

Monitoring and analysis of urban growth process using Remote Sensing, GIS and Cellular Automata modeling: A case study of Xuzhou city, China

By

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Abstract

The most extreme anthropogenic land cover/use transformation caused by urbanization has been a universal and important socioeconomic phenomenon around the world. Although urban areas cover a very small percentage of the world's land surface in comparison with other land cover types, their rapid expansion has marked effects on environment and socio-economy. Given the rapid urban growth and importance of its long term effect, it is becoming increasingly important to monitor and analyze the urban land cover change, as well as to adopt appropriate sustainable land use plans.

The previous studies presented some major challenges. Lack of geospatial database persists in developing countries, which makes the analysis and monitoring of urban land cover change more difficult. Furthermore, due to the complexity of the urban system, the analysis of urban growth suffers from a lack of knowledge and understanding of the urban growth process, as well as the physical and socioeconomic factors. In addition, the performance of urban growth models is significantly influenced by calibration, validation, and designing scenarios, which less attention has been given to. Considering these challenges and limitations in previous studies, the dissertation aims to propose an improved methodology for monitoring and analyzing urban growth process in order to understand them better and to support effective urban planning towards urban sustainable development. Xuzhou city in China is used as the case study.

The improved Remote Sensing (RS) image classification method that integrates Vegetation-Impervious Surface-Soil (V-I-S) model with hierarchical classification approach was proposed in order to classify multi-temporal Landsat images in 1990, 2001, 2005, and 2010. Furthermore, a set of spatial metrics were applied for quantifying the urban spatial patterns. The results confirm the effectiveness of the proposed classification method and the spatial pattern analysis for monitoring urban growth process. By comparing with Dortmund city region, Xuzhou city was characterized by rapid urban growth. The allocation of urban area included both the developing outward from the original urban core and the growth of new individual urban patches. As the increasing rapid urbanization process, Xuzhou experienced diffuse sprawling development.

The combination of Geographically Weighted Regression (GWR) and logistic regression models were suggested and applied to explore the underlying cause-

effect relationships in the urban growth process. The new methodology extends the previous studies by investigating spatio-temporally varying effects of urbanization instead of global effects. Both negative and positive effects of urbanization on variation of spatial metrics values were explored. The effects of urbanization on the variations of spatial patterns varied over the study period, which can be explained by the socioeconomic processes and the consequence of urban development policy. In addition, the results generated from logistic regression model indicate that the historical urban growth patterns in Xuzhou city can, in considerable part, be affected by distance to CBD, distance to district centers, distance to roads, slope, neighborhood effect, population density, and environmental factors with relatively high levels of explanation of the spatial variability. The optimal factors and the relative importance of the driving factors varied over time, thus, providing a valuable insight into the urban growth process.

By involving natural and socioeconomic variables, the developed Cellular Automata (CA) model has proved to be able to reproduce the historical urban growth process and assess the consequence of future urban growth. The hybrid calibration method combining logistic regression with trial and error was designed to calibrate the CA model, which can capture the complex interaction of various variables and promote the computational efficiency of the calibration. The existing validation method was improved by considering both the location and spatial pattern similarity to ensure that the CA model can produce more accurate result. Furthermore, five scenarios for 2020 (business as usual, planning strengthened, compact development, dispersed development, and moderate development) were designed with focusing on specific urban development strategies. The dissertation proposed the integration method of Multi-Criteria Evaluation (MCE) and Analytic Hierarchy Process (AHP) that can be utilized to effectively translate the qualitative descriptions for scenarios into quantitative spatial analysis. Finally, the evaluation and comparison of the different scenarios presented in this dissertation provide an effective method for analyzing the impacts of different urban development strategies on urban spatial patterns at global and local scale and for supporting urban planning.

The CA modeling results have proved that the design of development scenarios, identification of parameters as well as the evaluation of scenarios are able to establish connection between CA models and the urban decision making processes. The evaluation of the scenarios suggests that the current urban development

process was in a critical stage. If it continues as indicated by the business as usual scenario in the future, the new urban areas are sparsely developed in fringe and rural areas. The conflict between rapid urban growth and limited land resource becomes more apparent. Comparing with other scenarios, the moderate development scenario could be considered as the best one in achieving the objectives of compact urban form, good residential environment, as well as environmentally and economically efficient development.

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List of abbreviations

AHP	Analytic Hierarchy Process
AICc	Corrected Akaike Information Criterion
AMR	Academy of Macroeconomic Research
ANN	Artificial Neural Networks
AREA	Patch Area-Class Area-Landscape Area (depending on the respective context)
AUC	Area Under the Curve
AWMFD	Area-Weighted Mean Patch Fractal Dimension
BUS	Business as Usual Scenario
CA	Cellular Automata
CBD	Central Business District
CDS	Compact Development Scenario
CI	Consistency Index
CLUE	Conversion of Land Use and its Effects
CONTAG	Contagion Index
CR	Consistency Ratio
CV	Cross Validation
DDS	Dispersed Development Scenario
DEM	Digital Elevation Model
DOS	Dark Object Subtraction
ED	Edge Density
ENN_AM	Area Weighted mean Euclidean distance neighbor distance
FAO	Food and Agriculture Organization
FR	Frequency Ratio
GA	Genetic Algorithm
GCPs	Ground Control Points
GDP	Gross Domestic Product
GHG	Green House Gas
GIS	Geographic Information Systems
GLCF	Global Land Cover Facility
GWR	Geographically Weighted Regression
IGBP	International Geosphere-Biosphere Programme

IHDP	International Human Dimensions Programme
LAI	Leaf Area Index
LPI	Largest Patch index
LSI	Landscape Shape Index
LULCC	Land use and land cover change
MCE	Multi-Criteria Evaluation
MDS	Moderate Development Scenario
MLC	Maximum Likelihood Classifier
MNN	Mean Nearest Neighbor distance
NDRC	National Development and Reform Commission
NDVI	Normalized Difference Vegetation Index
NP	Number of Patches
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PLAND	Percentage of Landscape
PR	Patch Richness
PSS	Planning-Strengthened Scenario
Rd	Relative Difference
RI	Random Index
RMSE	Root Mean Square Errors
ROC	Relative Operating Characteristic
RS	Remote Sensing
RVI	Ratio Vegetation Index
SHAPE	Shape index
SHAPE_AM	Area Weighted mean shape index
SHAPE_MN	Mean shape index
SHDI	Shannon's Diversity Index
SHEI	Shannon's Evenness Index
SVM	Support Vector Machine
TCT	Tasseled Cap Transformation
UII	Urbanization Intensity Index
USGS	U.S. Geological Survey
UTM	Universal Transverse Mercator

V-I-S Vegetation-Impervious Surface-Soil

1. Introduction

The motivation of the present study is the awareness of a number of environmental and socioeconomic problems caused by the rapid urbanization process. The first chapter of the dissertation is to briefly state the problems related to the urbanization and to illustrate the importance of using modified methods to better understand urban growth process. Subsequently, the research objectives and questions of this study are presented as well as the structure of the dissertation.

