 2-dimensional plane, where an optimization is used to connect nodes. Barthélemy and Flammini (2006) introduced an optimal traffic network by using a cost function, which depends on both the length and the traffic along the links. A final optimization is given by:

$$\varepsilon = \sum_{e \in T} b_e^{\mu} d_e^{\nu} , \tag{3-18}$$

where b_e is the betweenness and d_e is the geometrical distance. Thus ε involves a combination of metric and topological quantities. Power-law betweenness centrality distribution is found for both minimum spanning tree (MST) and optimal traffic tree (OTT). Furthermore, Hierarchical organization emerges from the OTT (Figure 3.5).

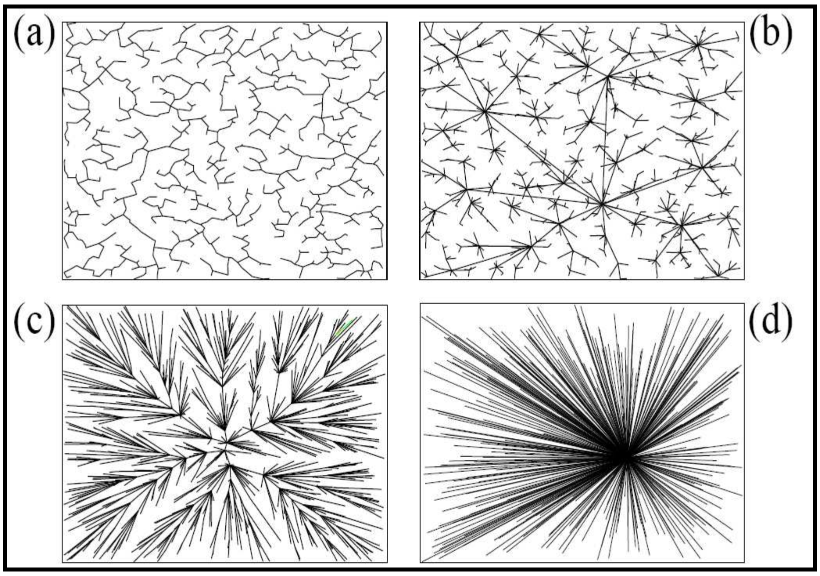

Figure 3.5: Different obtained spanning trees after global optimization. (a) Minimum spanning tree for $(\mu,v) = (0,1)$. (b) Optimal traffic tree for $(\mu,v) = (1/2,1/2)$. (c) Minimum Euclidean distance tree for $(\mu,v) = (1,1)$. (d) Optimal betweenness centrality tree for $(\mu,v) = (1,0)$, which is also a shortest path tree (Source: Barthélemy and Flammini 2006).

Gastner and Newman (2006) defined a route factor as the ratio between the shortest distance along the edges and the direct Euclidean distance from node *i* to the root node. At each time, a new edge is added with the global minimum value of $\omega_{ij} = d_{ij} + \alpha(d_{ij} + l_{j0}) / d_{i0}$. Some other models use two antagonistic quantities to optimize the networks globally by considering the link density and the average shortest path (Ferrer i Cancho and Sole 2003) or the total length and the average shortest path (Gastner and Newman 2006, Aldous 2008, Brede 2010).

Xie et al. (2007b) proposed another growth model with a local optimal principle. *m* nodes exists initially, and at the t^{th} time step one node is added and connected to the existing network according to the following measure:

$$\omega_i = \left|\vec{r}_i - \vec{r}_t\right|^2 / k_i^{\alpha}(t), \tag{3-19}$$

where $k_i(t)$ is the degree of the node *i* at time *t*. They found a power-law degree distribution for $\alpha = 1$ and distribution is more exponential when $\alpha = 0.5$ (Figure 3.6).

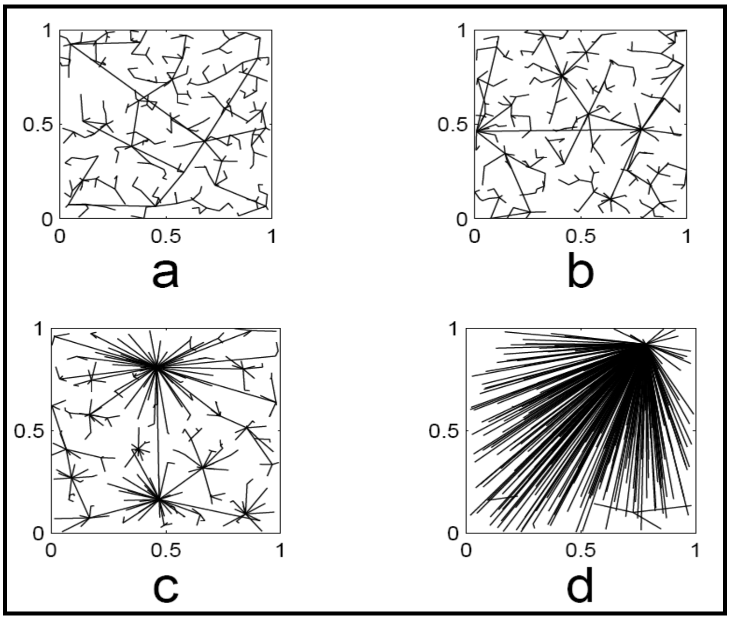

Figure 3.6: Network growth with different parameters: (a) $\alpha = 0$, (b) $\alpha = 0.5$, (c) $\alpha = 1$ and (d) $\alpha = 2$. (Source: Xie et al. 2007b)

3.2.5.2 Modes for street and road networks

The models discussed in the previous section are mostly trees without loops and not planar graphs, thus they are not suitable to model road networks. Masucci et al. (2009) proposed a novel growing random planar graph, and pointed out that it shows more articulated properties than its static counterparts after comparing properties of the London street network with three different models based on the Erdos-Renyi random planar graph, growing random planar graph and regular grid.

An interesting urban street model is proposed by Barthélemy and Flammini (2008, 2009). Their concept is simple in that the network grows by connecting to new centers, which are generated and located randomly. If two or more new nodes are supposed to connect to the same node in existing road network, they take economic considerations by building the roads with the minimum length (Figure 3.7). A single new road portion with the fixed length *d* grows from *M* to *M'*. $\overrightarrow{MM'} \propto \overrightarrow{MA} + \overrightarrow{MB}$. Meanwhile, the relative neighborhood rule is adopted to generate loops.

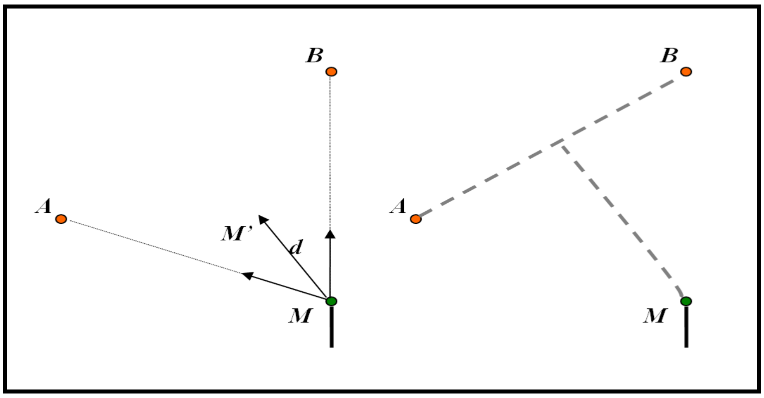

Figure 3.7: Road growth mechanism. *M* is the closet node to both new centers *A* and *B*. The first grow step is from *M* to *M'* in order to minimum the total distance from *M* to both *A* and *B*. Right picture is the final connection result.

Barthélemy and Flammini (2009) also studied the location of centers. There are many factors influencing the growth of the road network and they simply focused on rent price and accessibility. The final equation is:

$$P(i) = e^{\beta(\lambda \bar{g}(i) - \rho(i))} / \sum_j e^{\beta(\lambda \bar{g}(i) - \rho(i))}, \qquad (3\text{-}20)$$

where $\bar{g}(i)$ is the average betweenness centrality, and $\rho(i)$ is local density of node i. The interaction between rent costs and accessibility demand results in transitions in road network patterns and population density.

Another organic growth model was recently proposed by Courtat et al (2011). They adopted several parameters which succeed in generating a large diversity of city patterns and reproduce some general properties in empirical studies (Figure 3.8). Some important parameters are organization probability P_e, construction ω, radius of the rejecting tube λ_0 and sprawling probability f_{ext}. They also pointed out simulations with varying parameters are more realistic to real cities.

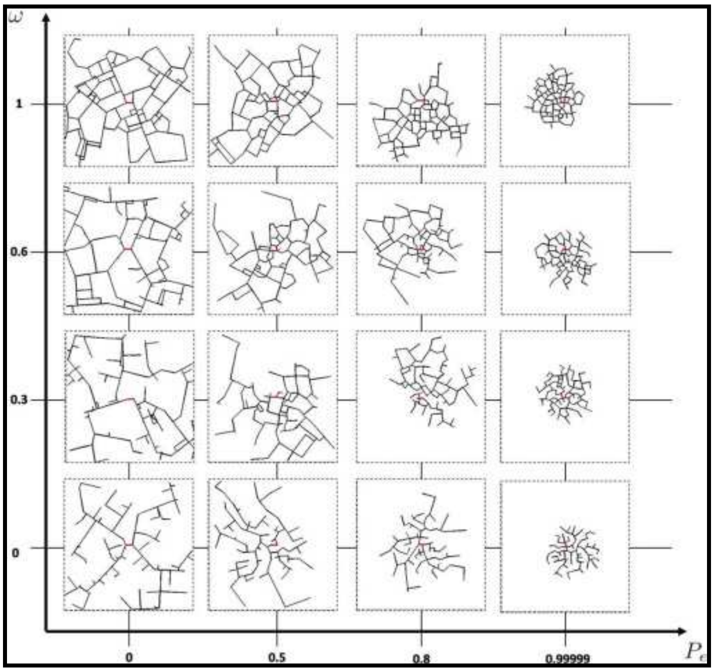

Figure 3.8: Simulations of the morphogenesis model, with various parameters of the organization and construction (Source: Courtat et al. 2011).

4. Methodology

4.1 Overview

Urban growth modeling is an interdisciplinary field since it involves many scientific and technical areas, e.g. geographical information science, remote sensing, urban geography, complexity theory, complex networks, computer science, etc. Understanding urban growth and planning urban development are both closely related to these areas.

Because land use and road network are the two most important sub-systems determining long-term urban morphological changes, this thesis models urban growth based on land-use changes and road network expansion.

(1) Modeling urban land-use changes in section 4.2. **Paper I** applies a 'bottom-up' MAS approach to simulate land-use changes in the GTA. Agents represent different types of interactive individuals while a cellular model is the simulation environment and visualizes urban dynamics. **Paper II** develops a hybrid urban growth model by combining land-use simulation with procedural road network growth. Another traffic computation module is used to control growth of major roads and the idealized traffic flow is for the accessibility calculation in land-use simulation.