1.1 Background

In recent decades, urbanization, the most extreme anthropogenic land cover/use transformation has been a universal and important socioeconomic phenomenon around the world. Urban growth has been accelerating with the significant increase in urban population. The world urban population was only nearly 3 % of the global population in the 1800s, but increased to about 30 % in 1950 (Wu & David, 2002). Currently, over half of the world population live in urban areas, and the figure is projected to reach 67.1 % (6.25 billion) by 2050 (United Nations, 2012).

Though urbanization promotes socioeconomic development and improves quality of life, it is the most powerful and visible anthropogenic force that has caused the fundamental conversion in natural to artificial land cover in the cities around the world (Clarke et al., 1997; Luck & Wu, 2002). As urbanization has occurred, lands making up the natural resource base, such as agriculture, forest and wetlands, have been replaced by urban land (Jantz et al., 2004). Land cover dynamics constitute an important component of the human dimension of global change (Turner et al., 1990). Although urban areas cover a very small percentage of the world's land surface in comparison with other land cover types, their rapid expansion has marked effects on environment and socio-economy, such as loss of natural vegetation and farmland (Tan et al., 2005), local and regional climate change (Kaufmann et al., 2007), decline in biodiversity (Zimmermann et al., 2010), hydrological circle alternation (Barron et al., 2013), etc. Without effective planning, there is no doubt that the pressure for sustainable development will continue to increase (Dewan & Yamaguchi, 2009a; Lambin et al., 2001).

The majority of urban growth due to human activities is currently proceeding more quickly in the developing countries than in the developed countries. As the largest developing country in the world, China has recently experienced dramatic economic growth and rapid urbanization since 1978. The percentage of urban population

increased from 17.9 % in 1978 to 52.6 % in 2012 (China National Bureau of Statistics, 2013). Like other developing countries, the rapid urbanization process resulted in an unprecedented scale and rate of urban growth over the last two decades (Seto & Kaufmann, 2003). The urban land is expected to expand at a very rapid rate because 77.3 % of the population will be living in urban by 2050 according to a UN projection (United Nations, 2012). Therefore, China has much more pressure in achieving sustainable development.

Given the rapid urban growth and importance of its long term effect, it is becoming increasingly important to monitor and analyze the urban growth process, as well as to adopt appropriate sustainable land use plans. Continual, historical, and precise information about the urban land cover change is a prerequisite to the further analysis and sustainable development, which has been greatly emphasized. In order to obtain better understanding of urban growth process, recent issues related to urban growth have attracted increasing attention, ranging from spatial and temporal land cover patterns, the factors affecting the urban growth, to urban growth scenarios by using remote sensing (RS), Geographic Information Systems (GIS) and modeling (Deng et al., 2009; Wu & Zhang, 2012; Yuan et al., 2005).

However, previous urban growth studies presented us with some major challenges. Although most of the developed countries are well equipped with detailed land cover information, the lack of geospatial database still occurs in the developing countries, especially in China, which makes the monitoring and analysis of urban growth process more difficult. The study of urban growth is limited by the quality of data derived from remote sensing images. Furthermore, the complexity of the urban systems is usually an impediment, which is enhanced in the developing cities where many factors increase the unpredictability of the system (Barredo et al., 2004). Consequently, the analysis of urban growth suffers from a lack of knowledge and understanding of the urban growth process, as well as the physical and socioeconomic factors. In addition, the performance of urban growth models is significantly influenced by calibration, validation, and designing of scenarios, which less attention has been given to. Considering these challenges and limitations in previous studies, it is necessary to adopt modified methods in order to better understand the urban growth process.

1.2 Research objectives and key questions

1.2.1 Research objectives

The main objective of this dissertation is to propose an improved methodology for monitoring and analyzing urban growth process in order to understand them better and to support effective urban planning towards urban sustainable development. The focus is on the investigation of spatio-temporal dynamics of land cover change pattern from remote sensing images; assessment of the underlying cause-effect relationships in urban growth process; simulation of the urban growth. The specific objectives are, using multi-temporal Landsat data together with natural and socioeconomic data:

- 1) To extract and compare the historical land cover information for the investigation area through the interpretation of remote sensing images and the using of quantitative measures. Because of the relatively coarse spatial resolution of Landsat images and heterogeneous nature of urban environments, accurate classification of Landsat images remains a big challenge.
- 2) To examine the underlying cause-effect relationships in the urban growth process. The question is the spatial and temporal heterogeneous are usually involved in the relationships between factors and urban growth. Therefore, the spatio-temporal dynamics effects of the factors on urban growth need to be investigated to provide insight into how driving factors contribute to the urban growth.
- 3) To generate future scenarios by taking into account the different urban development strategies. The creation of the scenarios is strongly linked to the current concerns of policy makers of the region addressing the key questions. Scenario based simulation provides an environment to support “what if” experiments. In addition, it is important to examine the impacts of the urban development strategy on urban growth based on the evaluation and comparison of future scenarios.

1.2.2 Research questions

In this context, the main challenge of this research is to provide a better understanding of urban growth process and to support urban planning aimed at sustainable development. Under this challenge the following questions are raised and need to be answered:

- 1) How to improve the classification accuracy in order to provide the high quality land cover information for the further analysis?
- 2) Which indicators can be used to reflect and quantify the urban growth patterns?
- 3) How to explore the underlying cause-effect relationships in the urban growth process?
- 4) How to determine the parameters values of cellular automata (CA) models in order to accurately reproduce historical urban growth?
- 5) How to connect the CA models with the urban decision making process?

1.3 Organization of the dissertation

This dissertation consists of six chapters. After the introduction provided in this chapter, a theoretical background for this study is introduced in chapter 2. First, it provides the conceptual basis in the context of land cover change, urban growth, sustainable urban form and complexity of urban systems. Following the theory and history of related approaches and their strengths and limitations are also introduced. Since urban growth is a complex process, this chapter is important to provide a basis for monitoring and analysis work to be conducted.

Chapter 3 is concerned with the study area of Xuzhou city, China. After having established the theoretical framework, the socioeconomic characteristics of Xuzhou city is introduced in the national context of China. Furthermore, a spatial database for this study is described, which includes the remote sensing data as well as other spatial variables.

Chapter 4 describes the methods used in this study. It consists of three parts. In the first part, the integration method of maximum likelihood classifier, sub-pixel classifier and multiple Normalized Difference Vegetation Index (NDVI) values based on Vegetation-Impervious Surface-Soil (V-I-S) model is proposed in order to classify multi-temporal Landsat images. Furthermore, a set of spatial metrics for quantifying the urban spatial patterns are described. Geographically weighted regression (GWR) is introduced to explore the spatio-temporally varying relationships between the spatial patterns and urban growth. In addition, driving factors are identified and adopted to evaluate the spatial influences of each factor on urban growth by using logistic regression method. The third part presents cellular automata (CA) model to reproduce the historical urban growth process and assess the consequence of future urban growth with a case study of Xuzhou city in China. Natural and socioeconomic variables are involved to generate transition potential of urban growth during the study period. For estimating more accurate parameter values, the hybrid calibration method is proposed. The historical simulation results are compared with observed urban land use using figure of merit value and spatial metrics. Five scenarios are designed and developed to present different urban development trends. Moreover, the different scenarios are evaluated and compared in order to analyze the impacts of different urban development strategies on urban spatial patterns and to support urban planning.

Chapter 5 presents and discusses the findings generated by the methods in chapter 4. In addition, some implications of urban development in Xuzhou city are given. In chapter 6, finally, answers to the research questions proposed in chapter 1 and major findings are provided. Based on the study findings, the development recommendations and the future work are also presented.

2. Theoretical background

Since the emphasis of this study is the integration of RS, GIS and CA for monitoring and analyzing the urban growth process, this chapter provides a brief outline of the theoretical fundamentals of this theme. The key concepts related to the urban growth are explained. After that, the related methods in the monitoring and analysis are introduced and compared to give a general impression about the advantages and disadvantages of these methods.

2.1 Conceptual basis

2.1.1 Land use and land cover change

Land use and land cover change (LULCC), is a general term for the human modification of Earth's terrestrial surface. It is a central component of global environmental change with direct impact on climate, environment, and human societies (Campbell et al., 2005; Turner et al., 1990). Although humans have been modifying land for thousands of years in order to obtain food and other essentials, current rates, extents and intensities of LULCC are much greater than ever in history (Ellis, 2007). Changes in land use and land cover are among the most important drivers of global change (Turner et al., 1990; Vitousek et al., 1997).

LULCC consists of two different terms, Land cover and land use. Land cover refers to physical and biological cover over the earth's land surface and immediate subsurface (Lambin et al., 2003). It includes water, vegetation, bare soil, and/or artificial structures. Foody (2002) proposed that land cover is a fundamental variable that affects and links many parts of the human and physical environments. Land use is a more complicated term. It is the intended human employment and management of a land cover: the ways and means of its exploitation to meet human demands (Meyer & Turner, 1996), for example, industrial land, commercial land. There is a strong relationship between land use and human activities in the environment (Allen & Barnes, 1985; Turner et al., 1990). Food and Agriculture Organization (1995) stated that "land use concerns the function or purpose for which the land is used for the local human population and can be defined as the human activities which are directly related to land, making use of its resources or having an impact on them". It comes out from the above definitions that land use and land cover are not equivalent although they may partially overlap.

Changes in land cover are the results of anthropogenic or natural processes such as climatic change, volcanic eruptions, changes in river channels or the sea level, etc

(Briassoulis, 2000). With human activity increasing, however, most of the land cover changes of the present and the recent past are due to human activities, i.e. to uses of land for production or settlement (Turner, 2009). More specifically, Meyer and Turner (1996) suggested that land use changes land cover in three ways: "converting the land cover, or changing it to a qualitatively different state; modifying it, or quantitatively changing its condition without full conversion; and maintaining it in its condition against natural agents of change". Two types of land cover change can be identified: conversion and modification (Lambin et al., 2003). Land cover conversion means the change from one cover type to another while land cover modification refers to the alterations of structure or function without a total change from one type to another (Skole, 1994).

The importance of land cover change has been recognized since 1970s, when studies revealed the significant relationships between land cover and climate change. Otterman (1974) found that land cover change may lead to the change in the albedo, and thus modify the surface-atmosphere energy balance, resulting in climate change. During the following years, it was concluded that land cover change contributes to global carbon emissions through the creation and especially diminishment of carbon sinks (Lambin et al., 2003). In addition, many studies demonstrated that the land cover change is a major factor for global change because it has a strong impact on the ecosystem, including soil erosion (Cebecauer & Hofierka, 2008), desertification (Wu et al., 2011), a loss of biodiversity (Zimmermann et al., 2010), declining human health (Xu et al., 2008), and threat to ability of biological systems to support human needs (Vitousek et al., 1997). This is particularly the case in the economic-developed regions where significant land cover changes in urban areas have resulted in serious issues threatening urban sustainable development (Eastman & Fulk, 1993; Li & Yeh, 2004).

Over the last few decades, many researchers have improved measurements of land cover change, the understanding of the causes, and land cover modeling, in part under the auspices of the LULCC Project conducted by International Geosphere-Biosphere Programme (IGBP) and International Human Dimensions Programme (IHDP) on Global Environmental Change (Lambin et al., 2003; Meyer & Turner, 1996). This project represented that the recognition of land cover change as a full element of global environmental change.

2.1.2 Urbanization and urban expansion

Urbanization is simply defined as “the movement of people from rural to urban areas with population growth equating to urban migration” (United Nations, 2005). Urbanization is also a social process which involves the changes of behavior and social relationships as a result of people living in urban area (Bhatta, 2010). Essentially, it involves the complex change of life styles which result from the impact of cities on society (Bhatta et al., 2010). Nowadays, however, urbanization is commonly used in more broad sense and it refers to much more than simple urban population growth; it involves the physical growth of urban areas as well as the changes in the socioeconomic and political structure of a region as a result of population immigration to an urban area (Cohen, 2004; Deng et al., 2009; Li et al., 2013a).

Urbanization has been a dynamic complex phenomenon taking place all around the world. This process, without a sign of slowing down, has led to the significant changes in land cover and landscape pattern (Braumoh & Onishi, 2007; Deng et al., 2009). Dramatic urbanization, especially in the developing countries, will continue to be one of the important issues of global change influencing the human dimensions (Deng et al., 2009).

Associated with the process of rapid urbanization, the spatial expansion of built-up areas has been accelerating. Though urbanization promotes socioeconomic development and improves quality of life, urban growth inevitably results in significant land cover changes in urban area, such as the conversion from the forest and wetlands into agricultural or built-up lands since more land is used for the production of goods and services, and more residential land is required for the people living in the urban. While urban areas currently cover only 3 % of the Earth’s land surface (Dewan & Yamaguchi, 2009a), the conversions resulted from the urban growth are among the most significant types of anthropogenic land cover dynamics, and the ecological and environmental impacts of urban growth go far beyond the urban boundaries (Wu et al., 2011; Liu & Lathrop, 2002). This is particular the case in the fast developing regions where land cover change caused by rapid urban growth resulted in serious issues threatening urban sustainable development, for example, local and regional climate change (Kaufmann et al., 2007), hydrological circle alteration (Barron et al., 2013; Yang et al., 2011), forest loss and fragmentation (Miller, 2012) and etc.

The process of urban growth can be described as either a change in the area of urban (a measure of extent) or the pace at which non-urban land is converted to urban uses (a measure of rate) (Seto & Fragkias, 2005). However, the extent and rate of urban growth cannot provide detailed information about spatial patterns of urbanization or the underlying processes. Therefore, the urban spatial pattern has been the other subject of interest for geographers and economists to study the changes in urban areas.

In the context of urban growth pattern, urban sprawl has received much attention (Hasse & Lathrop, 2003; Jantz et al., 2004). In the late 1950s, urban sprawl phenomenon in USA has been widely studied. It is regarded as a phenomenon with the low-density outward expansion of the urban areas. Later on, similar urban sprawl processes were described in most of all cities including the cities in developing countries.