Note that the hybrid model (**paper II**) is introduced in section 4.2 because it can be counted as an extension of land-use model and the road network growth module does not use the methodology presented in section 4.3.

(2) Modeling the growth of road networks in section 4.3. **Paper III & IV** build a weighted network model with nonlinear weight growth and neighboring connections, and investigate the preferential attachment mechanism. As a weighted planar graph, urban street network is consequently modeled in **paper V** through competition, connection and loop construction processes.

(3) In section 4.4, **paper VI** studies the relationship between land use and road network in Stockholm. Road network is measured by street centralities at both global and local levels in both primary and dual representations. The correlation coefficients between adaptive kernel density maps of different land-use types and street centralities are examined.

The following sections will introduce the proposed models and analysis in detail.

4.2 Modeling urban land-use changes

4.2.1 Multi-agent simulation for land-use changes

The proposed multi-agent model in paper I consists of three types of agents including residents (new and existing), developers and government. The decision-making of individuals change the environment in which they live. The geographic space is represented as a two dimensional square lattice (grid). Each cell has several exogenous characteristics such as land-use type, terrain, nature quality, accessibility and public services.

Figure 4.1 shows the decision and information flow of the MAS model. New residents make choices for their living places. Developers send development proposals to government. Government agent makes the final decision after considering master plan and protest from existing residents. The new land development changes the environment, which in turn influence the agents in the next iteration.

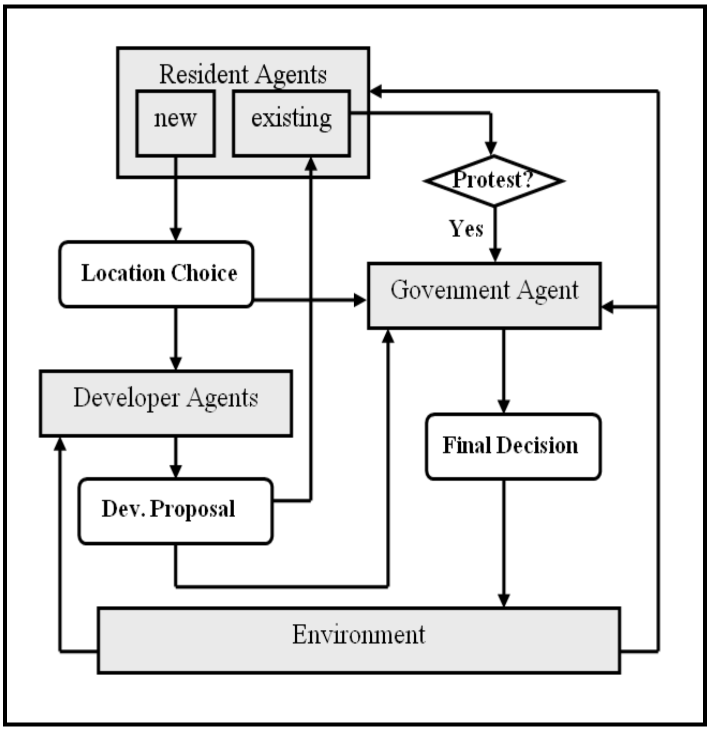

Figure 4.1: Model decision and information flow.

For new residents, the utility function of location choice can be expressed as follows: $P_{NR}=k_A E_A + k_{NQ} E_{NQ} + k_F E_F + \varepsilon$, where E_A, E_{NQ}, E_F are the factors of accessibility, natural quality, and other facilities. The parameters of k are the preferences for each factor and ε is a random term. Existing residents usually want to live in low density areas and do not like their neighborhood to be developed (Rand et al. 2005). The protest of existing residents is described by counting the number of residential cell within a 3 × 3 window.

Developers tend to select the areas close to developed districts in order to low risk of their investment. Elevation is also considered by developers (Watson 2006). The final development probability for developer agents is calculated as: $P_{DEV}=N_{ij}E_T$, where N_{ij} is the number of developed cells in the neighborhood within a 5 × 5 window; E_T is the inverse of altitude change rate at each cell.

The government agent will make the final decision on land development according to the following factors. First of all, the constraint function F_{CON} is defined as come types of land use are not allowed to change. Secondly, the initial approval probability P_{ACCEPT} is calculated as the percentage of each land-use type that translated into developed urban area based on two given classified images from 1985 and 1995 respectively. The government agent makes a decision: $P_{GOV} = P_{ACCEPT}F_{CON}$. As the final decision-making institute in the model, the government agent decides whether to approve or deny the development proposal after considering the demands from new residents, the proposals from developers, and the protest from existing residents. The probability of a location to be chosen can be expressed as: $P=k_{NR}P_{NR} + k_{ER}P_{ER} + k_{DEV}P_{DEV} + k_{GOV}P_{GOV}$.

4.2.2 Hybrid urban growth modeling

The hybrid urban growth model in paper II includes a vector road network growth sub-model and a grid land-use development sub-model. A traffic sub-model provides the estimated traffic flow as growth control of the road network and accessibility calculation of the land-use simulation.

4.2.2.1 Road network growth

The road network in this work mainly consists of major roads and minor roads. Major roads start to grow from a user defined city center with the heading h_1. Angle of deviation θ_1 decides road patterns (Figure 4.2).

(1) Suppose node *A* is an intersection or end node. It proposes several segments radially with the step length *L*.

(2) The segment with the minimum elevation difference is chosen, i.e. segment *AB*.

(3) The angle between proposed segment *AB* and each neighboring existing segment is calculated. A minimal angle θ_2 is assumed to meet a threshold.

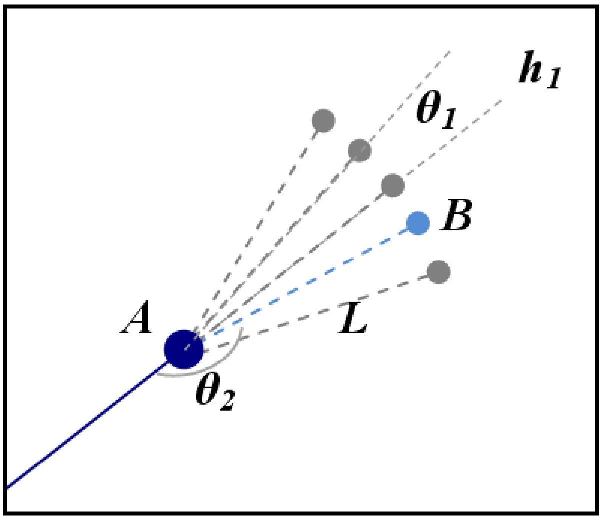

Figure 4.2: The growth of a road network from the node *A*.

The model can implement three road patterns: grid, radial and organic. Radial and organic patterns are applied to major roads while minor roads adopt a grid-like pattern, which is implemented by setting that angle θ_2 is around 90 and no more than 4 segments with the same intersection are allowed. Other important parameters are the step length L and the density of intersections. Finally, the new proposed segments have to meet the constraints as follows:

(1) Ensure that the node *B* is located in a legal area.

(2) The proposed segment has to pass tests with the existing network.

The algorithm is illustrated in the pseudo code below and figure 4.3. Compared with other models used in geometric urban simulation (Parish and Müller 2001, Kelly and McCabe 2007), this model is dynamic and generation is traffic-based.

Function SegmentsLegalityTest (proposed segment *AB*, current road network)
  While new end *B* inside an illegal area
    While rotated angle < threshold
      Rotate the proposed segment *AB* with a small angle
  If segment *AB* intersects with any other road segment
    Then calculate the intersection *E*
      If node *E* closes to one end of segment *CD*
        Then move node *E* to the position of node *C*
  Else if node *B* closes to an existing node *C*
      Then delete segment *AB* and connect *AC*
    Else if node *B* closes to an existing segment
        Then prolong segment *AB* to this segment
  Rebuild the topology

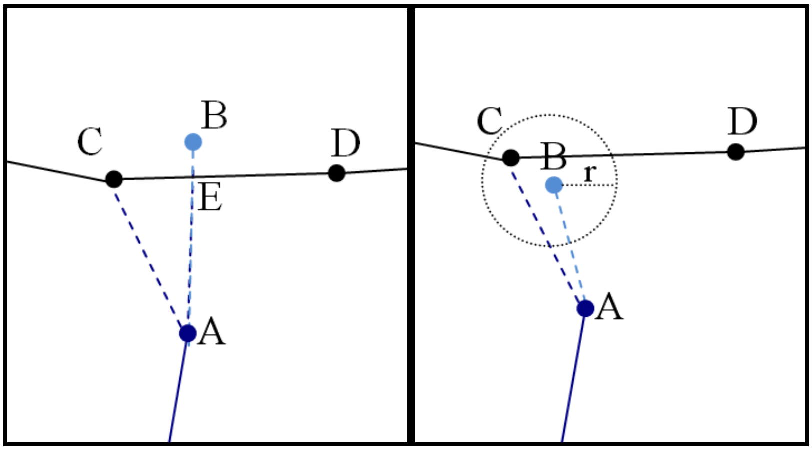

Figure 4.3: Intersection and snapping tests.

4.2.2.2 Traffic computation

Major roads are selected according to predicted traffic flow, which is also used for accessibility calculation in the sub-model of land-use changes. The space syntax metric (integration) is introduced to estimate idealized traffic flow.

(1) To calculate the integration for a node *A*, the first step is to calculate the shortest distance from other nodes to node *A*. Suppose the maximum value of the shortest distance between all pairs of nodes is denoted by d_{max}.

(2) Count N_d as the number of nodes with the distance *d* to the node *A*.

(3) The final expression is $\sum_{d=1}^{m} d \times N_d$. It means the connectivity (degree) when $m = 1$ and global integration when $m = d_{max}$. If $1 < m < d_{max}$, it is a local integration expression.

Local integration is a default metric to estimate traffic flow in the field of space syntax. Usually depth (m) is set to 2 in the calculation. The following steps are taken to expand the road network.

(1) The first step is to join road segments into individual roads based on the self-best-fit join principle which is the best choice for metric-flow correlation (Jiang et al. 2008).

(2) Characteristic points are then derived from existing nodes to draw a visibility graph (Jiang and Claramunt 2002).

(3) After the computation of the local integration for each node, they are summed into each individual road to express the traffic flow.

(4) The roads with high value of local integration are chosen as major roads.

(5) Confirmed major roads are modified to well connect with existing road network.

(6) Once one area is serviced by major roads, minor roads are created in the area with a grid-like pattern.

4.2.2.3 Land use simulation

Land-use type determines the demographic distribution and affects travel demand. Different road patterns may fit different land-use types. Five land-use categories are defined: residential area, commercial area, industrial area, transportation area (road infrastructure) and parks (parks and natural areas). Roughly 60% of the total urban area is set as residential, commercial and industrial areas. The percentage of the road infrastructure is around 25%.