Owing to its diversity and complexity, a variety of definitions for sprawl have been proposed. For instance, Fulton et al. (2001) proposed that urban sprawl occurred when land is consumed at a faster rate than the population growth. Ewing et al. (2002) defined urban sprawl as a type of low-density development with residential, commercial and industrial areas that are separated, a lack of thriving activity centers, and limited choices in travel routes. Similarly, Burchell et al. (2005) pointed out that urban sprawl has its particular spatial patterns: unlimited outward and leapfrog expansion of low density new development. Though there is no commonly accepted definition of urban sprawl, a general consensus on depicting urban sprawl as a specific type of urban expansion characterized by a low-density, dispersed spatial pattern with both environmental and social impacts (Aguilera et al., 2011; Hasse & Lathrop, 2003; Yuan et al., 2005).

2.1.3 Sustainable urban form

Sustainable development refers to “development that meets the needs of the present without compromising the ability of the future generations to meet their own needs” (World Commission on Environment and Development, 1987). The existing of all the above-mentioned problems caused by urbanization indicates our cities are not sustainable (McGranahan & Satterthwaite, 2003). Due to the problems caused by the rapid urban growth, the current changing urban spatial pattern is a great challenge for sustainable development. A range of reasons related to the sustainable development are brought forward: to preserve important natural habitat and

agricultural land; to reduce energy and materials consumption as well as Green House Gas (GHG) emissions.

A sustainable city must “achieve a balance among environmental protection, economic development, and social wellbeing” (Wu, 2010). Urban sustainability consists of minimizing the consumption of resources and land, optimizing urban form to facilitate urban flows, protecting both human health and ecosystem, ensuring equal access to resources and services, and maintaining cultural and social diversity and integrity (Alberti & Susskind, 1996; Spiekermann & Wegener, 2003). However, developing sustainable cities is a difficult task because cities are the centers of socio-economic developments, the main sources of major environmental problems, and the living place of nearly half of the world population (Wu, 2008).

The relationship between urban form and sustainability is currently one of the most hotly debated issues in the international environment research. Jenks et al. (1996) pointed out that there is a significant relationship between urban form and sustainable development, although it is not simple and straightforward. The costs and negative environmental impacts of urban sprawl have been widely studied and documented. The particular concerns over urban sprawl is the inefficient utilization of energy (Bhatta, 2010), increasing of infrastructure and public service costs (Buiton, 1994), land use fragmentation and loss of farmland (Nelson, 1990; Tan et al., 2005; Zhang et al., 2007). Urban sprawl is therefore regarded as one of the main challenges in sustainable development and spatial planning. From this point of view, the sustainable city “must be of a form and scale appropriate to walking, cycling and efficient public transport, and with a compactness that encourages social interaction” (Elkin et al., 1991, p.12). Therefore the particular issue in developing a sustainable city is to search for the most suitable urban forms that can help to sustain development, especially for reducing the unnecessary loss of land resources and the consumption of energy. In the discipline of urban growth, a new word has emerged—compact city to attain the goals of sustainability. The term of compact city was first coined by Dantzig and Satty (1973) as the alternative planning strategy to the problems linked to dispersed city. With the unprecedented and ongoing growth of urban areas globally accompanied by negative impacts, there has been tremendous opportunities to apply this concept in order to achieve the sustainable urban form. Sustainability has been incorporated in urban planning theory through the promotion of a compact policy for urban growth rather than urban sprawl (Arbury, 2005).

However, there are inherent difficulties in defining the compact city. Clearly, there is more than just an increase in population density for the compact city (Burton, 2002). It has been proposed that an increase in dwelling density (Goodchild, 1994), the advancement of mixed use development (Williams et al., 1996), and a reaffirmed focus on the nature and quality of development (Elkin et al., 1991) are all important aspects in the compact city theory. The morphology of a city is an important feature in the compact city theory (Jenks et al., 1996).

Many researchers believed that compact cities have environmental, social and fiscal advantages and results in energy saving (Burton, 2002; Frey, 2004; Hillman, 1996; Thomas & Cousins, 1996), thus are an important way to solve problems linked to dispersed form and to achieve the sustainable development. Hillman (1996), for example, argued that compact city can reduce travel distance, and therefore decreasing emissions of GHG. He also pointed out that urban residents could enjoy lower transport expenditure, less pollution and lower heating costs in compact city. In addition, the re-use of infrastructure and developed land, a regeneration of existing urban areas and urban vitality can be achieved through the implementation of compact city (Thomas & Cousins, 1996).

However, as pointed out by Burgess (2000), interests in compact city studies were concentrated on the developed countries, with insufficient studies conducted in the developing countries. With the recognition of its significant impacts in the developing countries, it is important to consider the implementation of compact city policy in developing countries (Jenks, 2000).

A heated debate regarding the compact city has dominated the urban planning literature since the middle of 1990s. The realistic experience of cities have shown some problems related to the compact city, such as congestion (Catalán et al., 2008), shortage of open space near to residential areas (Williams et al., 1996). Some researchers argued that dispersed urban form is attractive at an individual level since it satisfies individual preferences, such as more space for per housing unit and quick access to open space, and lower housing prices (Gordon & Richardson, 1997; Wassmer & Baass, 2006). Therefore, how to balance the conflict between compact and dispersed urban form is an important issue for sustainable development.

2.1.4 The complexity of urban systems

Complex systems theory is a new approach that can be used to investigate how relationships between parts bring about the collective behaviors of a system and how

the system interacts (Bhatta, 2010, p.110). While no precise definition of a complex system exists, complex systems are often defined in terms of the strength of dynamic linkage between components. Batty (2009, p.51) proposed that the complex systems “show surprising and unanticipated or ‘emergent’ behaviours as shown in patterns that arise at the aggregate level from the operation of system processes at the micro of agent level”. With respect to urban dynamics systems, Parker et al. (2003) defined that complex systems are regarded as dynamic systems that present recognizable patterns of organization across spatial and temporal scales.

Cities have long been recognized as complex systems, which are composed of a large number of interacting individual components (Batty, 2007). Even a slight change in one component could affect the states of other components that are potentially linked. What emerges from these interactions cannot be predicted simply by analyzing its components. The complexity of urban growth is mainly due to the complex way in which humans and the environment interact to each other, whereby these interactions are regulated by a wide range of factors influencing land-use decisions at different temporal and spatial scales (Torrens, 2000). Feedback mechanisms among the components of this coupled human environment system even enhance the level of complexity, possibly resulting in an emergent system, which cannot be explained by analyzing the single component of the system. Complexity occurs from both decision making and the spatial aspects of the city environment (Parker et al., 2003). Torrens (2000) suggested that cities exhibit several distinguishing characteristics of complexity: emergence, self-organization, fractal dimensionality, and self-similarity.

In emergent systems, like cities, a small amount of rules applied at a local level are able to generate surprising complexity and ordered patterns in aggregate form (Torrens, 2000). Emergence implies that although the behavior of a complex system is dependent on the behavior of its components, the outcome behavior of the whole is much more than that of the local interactions, in simple words, the actions of the parts do not sum to the activity of the whole. It is best summed up in the phrase: “the whole is greater than the sum of its parts” (Von Bertalanffy, 1972, p.18). This is viewed as the critical point in studying cities as complex systems (Batty, 2000). In the city context, the sum of the parts represents the urban morphology, while the whole corresponds to urban patterns dynamics (Barredo et al., 2003).