The mobility algorithm removes a subset S_t of land developers to new places in each time step. Developer agents work for residential, commercial or industrial development. $S_t = \alpha D_t$ at time t, where α is a small number and D_t is the set of developed land areas. S_t is put into a waiting list L_t and then is removed from D_t. When an urban area expands, population is growing and new lands are changed to urban area. The demands of new residents are represented as developer agents, which are put into the waiting list L_t. For each developer agent in the location choice model, the candidate area must be undeveloped areas and are already served by roads. The selection depends on the utility value at the candidate location (Li and Liu 2008).

The transportation infrastructure area is derived from the vector road network. Large greenbelts or parks are in an uneven terrain or flood plains. However, the location choice of residential, commercial and industrial development relates to many factors.

(1) Proximity to center. Commercial areas are generally close to city center.

(2) Proximity to water and flatness. Commercial and some industrial developers want closeness to water. Industrial developers like even terrain.

(3) Accessibility. Industrial developers choose the areas close to major roads. Commercial areas always have a higher value of accessibility than residential areas.

(4) Clustering of the same land-use type. Residential developers, as well as industrial developers, intend to cluster in order to low the risk of investment and development.

(5) Neighborhood of different land-use types. Residential areas are apart from industrial areas while commercial areas are usually developed near residential areas.

For residential agents,
$U_r = \beta_{Dw} x_{Dw} + \beta_A x_A + \beta_{Nr} x_{Nr} + \beta_{Ni}(1 - x_{Ni})$.

For commercial agents,
$U_c = \beta_{Dc} x_{Dc} + \beta_{Dw} x_{Dw} + \beta_A x_A + \beta_{Nc} x_{Nc} + \beta_{Nr} x_{Nr}$.

For industrial agents,
$U_i = \beta_T x_T + \beta_{Dw} x_{Dw} + \beta_{Apr} x_{Apr} + \beta_{Ni} x_{Ni} + \beta_{Nr}(1 - x_{Nr}) + \beta_{Nc}(1 - x_{Nc})$.

In these equations, β is the weight for each variable. x_{Dw} and x_{Dc} are the closeness to water and city center. x_T means the terrain slope or flatness. x_N indicates the clustering and neighborhood factors for all land-use types. x_A represents the accessibility. $x_A = \gamma_{Apr} x_{Apr} + \gamma_{Asr} x_{Asr}$. x_{Asr} and x_{Apr} are the accessibility to minor roads and major roads respectively. $x_{Apr} = \sum (1 - \exp(- \gamma' LI)) \exp(- \gamma' d)$, where LI indicates the value of local integration. Accessibility can be simply calculated with the distances from roads, or modeled with social, spatial indicators (Hansen 2009, Ahlström et al. 2011). Here local integration is used as the weight for the equation and the influences of each road are added together. The equation implies that if one place closes to more important roads, then it has a better accessibility.

4.3 Modeling the growth of urban street networks

4.3.1 Nonlinear weight growth and neighboring connections

Many real-world networks are considered to be weighted, such as the scientific collaboration networks (Newman 2001, Barabási et al. 2002), the worldwide airport networks (Barrat et al. 2004c, Guimerá et al. 2005), and the metabolic networks (Almass et al. 2004). Numerous evolving weighted network models have been proposed to study the non-trivial correlation and association between weights and topological quantities (Boccaletti et al. 2006, Ma et al. 2009, Zhou et al. 2009). One well-known growing model for weighted networks was presented by Barrat, Barthélemy, and Vespignani (BBV). The BBV model is based on a weight-driven mechanism and generates scale-free properties of the degree, strength and weight distributions. (Barrat et al. 2004a, 2004b). A variety of improved models have later been proposed, involving other growth mechanisms (Xie et al. 2007a, Barrat et al. 2005, Wang et al. 2008, Zhang et al. 2009, Tong et al. 2011). These models exhibit a linear strength-degree relationship. However, strength and degree are not always linearly correlated in many real-world systems (Onnela et al. 2007). Therefore, the proposed model in paper III aims to obtain a non-linear relationship. The new weights grow nonlinearly over time. It is different with traditional accelerating networks, where the number of edges grows nonlinearly. Another concept to consider is the local world, which usually consists of several randomly selected nodes (Li and Chen 2003). A new local world is defined in paper III as a node and the nearest neighbors.

The model proposed in paper III starts with a small network of N_0 nodes and e_0 edges. Two coupled mechanisms are involved: topological growth and weight dynamics.

(1) Topological growth.

A number of m existing nodes are selected to connect to the new node n. The first node i is selected globally based on the global strength-driven preferential probability:

$$\prod_{n\to i} = \frac{s_i}{\sum_{l\in all} s_l}. \tag{4-1}$$

The first selected node i is named as the central node. This central node and its neighbors are defined as the neighborhood local world (NLW). In the selected NLW, $m - 1$ nodes are chosen to connect according to the local weight-driven preferential probability:

$$\prod_{n\to j} = \frac{w_{ij}}{\sum_{l'\in\Omega i} w_{il'}} = \frac{w_{ij}}{s_i}, \tag{4-2}$$

where Ωi is the set of neighbors of node i (Figure 4.4).

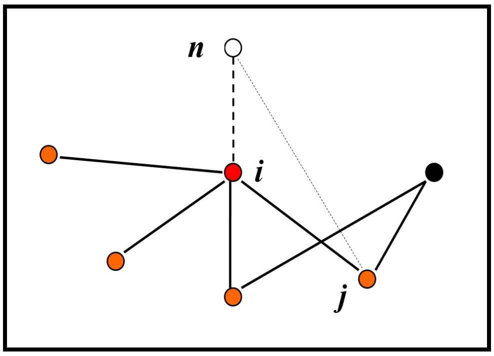

Figure 4.4: Model construction. Node *i* is the central node and its neighbors are in orange color.

(2) Weight dynamics.

After a new edge (n, i) added into the network, its initial weight value w_0 will introduce variations of weight across the network. Based on the same rule in the BBV model, weights on the edges (i, l') are rearranged according to the rule:

$$w_{il'} \rightarrow w_{il'} + \delta \frac{w_{il'}}{s_i}, l' \in \Omega i, \tag{4-3}$$

where δ is the increment of weight, which is proportionally distributed to edges intersecting at the node i. This allocation leads to $s_i \rightarrow s_i + w_0 + \delta$. After the update of weight, a new iteration begins until the whole network achieves the expected size.

In the classic BBV model, m and δ are constants. In accelerating network models, $m = t^{\theta}$, where θ is the acceleration parameter. Paper III studies the accelerating growth of new weights to be assigned on edges based on empirical observations. For simplicity, we set $w_0 = t^{\theta}$, $\delta = \alpha\, t^{\theta}$, where $0 \leq \theta < 1$. When $\theta = 0$, it is consistent with a special case of the BBV model. Because w_0 increases over time, this model also highlights the importance of new nodes.

4.3.2 Road network growth modeling

The urban street growth model proposed in paper V grows from one node preset in the middle of the simulation area. In each time step, N nodes are created randomly and only one of them is going to win the competition process based on utility value. Then, the connection process will make sure that this new confirmed center node links to the existing road network according to one optimization principle. Loop construction is the final process.

Some types of nodes are defined foe modeling as follows. The intersections and dead-end nodes are defined as the characteristic nodes (V_c) in a road network.

Nodes with a degree of 2 are ignored since most empirical studies did not consider it. Suppose there are many nodes uniformly distributed along road segments and they are named the virtual nodes (V_v). Virtual nodes are not involved in the analysis until they are linked and became intersections. Visible nodes (V_i) are those characteristic and virtual nodes which are visible to the center i in the connection process.

(1) Competition process

Each new center node represents one new demand for residential, commercial or industrial development. The locations of new centers are determined by many social, economic and geographical factors in the real world. This model concentrates on the density and degree of nodes. Node density indicates population density and their demands while node degree implies the importance in terms of topological property. For N ($N > 1$) randomly generated potential centers in each time step, their utility values $U(r)$ are calculated as follows:

$$U(r) = \sum k_{j'}, \tag{4-4}$$

where j' is one characteristic node within radius r of one potential center node. $k_{j'}$ is the degree of node j'. If the minimum value of U is chosen, new confirmed centers are apart from existing road network and density of road network is finally uniform. However when the maximum value of U is selected, significant different road patterns emerge based on different values of attraction radius r.

(2) Connection process

First of all, all visible nodes V_i of the center node i are extracted. For each node j in V_i, S_j is calculated according to:

$$S_j = d_{ij}/k_j^{\alpha}, \tag{4-5}$$

where d_{ij} is the geographical distance between node i and j, and k_j is the degree of node j. The node j with the minimum value of S is chosen, which means that the new center node i links to its visible node with large degree and short distance. When $\alpha = 0$, only distance is in consideration. This optimization is implemented locally in spatio-temporal aspects during the network growth in order to reflect planning limitation of real-world cities.

(3) Loop construction process

Up to now, a tree-like structure has been generated. The final step is a loop construction process with the construction probability P_l. Larger P_l indicates more loops. There are two methods to generate loops. The first one is the relative neighborhood. For a center node *i* and its visible node *j*, the geographical distance between them is d_{ij}. Suppose the local area for node *i* is set within the radius d_{ij}, and the same operation for node *j*. If the intersection of local areas of node *i* and node *j* (gray area in Figure 4.5) contains no other node, then node *j* is in the relative neighborhood of node *i* and node *i* connects to node *j* (Barthélemy and Flammini 2008). The second method is to create approximate rectangles. Note that d_{ij} is not allowed to be too longer than the segment generated in the connection process. Upper limit is set as triple length in this model.

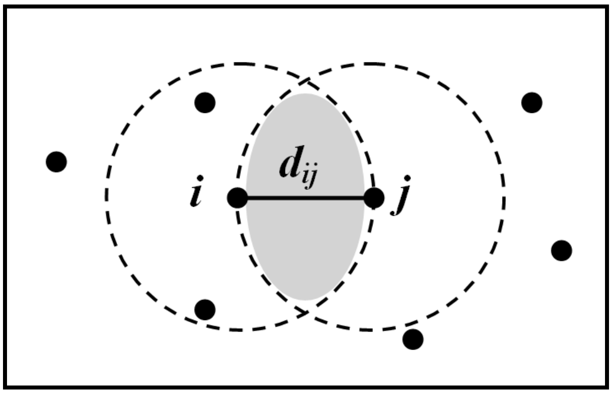

Figure 4.5: Illustration of the computation of relative neighborhood. Black points are center nodes.

4.4 Relationship between road network and land use

Paper VI examines the relationship between land use and the road network in an urban area. Because the structure of the road network determines the general traffic distribution and human activities, and therefore influences the land development, it is meaningful to investigate how different land-use types are correlated with the urban street network. The properties of the road network are described through centralities.

First of all, centrality indices are calculated at both global and local levels in the primary and dual representations of the urban street network. Then, both vector centrality data and raster land-use data are transformed into one continuous raster framework for further comparison using adaptive kernel density estimation (KDE). Spearman correlation is finally calculated to examine the relationship between different centralities and land-use types.

4.4.1 Street centralities

There are various centrality measures. Among them, closeness, betweenness, and straightness centralities are the most widely used (Porta et al. 2006a, Crucitti et al. 2006). In addition to the global centrality indices, local closeness and local straightness centralities are calculated by setting a local area for a node *i* as nodes within a certain distance *d* from the node *i*. Normally global centrality values near the edge of the whole network are quite low, especially for closeness. However, local centrality has advantages in overcoming this edge effect (Porta et al. 2006a).

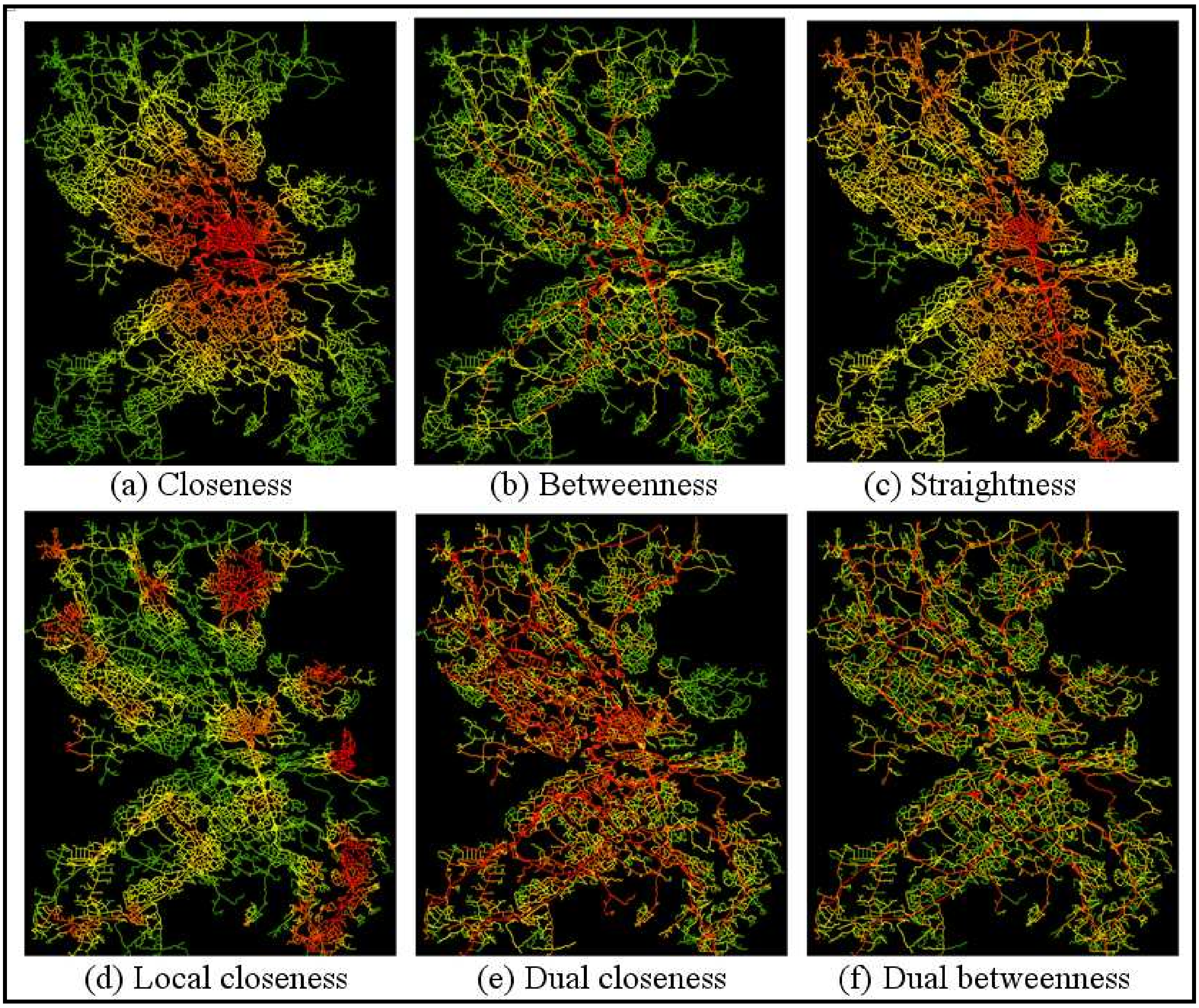

Figure 4.6: Centralities of (a) closeness, (b) betweenness (c) straightness, (d) local closeness, (e) dual closeness and (f) dual betweenness for the road segments. Red color indicates high value while blue color means low value.

Moreover, local centrality nicely captures the network properties on a local scale and reveals human activities at regional level. The final measurement is to calculate closeness and betweenness centralities in the dual representations of the urban street network. The dual graph describes how people navigate the city.

In total, paper VI calculates seven types of centrality indices, i.e. three global centralities, two local centralities in the primary representation and two global centralities in the dual representation. Figure 4.6 shows different centralities. Note that the classification for betweenness and dual betweenness is based on head/tail breaks (Jiang 2012).

4.4.2 Adaptive kernel density estimation

Kernel density estimation (KDE) generates a density of events as a continuous raster map by weighing nearby events more than distant events within a bandwidth based on a kernel function (Silverman 1986, Lloyd 2007) as shown in figure 4.7. Previous studies have found that the selection of bandwidth *h* is always more important to the outcome than the choice of various kernel functions (Epanechnikov 1969). More recently, an adaptive bandwidth rather than a fixed one has been suggested to use (Brunsdon 1995, Levine 2004), i.e. bandwidth is larger in areas where events are sparser whereas bandwidth is smaller in areas that have a high concentration of events. Because roads and land use data is not evenly distributed in space, adaptive KDE is adopted in this work in order to provide constant precision for the estimation result over the entire region.

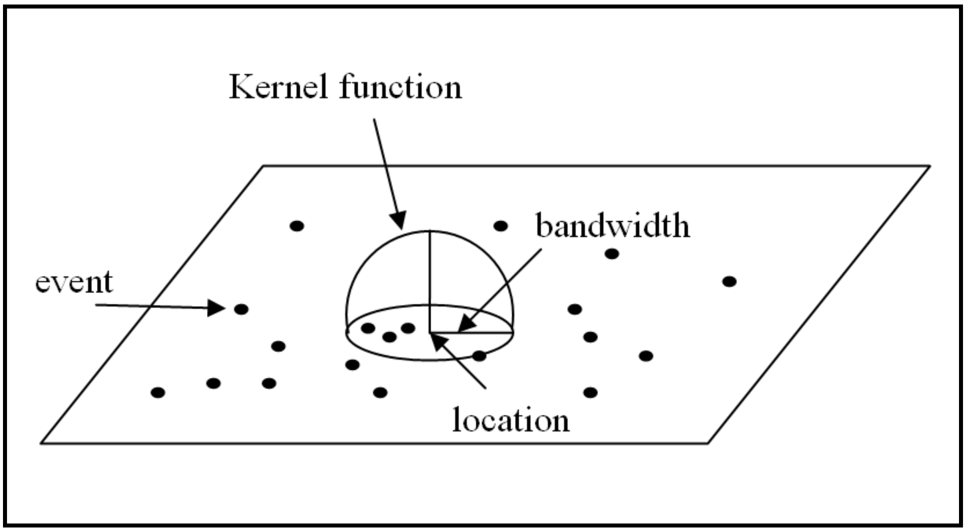

Figure 4.7: Diagram of the kernel density estimation.

For different land-use types, polygon land use data is transformed into point data with a value of 1. Then an adaptive KDE is performed for the points of each land-use type with no weight. For the street centralities, polyline street network data is transformed into point data and each point inherits the centrality value from the polyline road segment. Then, an adaptive KDE is computed for the points of each centrality type with the centrality value as input weight. Figure 4.8 shows results of three centralities. Because accessibility means the ease with which people can get to other places through the transport network (Hansen

2009), the density maps of centralities can be defined as the centrality accessibility.

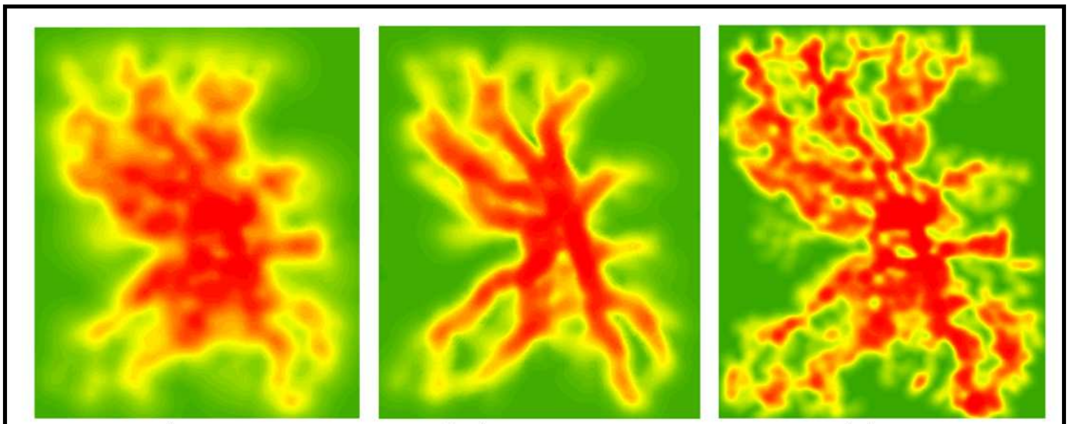

Figure 4.8: Adaptive KDE maps of (a) betweenness, (b) closeness and (c) straightness. Red color indicates high value while blue color means low value.

4.4.3 Spearman correlation

Density maps of seven centralities and six land-use types are resampled to the same resolution. Correlation analysis is examined to reveal the statistical relationship between centralities and land uses. Because all data were found to be positively skewed, the Spearman's rho correlation was applied and calculated. The Spearman Rho correlation gives the magnitude and direction of the association between two datasets which are on an interval/ratio scale. The assumption is that both variables are not normally distributed. If they are normally distributed, it is better to use a Pearson R correlation. The two hypotheses are: H_0, there is no association between the two variables. H_1, there is an association between the two variables.

5. Results and discussion

This chapter summarizes main results of the listed six papers and discusses the contributions to the knowledge in urban modeling and related research fields. The connections between the papers are illustrated in Figure 1.1.

This thesis presents a series of models, which are evaluated by real applications and show good simulation results. In section 5.1.1(**paper I**), the MAS model is applied to simulate land-use changes in the GTA from 1985 to 2005. The hybrid urban growth model in section 5.1.2 (**paper II**) is used to simulate long-term growth in central Stockholm and show how the interaction between land-use changes and road network growth influences urban forms.