The second law of the thermodynamics in physics states that the closed systems progressively evolve to a state of maximum entropy (Barredo et al., 2003). In contrast, the open systems like cities show the different tendency, which presents the evolution to ordered state even when starting from disordered states (Wolfram, 1994). Such open systems can be viewed as self-organizing. Self-organization in complex systems refers to the tendency for system structures to development ordered patterns on a large-scale (Krugman, 1996). Furthermore, both spatial and temporal dimensions are able to reflect self-organization.

White and Engelen (1993) used fractal dimension as a measure to characterize the ordered properties of cities. In cities, the recursive local-scale dynamics that generate well-defined geometrical structures in two-dimensional space often produce similar structural geometries (Batty et al., 1997). Furthermore, cities can be defined as a bi-fractal structure, which is characterized by two zones, the inner zones and outer zones (Torrens, 2000). The inner zones represent a well-organized core of a typical concentric city, which is composed of compact built-up land. In the inner zones, urban patterns are stable and ordered; the urbanization process is completed. While outer zones are less organized, in which urbanization is still underway (White et al., 1997). The fact that cities have fractal structure introduces the concept of self-similarity. With self-similarity, the patterns of new areas in cities are indistinguishable from the whole of the cities. In addition, the structure of the pattern is independent on scale (Wolfram, 1994).

2.2 Analyzing of spatio-temporal dynamics of urban growth

2.2.1 Land cover change

Mapping and monitoring land cover have been widely recognized as an important step to better understand and provide solutions for social, economic, and environmental problems (Adb El-Kawy et al., 2011; Dewan & Yamaguchi, 2009b; Foody, 2002). Therefore the continual, historical and precise information of land cover and land cover change is becoming increasingly important for urban planning towards sustainable development (Barnsley & Barr, 1996; Ramankutty & Foley, 1999).

Although most of the developed countries are well equipped with detailed land cover information (Dewan & Yamaguchi, 2009b), Longley and Mesev (2000) argued that our current understanding of the land cover change and its effects are largely limited by the lack of accurate and timely land cover data in the developing countries. Land

cover data are inadequate or unavailable, of inconsistent quality, and out of date; while generating it is time consuming and expensive (Haack & English, 1996). This is attributed to the difficulties in accessing some regions because of equipment or funds to collect information properly, lack of trained personnel; or rapid changes (Defries & Townshend, 1999). With the wide requirement and application of land cover data, there has been an increasing interest in obtaining the data.

Since the launch of the first Earth resource satellite Landsat-1 in 1972, satellite remote sensing has become an increasingly powerful and effective tool for monitoring and management of land cover (Zhang & Zhu, 2011). Compared with more traditional mapping methods such as field survey and basic aerial photointerpretation, land cover mapping has the advantages of low cost, large area coverage, repetitive data, digital format, and accurate georeferencing procedures (Jensen, 1996; Yuan et al., 2005). Consequently, land use information products from satellite images have become an essential database for land cover management and urban planning. Particularly, in developing countries, remote sensing is able to provide fundamental and cost effective land cover information that is not available from other sources (Dewan & Yamaguchi, 2009b; Miller & Small, 2003).

Several recent developments of sensor technology have the potential to significantly improve the capability of mapping urban areas. These relate to the availability of data from high spatial resolution satellites such as Quickbird, IKONOS, RapidEye, and GeoEye, as well as high spectral resolution satellites such as Landsat (TM & ETM+), ASTER. The increasing availability of satellite imagery with significantly improved spectral and spatial resolution has played an important role in more detailed land-cover mapping. Meanwhile, the rapid development of image process technologies has provided more powerful tools for satellite processing and analysis. It is now possible to monitor and analyze urban growth in a timely and cost-effective way (Deng et al., 2009).

An important task of satellite image processing is to develop image data analysis approaches suitable to a particular application. The classification of land cover types from satellite images is probably the most important objective of digital image analysis. It is a process of categorizing pixels in an image to one of land cover classes. The fundamental basis of remote sensing image classification is the spectral characteristics of earth surface features. While it is relatively easy to generate a land

cover map from remote sensing image, it is difficult to make it accurate (Zhang & Zhu, 2011).

In the past few decades, a variety of classification algorithms have been proposed to conduct the remote sensing image classification. Traditional multispectral classification methods make use of spectral information of different surface objects. Supervised and unsupervised multispectral classifications are the two main spectral recognition methods. Supervised classification aims to allocate pixels based on their similarity to a set of predefined classes that have been characterized spectrally (Foody, 2002). Therefore, it requires a priori knowledge of the study area to ensure the selection of the training sites.

The Maximum Likelihood Classifier (MLC) is the most commonly used supervised classification method, which creates decision surfaces based on the mean and covariance of each class (Srivastava et al., 2012). However, MLC presents less successes because the MLC assumption that the data follow Gaussian distribution may not always be held in complex areas (Xie et al., 2008). Artificial Neural Networks (ANN) and Support Vector Machine (SVM) originally proposed by Vapnik and Chervonenkis (1971) are recent addition to the existing image classification methods, which received increasing attentions in remote sensing applications (Dixon & Candade, 2008; Mathur & Foody, 2008; Szuster et al., 2011).

The unsupervised classification examines the unknown pixels in an image and aggregates them into land cover classes based on their relative spectral similarity. The advantage of unsupervised classification is that it is automated and does not require a priori knowledge of the study area (Lillesand et al., 2004).

These traditional classification methods have been widely used for remote sensing application and have generated fairly good results for a wide variety of images. However, there are some challenges in obtaining accurate land cover information in urban areas. A major difficulty in urban remote sensing processing is attributed to the high heterogeneity and complexity of the urban environment in terms of its spatial and spectral characteristics (Deng et al., 2009; Lu et al., 2011; Setiawan et al., 2006). Consequently, misclassification problems are often found in the land cover maps generated from tradition methods. According to the literature review, there are two major factors that are responsible for the misclassification problem. One of them is the mixed pixel problem which results from the occurrence of more than one land cover types in one pixel (Fisher, 1997; Lu & Weng, 2004). This is particularly true for

transitional pixels between land cover types. As a result, the spectral information obtained at the mixed pixel is a mixture of the spectral values of several different land cover types. The other factor is the close spectral similarities between different land cover types (Foody, 2002; Liberti et al., 2009).

In recent years, many efforts have been made to improve urban land cover classification accuracy. A survey of the existing literature suggests that three major methods can be identified:

1) Making more efficient use of spectral information.

Spectral information is the most readily available information in a satellite image. Considerable efforts are being made to develop new spectral classification methods.

A number of spectral indices were developed to aid the interpretation of remote sensing images by detecting small differences between different land cover types (Jones et al., 2011). It is based on the different band reflectance for the same material. For example the most commonly used Normalized Difference Vegetation Index (NDVI) (Jamali et al., 2014; Setiawan et al., 2006), Ratio Vegetation Index (RVI) (Zhang & Zhu, 2011), Leaf Area Index (LAI) (Jones et al., 2011).

In addition, Principal Component Analysis (PCA) enables redundant data to be compacted into fewer bands. These bands of PCA data are noncorrelated and independent, and are more interpretable than the source data (Rajani & Rajawat, 2011; Zhang & Zhu, 2011). Tasseled Cap Transformation (TCT) can convert the original bands of a RS image into a new set of bands that are helpful for vegetation mapping (Dymond et al., 2002; Li & Thinh, 2013).