The evolving weighted network model in section 5.2.1 (**paper III & IV**) is examined mathematically and numerically. This model is rather theoretical, but essential and important to understand growth mechanism for network evolution. The road network model in section 5.2.2 (**paper V**) succeeds in reproducing diverse urban patterns, whose properties are consistent with empirical studies.

In section 5.3 (**paper VI**), each land-use type in Stockholm is found to have a high correlation with a different street centrality. The following sections will introduce all finding in each selected paper in detail.

5.1 Urban land-use simulation

5.1.1 Land-use simulation in Toronto

In paper I, the MAS model for land-use changes introduced in section 4.2.1 is applied to the Greater Toronto Area (GTA). The study area includes the city of Toronto and four regional municipalities. GTA shows a remarkable urban growth in the past few decades due to the increasing population. Land-use maps of the GTA are obtained from the classification of three Landsat TM images in 1985, 1995 and 2005 respectively (Furberg and Ban, 2008). Population data, transportation network and DEM data are collected freely from the Census of Canada.

Firstly, the MAS model determines the total number of new resident agents according to the actual land consumption in the GTA from 1985 to 2005. The same weights were used for each equation because of the lack of prior knowledge about the choice of individuals. The model modifies the allocation by using a spatio-temporal criterion, i.e. it recalculates land consumption for each region in the GTA during each time period.

The MAS model in paper I was evaluated by comparing the simulated results with the actual development. Firstly, cell-by-cell comparison was used for developed and undeveloped land-use types. The total accuracy was 91.4%. Then quantity disagreement and location disagreement for map comparison is adopted to evaluation the simulation results instead of kappa coefficients. When there are only two categories: developed and undeveloped, the agreement was quite high, around 90%. When the agreement is calculated for five categories: urban area, water, agriculture, forest and green land, the accuracy decreased to around 80%. This is partly because in this model (1) existing urban and water areas are not allowed to change to other land-use types; (2) changes among agriculture, forest, and green land are not considered.

Generally, the MAS model with a spatio-temporal allocation criterion shows good results in simulating urban sprawl in the GTA.

5.1.2 Hybrid urban growth model

In paper II, expansion of the road network plays an important role in the hybrid urban growth model presented in section 4.2.2. At the end of each time step of road network growth, the estimated traffic flow is recalculated. After the selection and modification processes for major roads, minor roads are generated accordingly. This method is checked by calculating the local integration of the whole road network after the modeling and the proposed major roads belong to the backbone of the entire road network.

The long-term simulation combing road network growth with land development starts with a preset center. Figure 5.1 shows simulated urban growth from the period *t*1 to *t*3 for different land-use types. Road areas are transformed directly from vector data.

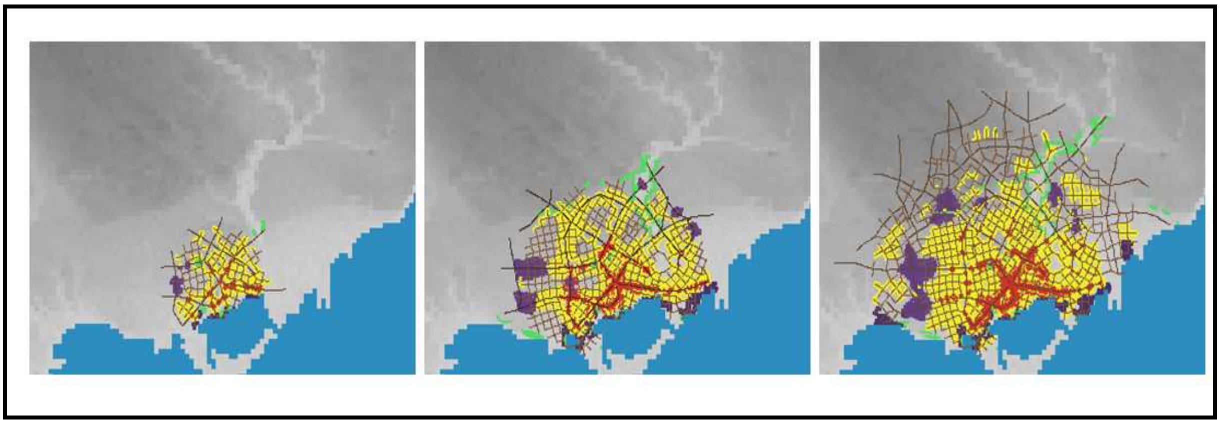

Figure 5.1: Simulation results of urban growth from the period *t*1 to *t*3. Residential, commercial and industrial areas are denoted by yellow, red and purple respectively. Major roads are wider and in darker gray.

The objective is to reproduce the typical urban patterns. The Simulation shows similar land use patterns compared to those in real cities (for example Houston in Fig.16, Lechner et al. 2006). Residential areas are located far away from industrial areas. Commercial areas are mainly located around the city center and close to major roads. Industrial areas develop in urban periphery. As cities grow, some factories move to new areas at urban fringe. Major roads form a skeleton of the expanding city and may become minor roads in the next period, because the estimated traffic flow changes over time and decides the road level. This change of road hierarchy over time reveals the evolution of real-world cities.

The model is also tested in Stockholm. The study area is in the central part of the capital (Innerstaden in Swedish or Stockholm City Centre). It has been well planned and has a grid-like structure even since almost 400 hundred years ago (panel (a) of figure 5.2). Thanks to no destruction by war, this urban structure shows good continuity and is convenient for our simulation.

In the hybrid urban growth model, street network expansion changes the accessibility and finally influences land development. Meanwhile, land-use change affects population density and requests new streets with different patterns to serve new developed land of different land-use types accordingly. The following experiment is going to explore this reciprocal influence between street network expansion and land development through different growth strategies. For some historical reasons, land-use types are reduced to urban area and non-urban area. Note that large green areas are extracted directly from the map in 1913 (panel (b) of the figure 5.2), however small parks are generated according to the rule described in the methodology part.

Scenario I: The influence is very weak, i.e. road network and land grow almost independently. Land development depends on the factors: distance to center, terrain, distance to streets and clustering.

Scenario II: The influence is very strong. Land development depends highly on the factor accessibility, which is not only calculated by the distance to streets, but also the local integration as the calculation weight. The land value of each block is then approximated as the population density distribution, which decides road expansion in the next iteration.

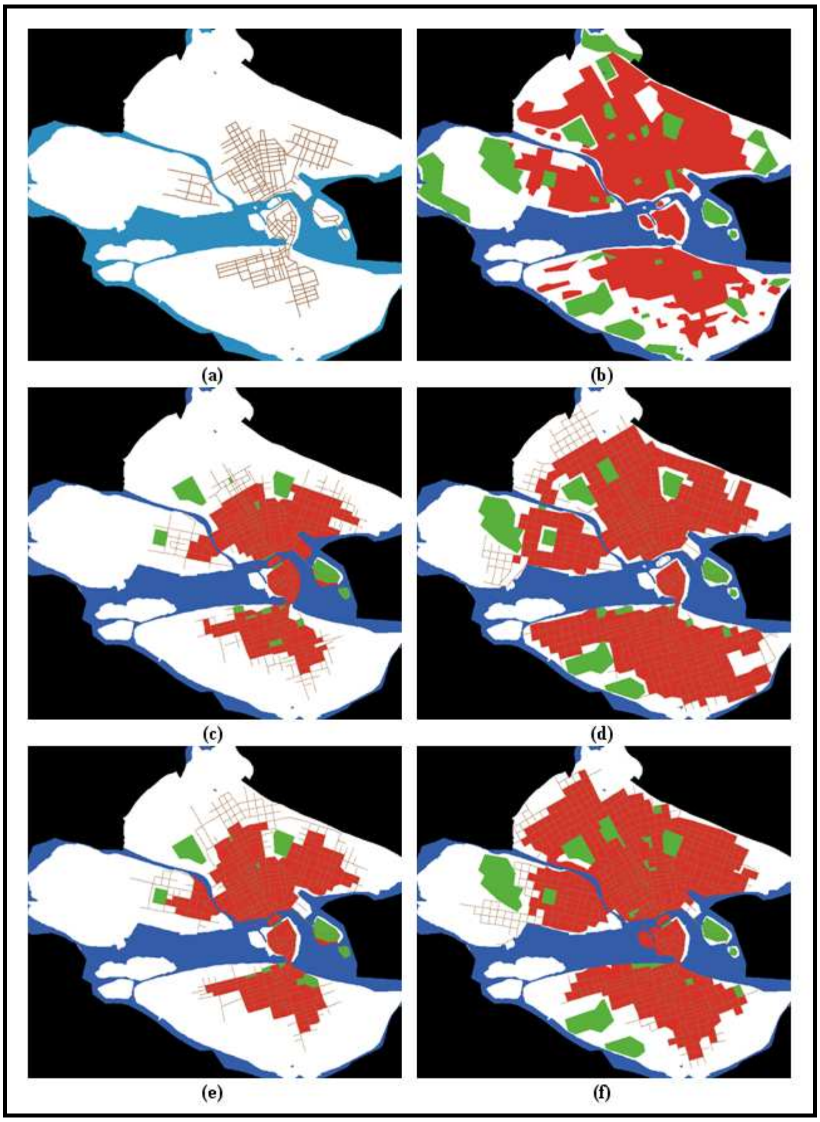

Figure 5.2: Simulation results under different scenarios.
(a) Street maps back to 1650's. (b) Urban areas and green areas in 1913.
Simulation results under scenario I at *t1* (c) and *t2* (d).
Simulation results under scenario II at *t1* (e) and *t2* (f).

The simulation starts with the given street network in 1650 and stops when the same amount of urban area in 1913 is achieved. Scenario I shows that the growth is affected by the distance to the center and thus the south part is over simulated (panel (d) of figure 5.2). Scenario II shows better results and is closer to real situation. The truth is that the initial structure in 1650 exhibits high integration values for the streets in the north area and therefore northern blocks are generally evaluated highly (Figure 5.3 is one example at time *t2*). This growth tendency can be clearly observed from historical maps. Statistically, cell-by-cell comparison is made when only two land use classes in the study area are considered: urban area and non-urban area. For error matrix calculation, the total accuracy improves from 80.3% in scenario I to 85.2% in scenario II. The preliminary results prove the assumption in the model: dynamic reciprocal influences between land-use changes and road network expansion during the growth.

Figure 5.3: Block values in scenario II at *t2*. Dark red indicates high land value.

The major contributions of paper II are:

- The proposed urban model is dynamic, not static.
- The urban growth model integrates road network expansion with land-use changes. The vector sub-model shows advantages in topological analysis for road networks; while the grid sub-model can easily visualize land development and can furthermore be used to spawn interactive agents with individual choices.
- The reciprocal influence between land use and road network is confirmed in the simulation of central Stockholm.