Ridd (1995) proposed Vegetation-Impervious Surface-Soil (V-I-S) model, which assumes that land cover in urban environment is a linear combination of three components: vegetation, impervious surface, and soil. The model provides a potential framework to deal with misclassification problem in urban area. Several studies used the model to map land cover/land use in urban areas and demonstrated the usefulness for the classification in urban areas (Li & Thinh, 2013; Lu & Weng, 2004; Ward et al., 2000).

2) Incorporation of multisensor data and ancillary spatial information.

Another basic strategy for improving the classification accuracy is to integrate more information with remote sensing images. Generally, two types of data are used in information fusion. The first way is the integration of multitemporal and

multiresolution data (Du et al., 2013; Gluch, 2002). The other way is to integrated original image with some other geographic data to improve accuracy of classification results, for example, Digital Elevation Model (DEM), zoning information, administrative boundaries, etc (Dewan & Yamaguchi, 2009a; Liberti et al., 2009).

3) Increasing use of spatial information.

Most of image classification methods are based on the statistical analysis of each separate pixel (Agüera et al., 2008). These methods have a good performance when images have relatively low spatial resolution (Wang et al., 2004). However, the spectral variability increases within the same land cover type in the high spatial resolution images. In order to solve this problem, different techniques have been developed that take into account the spatial information, which includes image texture, feature size, shape, etc (Agüera et al., 2008; Puissant et al., 2005). Because spatial based classification involves a more complex decision process, they tend to be much more computationally intensive than spectral based classification (Lillesand et al., 2004).

The choice of the method should consider different factors, such as data availability, costs and requirement of the specific case study.

Change detection is the process of identifying differences in the state of a feature or phenomenon by observing it at different times (Singh, 1989). The goal of remote sensing change detection is to (Im & Jensen, 2005):

- 1) detect the geographic location of change;
- 2) identify the type of change;
- 3) quantify the amount of change.

Change detection is useful in many applications related to land use and land cover changes, such as shifting cultivation and landscape changes (Serra et al., 2008), land degradation and desertification (Adamo & Crews-Meyer, 2006; Liberti et al., 2009), urban landscape pattern change (Mundia & Aniya, 2005; Yuan et al., 2005), deforestation (Rutherford et al., 2008; Shulz et al., 2010). Timely and accurate change detection of land cover provides a better understanding of relationships and interactions between human and natural phenomena. Change detection involves the analysis of multi-temporal datasets to quantitatively assess the temporal effects of the phenomenon.

There are various ways of approaching the use of satellite imagery for determining land cover change in urban environments. Martin (1989) divided the methods for

change detection into two classes: pixel-to-pixel comparison and post-classification comparison.

The first method conducts the pixel-to-pixel comparison of multi-temporal images without classifying the data. This method applies various algorithms, including image differencing (Sohl, 1999) and image ratioing (Nelson, 1983), to single or multiple spectral bands, vegetation indices (Guerra et al., 1998) or principal components (Fung & Ledrew, 1987), directly to multiple temporal images to generate change maps. Prior classification is not necessary for the comparison and errors from classification can therefore be avoided. However, the results of these methods could not provide information about the land cover conversion matrix.

The post classification comparison method is used to compare two or more separately classified images of different dates to produce land cover change maps, in which not only the amount and location of change but also the nature of change can be identified (Howarth & Wickware, 1981; Singh, 1989). In addition, this method can minimize the problems associated with multi-temporal images recorded under different atmospheric and environmental conditions (Lu et al., 2004). A major pitfall, however, the accuracy of change maps is strongly dependent on the accuracy of individual classification results (Yuan et al., 2005).

2.2.2 Urban growth patterns

As discussed above, remote sensing data can be used to provide detailed information about the type, amount, and location of land use conversion. Yet it lacks the ability to describe the underlying urban growth process that is responsible for the changing patterns of urban (Herold et al., 2005). The measurement of urban spatial pattern can fill this gap with allowing a more detailed analysis of the relationships between forms and processes.

Urban growth pattern has been studied in the contexts of urban planning, urban economics, urban geography, and urban sociology (Seto & Fragkias, 2005). The classic Von Thünen (1875) model of land use suggests that the configuration of urban and rural land use reflects transportation costs, land-intensiveness of productive activities and market prices. The spatial patterns of urban areas provide a better understanding of the urban growth process and its impact on environment (Luck & Wu, 2002).

The question then is how to quantify and describe changes in urban spatial patterns. Landscape metrics are already commonly used to quantify the shape and pattern of

vegetation in landscape ecology (Gustafson, 1998). Landscape metrics were developed in the late 1980s and incorporated measures from both information theory and fractal geometry based on a categorical, patch-based representation of a landscape (Herold et al., 2003). Patches are defined as homogenous regions comprising a specific landscape property of interest such as “urban” or “rural” (Dietzel et al., 2005). Landscape metrics are used to quantify the spatial patterns of individual patches, of patches belonging to a common class, and of the entire landscape consisting of all patches. Change of landscape patterns can be detected and described by the landscape metrics, which categorize complex landscape into identifiable patterns and reveal some ecosystem properties that are not directly observable (Antrop & Van Eetvelde, 2000; McGarigal et al., 2012; Schindler et al., 2008; Tian et al., 2014).

Given the background in landscape ecology, Herold et al. (2003) and Herold et al. (2005) used the term “spatial metrics” instead of landscape metrics for the research field of urban area. Spatial metrics characterize urban form, whereas in ecological landscape studies, landscape metrics are explicitly related to ecological functions (Luck & Wu, 2002).

Despite a plenty of spatial metrics were applied to describe spatial structure, they can be grouped into two categories (Table 2-1): those that measure the composition of the map without reference to spatial attributes, and those that measure the spatial configuration of the map (Gustafson, 1998; McGarigal & Marks, 1995). Composition refers to features regarding the variety and abundance of patch types within the landscape, but without considering the spatial character, placement, or location of patches within the mosaic (McGarigal et al., 2012). Spatial configuration refers to the spatial character and arrangement, position, or orientation of patches within a specific class or landscape (McGarigal et al., 2012).

Many different methods in representing spatial concepts have led to the development of various spatial metrics or metric categories as descriptive statistical measurements of spatial structures and patterns (Herold et al., 2005). Fragstats reports over 100 different metrics. Previous studies in the quantification of spatial pattern have suggested that the commonly applied metrics are patch size, number of patches and density, nearest neighborhood distance, fractal dimension, contagion, etc. Before any kinds of applications, these metrics have to be interpreted, analyzed and evaluated regarding their ability in capturing the thematic information of interest (Gustafson,

1998). Many studies suggested and compared a wide variety of different metrics. Their result shows the role of them in representing the composition, configuration of spatial pattern. However, there are not the best suitable metrics as the significance of specific metrics varies with the objective of the study and the characteristics of the spatial pattern under investigation (Parker & Meretsky, 2004). Furthermore, some authors reported that very few of these metrics contain unique information, and thus the calculation or reporting of all of them is redundant (Gustafson, 1998; Li & Wu, 2004).