5.2 Urban road network modeling

5.2.1 Evolving weighted network model

In the proposed model in paper III and section 4.3.1, the network size is increased by one within each time step. Therefore the time equals the number of nodes, i.e. at time t, the network has $N = t + N_0$ nodes and $mt + e_0$ edges. Meanwhile, the total strength increases by an amount of $2(w_0 + \delta) = 2(t^\theta + \alpha t^\theta)$, implying that the total strength $\sum s_i(t) \sim t^{\theta+1}$, i.e. the total strength grows nonlinearly with time.

Both mathematical analysis and numerical simulation are seriously studied for the time evolution of the average value of $s_i(t)$ and $k_i(t)$ of the ith node at time t. More details about the analysis can be found in paper III.

$s_i(t) \sim t^{\beta s}$ with $\beta_s = (1 + 2\alpha)(1 + \theta)/(2 + 2\alpha)$. If $\theta = 0$, the exponent is exactly the same β_s as the one in the BBV model, even though a local preferential attachment is involved in the proposed model in paper III. Finally, the equation $P(s) \sim s^{-\gamma s}$ is obtained with $\gamma_s = (3 + 4\alpha - \theta) / (1 + 2\alpha - \theta)$, which means that strength distribution is power-law and the exponent increases with decreasing α and increasing θ.

Meanwhile, $k_i(t) \sim t^{(1 + 2\alpha - \theta)/(2 + 2\alpha)}$. Therefore, this model gets a nonlinear relation between s and k with $s \sim k^{(1 + 2\alpha)(1 + \theta)/(1 + 2\alpha - \theta)}$. The exponent decreases with increasing α and decreasing θ. In particular, when $\theta = 0$, the proportionality relationship $s \sim k$ is obtained. Weight distribution also shows a power-law behavior. $P(w) \sim w^{-\gamma w}$, with the exponent $\gamma_w = (1 + 2\alpha - \theta) / (\alpha - \theta)$.

To validate the analytical predictions, numerical simulations are performed. The time evolution and cumulative distributions of degree, strength and weight for different combinations of parameters α and θ are consistent with the foregoing theoretical predictions. Figure 5.4 shows one example of the comparison between numerical simulations and analytical predictions of s_i VS k_i.

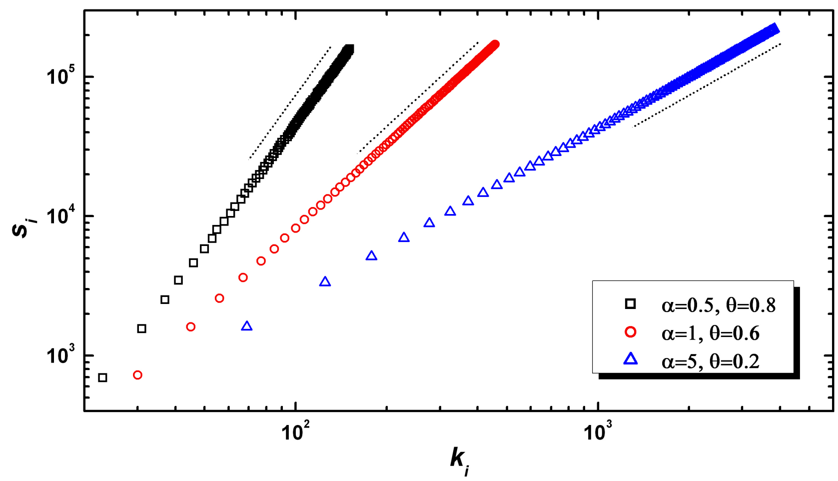

Figure 5.4 Comparison between numerical simulations and analytical predictions. s_i versus k_i for various values of α and θ ($N = 10^4$, $m = 3$). Simulation results are averaged over 50 independent runs and the dashed lines are theoretical predictions.

The average shortest path length L and the average clustering coefficient C are used to investigate the organizational structure of the network. Analysis shows that L increases with the parameter θ but decreases with α while the quantity C

shows the opposite behavior. A smaller L and a larger C are obtained if a smaller θ and a larger α is chosen. Compared with L and C in a random network, this mode gradually displays a small-world property because C is increasing and L is decreasing.

Paper III also examines the clustering-degree correlation mathematically and numerically. $C(k) \sim k^{-1}$ (Figure 5.5). This nontrivial correlation implies that the proposed model has a hierarchical organization, which is important and is observed in many artificial and real-life networks (Boccaletti et al. 2006).

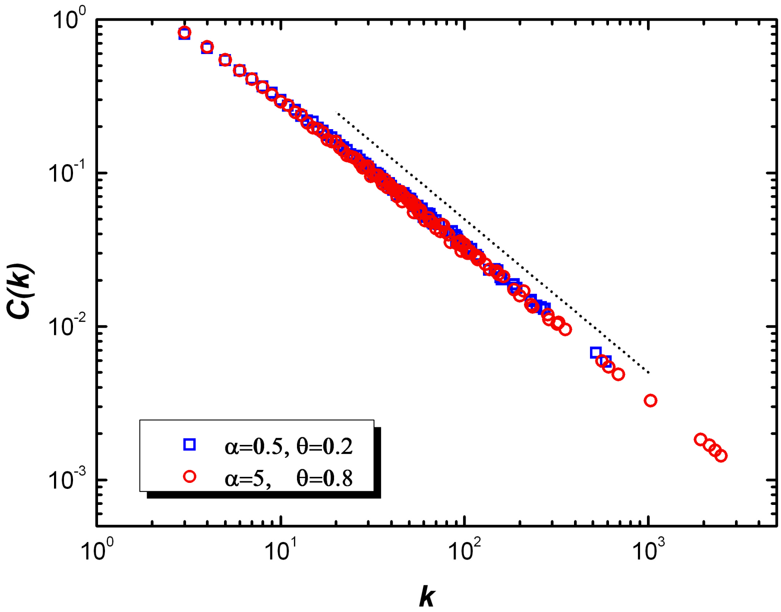

Figure 5.5: The clustering coefficient $C(k)$ as a function of degree k. Results are obtained by averaging over 50 independent runs ($N = 10^4$, $m = 3$). The dashed straight line shows the slope of -1.

The contribution of paper III is that a new model is developed with the following outstanding properties:

- The non-linear degree-strength relationship;
- The small-world property and a significant hierarchical organization.

In order to further investigate how neighboring connections affect the evolution of weighted networks, paper IV only focuses on neighboring connections. This model in paper IV (NPA model) has the same exponents of the power-law behaviors of node degree, strength and edge weight as the ones in the classic BBV model after the analytical calculations and numerical simulations. Paper IV provides full comparisons between the NPA model and BBV model by investigating the following important characteristics of network structure.

(1) Average shortest path length and clustering coefficient.

Compared with the BBV model, the NPA model displays a larger L when δ is small, but it decreases much faster and become smaller when δ is big enough. The clustering coefficient C of the NPA model is always larger than the one in the BBV model, especially when δ is small. It is unsurprised that the NPA model owns a higher value of the average clustering coefficient because of neighboring connections in local preferential attachment. The correlation between the clustering coefficient and degree in the model, $C(k) \sim k^{-1}$, implies a hierarchical structure.

(2) Epidemic spreading

A previous study has shown that the BBV model spreads an epidemic quickly when parameter θ or δ is small (Yan et al. 2005). Our NPA model is compared with the BBV model for different values of δ by plotting the density of infected individuals DI(t) versus time. The epidemic in the NPA model spreads more slowly than the counterpart in the BBV model. To get more precise information, the spreading velocity at the outbreak moment was investigated. The spreading velocity of each case peaks quickly (Figure 5.6). Compared with the BBV model, the NPA model shows a lower spreading velocity in an early stage but maintains a relative higher spreading speed for the rest time till all individuals get infected. The simulation results imply that the structure with close communities (more connections between neighbors) postpones the epidemic spreading and leaves us more response time to develop control measures.

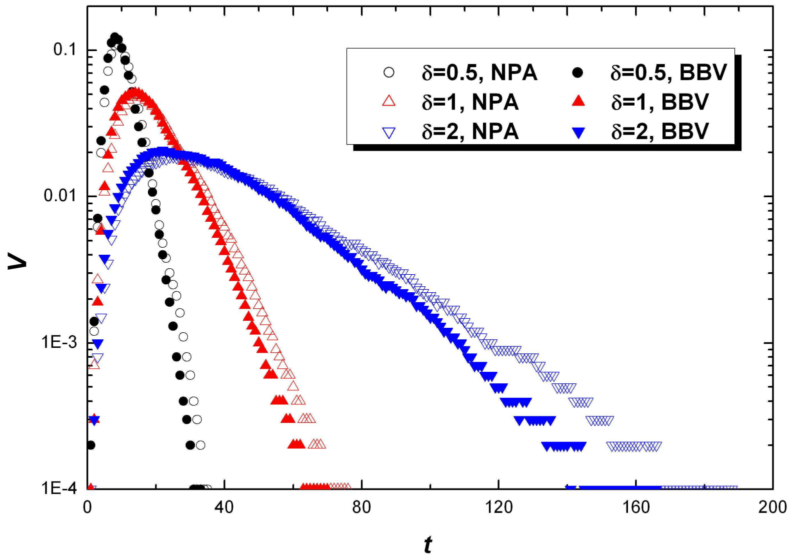

Figure 5.6: Spreading velocity versus time in the BBV model and the NPA model with different parameter of δ. $N = 5000$, $m = 3$, $\theta = 0.6$. The data are averaged over 200 realizations.

(3) Synchronization robustness and fragility

The NPA model is scale-free in structure, so generally "robustness and yet fragility" is unsurprised to be observed. The synchronizability can be enhanced by either increasing the value of *m* or δ. The second-largest eigenvalue of the NPA model increases more quickly from -0.2 to -1.17, but still it is far smaller than the one in corresponding BBV model (top panel in Figure 5.7). It indicates that synchronizability of the BBV model is much stronger especially when δ is small. Both models are particularly vulnerable to deliberate attacks (bottom panel in Figure 5.7). Considering that the two models own the same degree distribution, all comparison results imply that the clustering coefficient has a great influence on network synchronization and more neighboring connections will definitely weaken the synchronizability.