Recently, there has been an increasing interest in applying spatial metrics in urban environments because they can be a valuable tool for planners and decision makers to better analyze urbanization process and their environmental consequences (Herold et al., 2005; Kim & Ellis, 2009; Pham et al., 2011). The usage of spatial metrics with respect to urban studies can be grouped into three general categories:

1) Quantification of the urban spatial patterns.

A variety of metrics have been developed to quantify urban spatial patterns in the past studies. For instance, Schneider et al. (2005) investigated the spatial distribution of urban development by using spatial metrics (AREA, LSI) along seven urban-to-rural transects identified as key corridors of growth. Seto and Fragkias (2005) effectively compared the spatio-temporal pattern of urban land use changes in four Chinese cities, integrating three concentric zones with a set of spatial metrics (Class Area, NP, AREA, ED, AWMFD). In these studies, the fragmentation, irregularity caused by urbanization have been captured and measured using spatial metrics. These studies demonstrate that spatio-temporal spatial metrics can provide improved description of heterogeneous urban areas.

2) Linking to urbanization process.

A major goal of using spatial metrics is to understand the relationship between the urban spatial patterns and urbanization process. This issue has been identified by numerous of studies. Herold et al. (2003) applied spatial metrics (Class Area, NP, ED, LPI, MNN, AWMFD, CONTAG) to evaluate the impact of urban development in four districts in Santa Barbara, California, USA and to analyze the spatio-temporal dynamics of urban growth. Deng et al. (2009) explored the spatio-temporal dynamics, and evolution of land use and landscape patterns in response to the rapid urbanization process by integrating remote sensing technology and spatial metrics (NP, PD, ED, LPI, AREA, LSI, SHDI, SHEI). Pham et al. (2011) established the

relationship between certain changes of spatial metrics (Class Area, NP, ED, LPI, MNN, AWMFD) and a particular type of city planning based on the analysis of spatio-temporal dynamics of spatial metrics in Hanoi (Vietnam), Nagoya (Japan), Hartford (Connecticut, USA), and Shanghai (China). These studies demonstrate that spatio-temporal dynamics of spatial metrics can provide a link between the physical spatial structure and urban form, functionality and process. The results help to understand and reveal the processes that underlie the land cover change.

3) Interpretation, assessment and verification of urban models.

Alberti and Waddell (2000), Herold et al. (2005) substantiated the importance of spatial metrics in urban modeling. They applied specific spatial metrics to investigate the effects of the complex spatial pattern of urban land cover on social and ecological processes. These metrics allowed for an improved representation of the heterogeneous characteristics of urban areas, and of the impacts of urban development on the environment. A set of spatial metrics were also used in a detailed analysis and comparison of various scenarios simulated by urban models to provide a better understanding of future urban growth patterns (Mitsova et al., 2011; Zhang et al., 2011). From the perspective of investigating urban land-use system, it is crucial for urban models to successfully replicate realistic spatial land-use patterns as well as to predict the locations of new developments (Meentemeyer et al., 2013). Measures such as spatial metrics have been adopted to validate simulation models with respect to aggregate pattern similarity (Liu et al., 2010; Parker & Meretsky, 2004; Sui & Zeng, 2001).

It is widely acknowledged that urbanization is a key cause of changes in urban spatial patterns. Analysis of spatial patterns of landscape diversity and their implications should be regarded as a precondition for applying landscape diversity to assess the impact of urbanization on ecological processes and functions (Yeh & Huang, 2009). Combining gradient analysis with spatial metrics method, considerable studies on the qualitative relationships between urbanization and spatial growth patterns have demonstrated that urbanization plays an important role in the urban growth patterns (Luck and Wu, 2002; Weng, 2007). By adopting block sample, the spatial metric value of each block was plotted against the level of urbanization to represent the correlations between them (Yeh & Huang, 2009). The Ordinary Least Squares (OLS) regression is the primary statistical method, which was widely used to explore the quantitative relationship between spatial patterns and urbanization.

However, results generated from OLS only reflect the average relationships and consequently failed to address the spatial heterogeneities in the effects of urbanization on spatial patterns. The spatial and temporal heterogeneities usually exist in the relationships between factors and urban patterns (Su et al., 2011). In addition, analyzing the change of spatial patterns for one period would overlook the fact that an area experiencing the most intense urbanization is not necessarily static, but could shift its location within the urbanization process, so that the characteristics of urbanization process cannot be fully captured.

Table 2-1: Classification of landscape metrics

Principle aspects (measures)	Description	Commonly used metrics
Composition		
Proportional abundance	Proportion of each class relative to the entire map	Class Area (CA), Percentage of Landscape (PLAND), Patch richness (PR), Shannon's diversity index (SHDI), Shannon's evenness index (SHEI)
Richness	Number of different patch types	
Evenness	Relative abundance of different patch types	
Diversity	Composite measure of richness and evenness	
Spatial Configuration		
Patch size distribution and density	Fundamental attribute of the spatial character of a patch	Patch Area (AREA), Number of patches (NP), Patch density (PD), Edge density (ED), Largest patch index (LPI), Landscape shape index (LSI), Shape index (SHAPE), Area weighted mean fractal dimension (AWMFD), Euclidean nearest neighbor distance (ENN)
Patch shape complexity	Geometry of patches (simple and compact or irregular and convoluted)	
Core Area	Interior area of patches after a user-specified edge buffer is eliminated	
Isolation /Proximity	Tendency for patches to be relatively isolated in space from other patches of the same or similar class	
Contrast	Relative difference among patch types	
Dispersion	Tendency for patches to be regularly or contagiously distributed (i.e., clumped) with respect to each other	
Contagion & Interspersion	Tendency of patch types to be spatially aggregated	
Subdivision	Degree to which a patch type is broken up (i.e., subdivided) into separate patches	
Connectivity	Functional connections among patches	

Source: Own illustration; based on McGarigal 2012

2.2.3 Driving factors

It is important to understand several factors directly or indirectly contributing to urban growth. There has been an increasing interest in identifying and understanding the effects of the driving factors on urban land cover change because this knowledge is crucial not only for the development of spatial models (Arsanjani et al., 2013; Zheng et al., 2012), but also more important for effective urban planning and management strategies (Dubovyk et al., 2011; Thapa & Murayama, 2010; Wu & Zhang, 2012).

“What drives/causes urban growth?” has always been one of the most common research questions. Urban growth can be described by the complex interaction of behaviours and structural factors associated with the demand, technological capacity, social relations, and the nature of the environment (Lambin et al., 2001; Verburg et al., 2004a). However, there are no standard driving factors that are responsible for urban growth.

Various factors and their effects on urban growth have been identified in previous studies. The selection of the factors that are involved in the specific analysis often relies on prior understanding of the underlying processes of urban growth. According to the literature review, these factors considered in studies of urban land cover change can be grouped into four classes (Table 2-2): (1) natural factors, (2) socioeconomic factors, (3) spatial policies, and (4) neighborhood factors.

In urban environment, natural factors are correlated with the suitability and costs of a location for development. Topography often determines the location of new urban area because flat areas are suitable for urban development (Li et al., 2013a). Each location has a specific soil characteristic that determines the production of agricultural vegetation. The good quality agricultural land is not suitable for urban development in order to sustain future food supply (Li & Yeh, 2000).