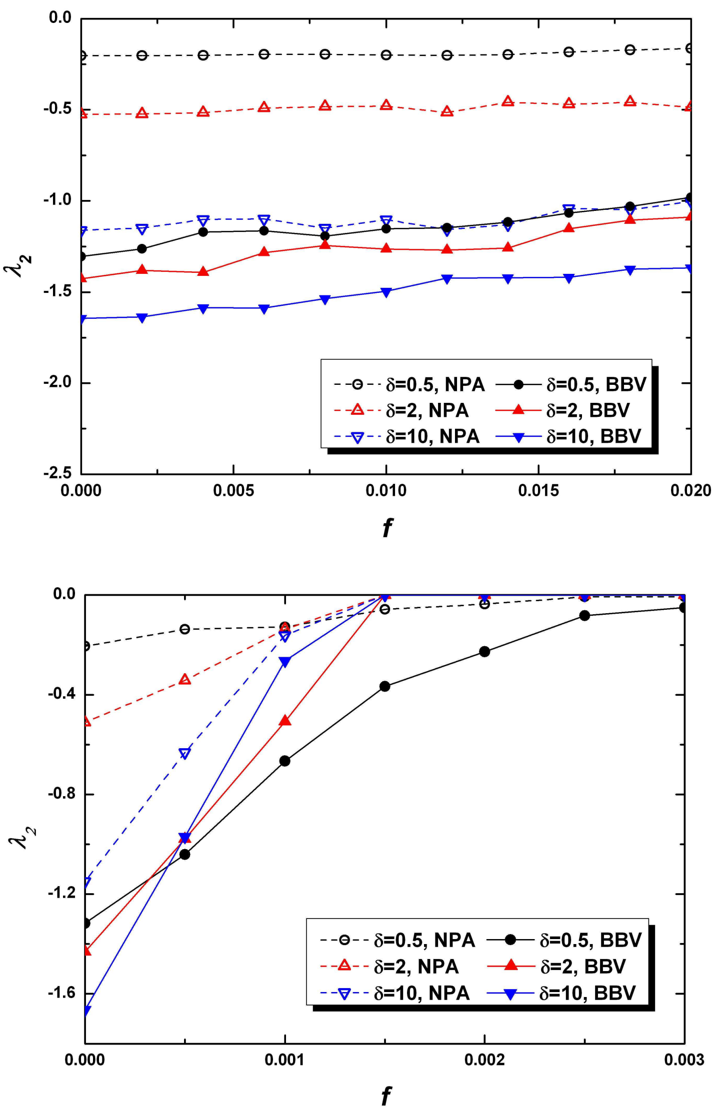

Figure 5.7: Synchronization robustness (top panel) and fragility (bottom panel) comparison between two models.

In summary, paper IV builds the NPA model, which has same exponent functions of the power-law distributions as the BBV model. However they show quite different properties as follows:

- The NPA model has a much larger clustering coefficient, longer average shortest path length, and hierarchical organization.
- The epidemic spreading theory shows a slower spread of epidemics in the NPA model.
- The NPA model has a much weaker synchronization.

The major contribution of this paper lies on the comparison above. All contrasts help to better understand how neighboring connections shape the structures and affect the properties of evolving weighted networks.

5.2.2 Evolution of road network and urban morphology

After the study of growth mechanism in theoretical modeling, paper V focuses on modeling urban street networks. The parameters α and P_l in local optimization, and the attraction radius r in the proposed model in section 4.3.2 are fully investigated. The comparison between the properties of diverse generated patterns and empirical studies is to evaluate this model and further understand the mechanisms behind the evolution of real-world cities.

5.2.2.1 Local optimization

The differences in terms of optimization between the proposed model in paper V and normal optimal network models are: (1) A growth model with a local optimal policy is built instead of a static one with a global optimization; (2) Road network is planar, and there is no edge crossing.

First of all, the meshedness coefficient M and the organic ratio r_N are investigated. A small value of P_l significantly decreases M and eventually results in a tree-like structure. When a medium value of P_l is chosen, M is close to the empirical data, which has an average of 0.219 in 20 real-world cities. Because r_N assesses the abundance of dead ends (degree k = 1) and T-shaped intersections (k = 3), when a larger α is set, more high degree nodes (k > 4) appear and r_N becomes smaller.

With increasing P_l, both the total topological length (L_T) and total geometrical length (L_G) increase. When a large α is set, a new center prefers to connect the existing node with high degree rather than short geometrical distance. The total number of hops or turns is reduced. Therefore, L_T decreases and L_G increases

With increasing α, the global geometrical efficiency $E_{glob,G}$ varies slightly, however the global topological efficiency $E_{glob,T}$ improves significantly. Conversely, $E_{glob,G}$ is more sensitive to P_l. When P_l is 0.6, $E_{glob,G}$ becomes around 0.8, which is observed in many real cases. A medium value of P_l generates a network having the largest value of $E_{glob,T}$, i.e. there is a limit on global topological efficiency for constructing loops. All diagrams can be found in paper V.

5.2.2.2 Overall morphological changes

Altering r from small to large values leads to morphological changes from an urban network (panel b in Figure 5.8), a polycentric city (panel c in Figure 5.8) to a monocentric city (panel d in Figure 5.8). When the attraction radius r is 0, a new center is selected randomly from N new generated nodes and node distribution is eventually uniform. Which value of r is suitable in modeling is decided by evaluating the fraction of dominating sectors (σ) and the Gini index. It is observed that σ decreases very fast with increasing r. When r is larger than 0.075, the value of σ does not vary too much. The Gini index reaches the peak when r is about 0.025. Large value indicates high inequality status for idealized traffic flow. Thus, this work in paper V chose values of r as 0, 0.025, 0.075 and 0.25 respectively in the modeling and analysis.

The area distribution $P(A)$ for different values of r was examined. When r is 0, $P(A)$ is exponential because of the uniform node distribution, which has already been discussed by Barthélemy and Flammini (2009). When $r > 0$, $P(A)$ shows a power-law behavior. The exponent of the power-law distribution decreases quickly from 4.6 ($r = 0.0125$) to 1.05 ($r = 0.05$), and then climbs to 2.5 ($r =0.25$) (Please see paper V for the diagram). The changes suggest that the obtained pattern with $r = 0.05$ is the most heterogeneous in structure. The simulation results are consistent with the observation of road network evolution presented by Strano et al. (2012).

The cumulative distribution of node betweenness centrality exhibits an exponential behavior with the coefficient s changing from 0.069 ($r = 0.025$) to 0.027 ($r = 0.25$). The pattern with $r = 0.25$ shows a symmetrical structure and betweenness values vary relatively narrowly. The pattern with $r = 0.025$ displays extremely high betweenness values for some nodes. These experiments are consistent with the observation of Venice city (Crucitti et al. 2006b) by considering that environmental and physical constraints can separate cities and result in a few road segments with extremely high traffic flow, because many paths have to pass through these crucial positions. Thus a polycentric city is very likely to have a lager s value compared with a monocentric one.

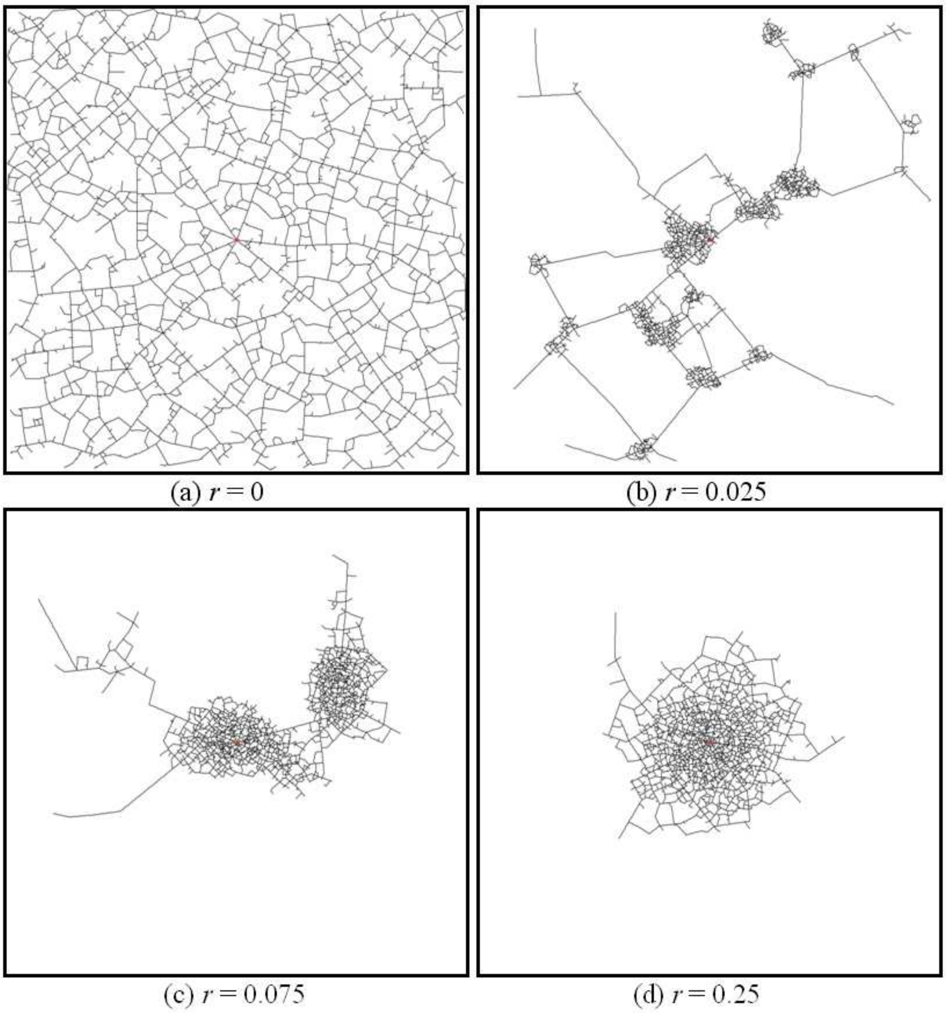

Figure 5.8: Road networks generated with different values of r. $\alpha = 0.5$, $P_l = 0.5$. The red star in the middle represents the initial node.

This work also investigated the varying r, because a constant r is unrealistic for modeling a city from an evolving perspective. The varying r can be decreasing and increasing respectively. Decreasing r is from 0.25 ($t = 0$) to 0.075 ($t = 200$), and to 0.025 ($t = 600$). In contrast, increasing r is from 0.025 to 0.075, and to 0.25. The model with varying r can reproduce two important multi-centered development processes. The pattern with decreasing r simulates how a city develops an asymmetric structure with some emerging sub-centers at the places of high accessibility. While the pattern with increasing r shows that the structure evolves from several towns towards one agglomerated urban area or a dominating city, i.e. some sub-centers originally from small towns later become engulfed by the main city.

The contribution of paper V is that the proposed growth model for self-organized urban street networks succeeds in reproducing a large diversity of road network patterns through varying the parameters.

- Local optimization in the connection and loop construction processes can reflect urban evolution strategies in real world.
- Different attraction radii in center competition process result in urban morphological changes from urban network to polycentric and finally to monocentric structures.

The similarity between the properties of generated patterns and empirical studies suggests that this model can be a useful tool to explore the evolution for different urban structures.

5.3 Effects of street centrality on urban structure in Stockholm

Paper VI investigates the relationship between different land-use types and various street centralities in Stockholm. The city is located on a series of islands and built-up areas have historically grown along transportation infrastructures. Therefore, Stockholm has a star-shaped urban pattern with wedge-shaped natural and water areas in between. The land cover dataset is obtained from the Lantmäteriet 2011 It includes commercial, industrial & public services areas (CIPS), high density residential area with fewer greenbelts (HRES), low density residential area with more greenbelts (LRES), urban greenbelts (UGB), agricultural land (AGRI) and forest. The data for major roads is received from the Swedish Transport Administration (Trafikverket 2010).

First of all, paper VI investigates the centrality within each land use polygon for each land-use type. Cells within each polygon are extracted and their centrality values in each KDE map are averaged. If one polygon area has a high average value of centrality, people in this area are supposed to have some location advantages according to structural properties of the road network. Basic descriptive statistics are then generated for different kinds of centrality accessibility and land-use types. Generally, commercial, industrial & public services areas (CIPS) have a higher value, while pasture and forest have a lower value. There are some interesting findings. High density residential areas basically show better centrality accessibility than low density residential areas. All three built-up land-use types show no significant difference for local closeness. Very similar performances between urban greenbelts and residential areas prove that the development of the greater Stockholm area successfully keeps the balance between its green and built-up spaces.

Then, the statistical distributions of the adaptive KDEs of both centralities and land uses were plotted. In general, the best centrality is concentrated in very few places and thus only a small part of the population can enjoy the best accessibility. Specifically, density distributions vary for different centrality indices. Global and dual betweenness density values decreases quickly and are almost exponential. While other centrality densities are more uniformly distributed with rapidly decreasing tails. For different land-use types, each cumulative distribution is very close to an exponential function with a heavy tail. The similar behaviors indicate an intrinsic stochastic process in land development, although the distributions of different land-use types are significantly different in space.

Finally, this work analyzed the correlation between different centralities and land-use types. Table 2 shows correlation coefficients between adaptive KDEs of different centralities and land-use types when the parameter k is 0.0025, 0.005, 0.01 respectively. Generally built-up areas and urban greenbelts display positive relationships with different centralities while agricultural areas and forests show negative relationships. CIPS has the highest positive correlation coefficients while forest shows the lowest negative coefficients. When $k = 0.01$, CIPS shows the highest value for betweenness centrality ($r = 0.732$). This observation is consistent with previous research (Porta et al. 2009). Both high and low density residential (HRES and LRES) areas display the highest correlations with the straightness centrality ($r = 0.668$ and 0.523 respectively), which means that residential areas generally have good efficiency according to the movement in the street network. All natural areas (UGB, AGRI and forest) are mostly correlated with the closeness centrality. Because global closeness centrality declines from the network geometric center (the old town in this study case), the coefficients imply that natural areas are not newly developed and are not influenced by human activities based on the road network. Urban greenbelts areas are generally close to city center; while agriculture and forest are distributed in the outskirts of the city, especially for the forest.

In addition, this work investigated the correlation for the centralities in the dual representation. The closeness in the dual representation displays an even higher correlation coefficient ($r = 0.776$) with the CIPS area than the global betweenness. This interesting result implies that for the location choice of CIPS area, people might care more about how to get to other places by changing the minimum number of individual roads instead of the shortest geometrical distance. Choosing the way with minimum number of individual roads to be changed is not only more convenient for our memory, but also more efficient by reducing the number of turns.

This work also investigated the local centralities and set the radius d in local area as 6 km, 8 km and 10 km respectively. Particularly, the relationship between LRES and local centralities is impressively strengthened. The coefficients are improved from 0.472 for global closeness to 0.663 for local closeness and from 0.523 for global straightness to 0.676 for local straightness (d = 10 km). Note that similar trends are observed for different values of k and d. Because during the long-term evolution, the development of LRES gathers in the old suburban of the inner city or around new sub-centers of the greater Stockholm area, the distribution of LRES shows a week global property in structure. The results suggest that for some particular types of land use (LRES, for example), local centrality indices may be better predictors than the global counterparts.

Table 2 Correlation coefficients between adaptive KDEs of different centralities and land-use types under different values of parameter k.

k		CIPS	HRES	LRES	UGB	Pasture	Forest
0.0025	Betweenness	0.641	0.481	0.332	0.493	-0.386	-0.604
	Closeness	0.636	0.577	0.476	0.580	-0.594	-0.764
	Straightness	0.655	0.611	0.521	0.537	-0.489	-0.695
	Dual betweenness	0.511	0.362	0.188	0.353	-0.191	-0.384
	Dual closeness	0.672	0.586	0.422	0.517	-0.427	-0.671
0.005	Betweenness	0.691	0.520	0.348	0.545	-0.431	-0.622
	Closeness	0.669	0.591	0.470	0.621	-0.620	-0.762
	Straightness	0.693	0.643	0.520	0.585	-0.521	-0.709
	Dual betweenness	0.568	0.410	0.196	0.393	-0.225	-0.408
	Dual closeness	0.725	0.626	0.423	0.569	-0.454	-0.687
0.01	Betweenness	0.732	0.568	0.381	0.604	-0.479	-0.630
	Closeness	0.691	0.602	0.472	**0.664**	**-0.633**	**-0.747**
	Straightness	0.726	**0.668**	**0.523**	0.638	-0.549	-0.708
	Dual betweenness	0.648	0.477	0.208	0.443	-0.263	-0.430
	Dual closeness	**0.776**	0.667	0.432	0.628	-0.479	-0.690

Major contributions of paper VI include:

- A detailed correlation analysis between different land-use types and street centralities reflects the influence of human activities on land development in Stockholm.
- Centrality measures in dual representation and at local level can provide a more comprehensive understanding of location choice for land development.
- Adaptive KDE is used with the advantage of providing constant precision for the estimation over the entire region, since both street centrality and land use data is unevenly distributed in space.

6. Conclusions and future research

6.1 Conclusions

Urban growth is a very complicated process and is driven by many interactive factors. Modeling is regarded as a good way to simplify the complexity. Good models are helpful for understanding evolving processes and to further improve urban planning and management. This thesis focuses on modeling urban growth phenomena based on land-use simulation, urban street networks modeling and analysis between land use and road network. The works carried out in this thesis vary from a very general theoretical weighted network model to the particular growth models of land use, urban street network and urban growth, and to the specific applications and statistical analysis in the GTA and Stockholm.

This thesis endeavors to address two big challenges in urban growth modeling: (1) Transportation networks are evolved instead of being held fixed. (2) Integration of multi-disciplinary knowledge is in urgent need. One major contribution in this thesis is to introduce the promising complex network science to advance spatial network modeling within the field of GIScience. Therefore, an evolving road network model has been studied and developed. In addition, an urban growth model has been designed which includes the dynamics of both land-use change and road network expansion.

The specific research objectives proposed in section 1.2.1 have been achieved with the following conclusions.

(1) Three main types of agents, including residential agents, developer agents and the government agent, interact with each other and have a reciprocal influence with the environment. This work uses a spatio-temporal criterion to allocate agents to get a better result. Compared with actual urban growth based on satellite data, the simulated results show that the multi-agent model is effective in simulating urban growth phenomenon in Toronto with a total accuracy of 90% for two classes: developed and undeveloped areas.

(2) A dynamic model was built to study long-term urban growth through modeling raster land-use change and vector road network expansion. The local integration from the field of space syntax is introduced to calculate the idealized traffic flow, which are then used to select major roads and calculate accessibility for the land-use simulation. The preliminary simulation results display similar growth patterns as observed in real-world cities. The model is also applied for the simulation in central Stockholm and results approved the reciprocal influence between two dynamics.

(3) A nonlinear growing weighted network model was proposed with neighboring connections. Both mathematical analysis and numerical simulation are studied rigorously. A nonlinear degree-strength relationship implies that the accelerating growth of new weights deserves more attention in the evolution of weighted networks. Another work focused on the influence of neighboring connections by comparing the proposed model with the BBV model through investigating the clustering coefficient, epidemic spreading and synchronization. All contrasts help us to better understand how neighboring connections shape the structure and affect the performance of a weighed evolving network.

A growth model for self-organized urban street networks was built after the study of quantitative similarities in real cases. In the local optimal attachment process, this research uncovers how local optimal connection and loop construction shape the structure. Most importantly, different values of attraction radius lead to overall morphological changes with several typical road patterns including urban network, polycentric and monocentric structures. Their properties are consistent with empirical studies. The experiments also imply that setting varying parameters is more realistic to model real cities and produces two scenarios of multi-centered developing processes. To sum up, the proposed model can be a valuable tool to explore the growth mechanisms of diverse self-organized urban street networks.

(4) Street centrality is calibrated at both global and local levels in both primary and dual representations of the road network in Stockholm. Kernel density estimation with adaptive bandwidth is used to transform the data sets of vector centrality indices and raster land-use types to the same framework for further comparison. Spearman correlation coefficients show that natural areas are most correlated with the closeness centrality, which means that their distributions are simply positively or negatively correlated to the city center. However it is more complicated when built-up areas are considered. Dual closeness and local closeness are mostly correlated with CIPS and LRES respectively. In summary, centralities from diverse aspects capture land development for different land-use types by reflecting idealized human activities and thus influence the formation of urban structure.

6.2 Future research and challenges

6.2.1 Limitations and future research

In the multi-agent simulation of paper I, more detailed social and economic data can be added into the model in order to define the types and properties of agents in a more accurate and detailed way. Besides, preference of each agent type needs to be modified in future through questionnaire surveys or empirical studies.

To improve the analysis of static relationship between land use and road network in paper VI, more accurate land-use categories (especially in built-up areas) is needed, which can give us a more comprehensive understanding about the influence of human activities on land development. It is also interesting to introduce different road network patterns (self-organized or well-planned) in real-world cities and analyze the stability of the correlation we observed in Stockholm.

There are many potential improvements for the proposed hybrid urban growth model in paper II with both land-use simulation and road network expansion. Location choice model and travel demand model for households and employment can be added into the land-use sub-model. The proposed road network growth model in paper V will be adopted to improve the road network growth sub-model. Moreover, the understanding of the dynamic relationship between land-use change and road network expansion is in urgent need. Such kind of case studies on large temporal scales can greatly refine the hybrid model.

6.2.2 General challenges

Advanced urban growth models are still under the way for further development. The following paragraphs list some main challenges, which are absolutely worthy of more attention in future research.

First of all, there are continuous and urgent needs to integrate new approaches from multiple disciplinary fields and build hybrid models. This is also one of the main objectives in the thesis. Urban simulation and evolving modeling require interdisciplinary knowledge (theories and methodologies) and new techniques to better represent various phenomena in urban systems.

Secondly, a higher level of integration from both spatial and temporal aspects deserves more attention, especially the interaction between spatial and temporal dimensions. The following issues need to be considered when dealing with multiple scales: the importance of the modeling extent to driving factors with different spatial scales; the influence of feedbacks on the modeling with different temporal scales.

Finally, the calibration, validation and evaluation of models are challenging tasks. Disaggregation in micro-simulation can reduce some of the bias. However, long-term forecasts retain significant uncertainty. In addition, the transferability and reusability of new urban dynamic models still need to be concerned in future.

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