Socioeconomic factors are the most important factors of urban growth. A wide range of urban growth studies are based on socioeconomic theory. Urban economists identify three underlying driving factors that contribute to the urban growth: population growth, rising household incomes, and accessibility improvement (Mieszkowski & Mills, 1993). Urban area must extend to a larger area to accommodate more people. In order to promote life quality, households need more living space as they become richer. In addition, they focus on the site characteristics of live space, including housing prices, level of services, quality of landscapes (Geoghegan et al., 1997; Mertens et al., 2000). Other than census based socioeconomic variables, accessibility also strongly affects urban growth (Hu & Lo, 2007; Linard et al., 2013). The improvement accessibility indicates faster and more convenient travel and lower commuting costs. Verburg et al. (2004a) pointed out that “the influence of the socioeconomic conditions in the region can be best characterized by the access that a location has to these facilities.”

Spatial policies at national or regional level have significant impacts on land cover change (Dieleman & Wegener, 2004). They define the legal regulations for future

land uses (Barredo et al., 2003). In particular, spatial policies can affect the urban development in two aspects. One is to serve as an accelerating factor to promote more new development in areas planned or proposed for development (Cheng & Masser, 2003), and the other is as a constraint to limit the development within a specific region, for example, the conservational or protected areas (Long et al., 2012; Verburg et al., 2004a).

“Everything is related to everything else, but near things are more related than distant things.” The neighborhood factor is related with the Tobler’s (1970) first law of geography. Land cannot be developed independently at each individual location; land cover patterns nearly always show spatial autocorrelation caused by a number of attraction and repulsion forces (Overmars et al., 2003). It is especially important to consider the neighborhood effect due to the fact that urban development can be regarded as a self-organizing system (Verburg et al., 2004b). A large number of studies demonstrated that locations are more likely to be converted to urban area if they are surrounded by more urban land. Neighborhood factors are introduced to consider the possible effects of spatial interaction and neighborhood characteristics by different approaches. For instance, the proportion of urban land and some other land cover types in the neighborhood of a cell (Braumoh & Onishi, 2007; He et al., 2008; Hu & Lo, 2007; Long et al., 2012); distance to existing urban areas (Poelmans & Van Rompaey, 2009).

2.3 Urban growth modeling

2.3.1 Overview of urban growth models

A model is a simplified representation of a physical system. By using models, the behavior and future evolution of the systems can be simulated. Therefore, they can be used as interpretative tools for analyzing system dynamics, and providing hints for data collection and design of experiments (Giudici, 2002). Urban models are the representations of functions and processes which produce urban spatial structure in terms of land cover, population, and transportation, commonly embodied in computer programs (Batty, 2009).

Modeling of urban growth process is an important technique to provide a better understanding of causes and mechanisms governing urban growth; to analyze alternative urban growth consequences, therefore, to support the appropriate urban planning and decision making responses to urban growth (Berling-wolff & Wu, 2004; Lambin et al., 2000; Li, 2011). Models of urban growth can be applied to predict the spatial pattern of changes by addressing the question “where are urban growth taking place?” or the rates of change by addressing the question “at what rate are growth likely to progress?” These two questions are associated with the location issue and the quantity issue (Pontius & Schneider, 2001).

Before the 1950s, most urban growth models were developed based on spatial economic theory. One of the most famous models is Von Thünen’s model based on land rent theory of concentric rings. In this model, the conversion to agriculture is influenced by the distance to the market. Land close to the market is used most intensively and the value of land decreases as the distance increases. Other models that were proposed during this period include Weber’s (1909) classical triangular model of industrial location, Christaller’s (1933) model of central places and Lösch’s (1940) theory of economic regions.

Since the 1950s, with the rapid development in computing, computer-based urban modeling has received many attentions. The early urban growth models were rooted in regional planning, concerned with the models of transportation and land use (Berling-wolff & Wu, 2004). Microeconomic and behavioral theories were the basis of these models. These models focus on individual land owners who make decisions with the objective to maximize expected gains from land (Harris, 1985). The Lowry model is one of the most well-known and used models of this type. It was first developed by Lowry (1964) to simulate the locations of residential and service

development. However, most of these traditional models cannot represent the complexity of urban growth system because they try to capture the totality of the urban system in a single model (Batty, 1979; Berling-wolff & Wu, 2004). In addition, these models do not take spatial dimension into consideration. White and Engelen (1993) pointed out that the spatial aggregate nature of the simulation results and the strong dependence on the general equilibrium assumption restrict their ability in urban planning and decision making.

Since the end of the 1980s, significant advances in the spatial representation of urban growth occurred (Couclelis, 1989). Spatially explicit urban growth models became the dominant modeling framework. Different models approaches have been used. According to modeling approach, the models can be classified into five groups, mathematical/statistical models, GIS based models, CA based models, agent based models, and rule-based models (Silva & Wu, 2012). For example, as a GIS based model, CLUE (Conversion of Land Use and its Effects) model (Verburg et al., 2001) can simulate the land use changes based on suitability of locations for specific land use types. The suitability is identified by considering a large number of factors including biophysical and socio-economic factors. However, the models do not consider the interactions in the neighborhood, which play an important role in land use change. The rule based models, such as UrbanSim model (Waddel, 2002) is a simulation system for supporting analysis and planning of urban development with considering the interactions between land use, transportation, the economy and the environment.

However, it is widely acknowledged that urban development is a complex dynamic process (Xie, 1996; Torrens, 2000), which involves a large number of physical and socioeconomic factors. The complexity occurs from the unknown amount of factors, the complex interactions among factors and their unpredictable dynamics. As discussed in chapter 2.1.4, cities are characterized by four signatures: fractal dimensionality, self-similarity, self-organization, and emergent. This suggests modeling city dynamics should deal with these characteristics. Torrens (2001) identified following key weaknesses for traditional urban models: “their centralized approaches, a poor treatment of dynamics, weak attention to detail, shortcomings in usability, reduced flexibility and a lack of realism”.

The great developments in computer techniques and in the areas of complex analysis had significant impacts on the approach in urban modeling. A modeling

framework that captures and simulates this complex behavior is essential for urban growth studies, such as agent and CA based models (Batty, 2005; Rickwood, 2011; Torrens, 2001).

CA based models are dynamic models for simulating the evolution of a system using local transition rules. They are able to handle large amounts of data and many fields of studies, such as population, land use, socioeconomic activity (Batty, 2005). CA based models are a powerful tool for representing and simulating spatial processes underlying the spatial decisions due to their simplicity, flexibility, and intuitiveness (Gronewold & Sonnenschein, 1998; Santé et al., 2010; Wu and Silva, 2010;). Temporal and spatial complexity of urban growth process can also be well modelled using CA based models (Barredo et al., 2003; White & Engelen, 2000; Wu & Webster, 1998). Additionally, CA models have become an experimental tool for urban planning by producing different scenarios under various urban planning policies (Fuglsang et al., 2013; Li, 2011). So far, CA based models are among the most popular ways to simulate the evolution of urban growth.

2.3.2 Basic concept of CA

CA was first introduced in 1948 by Von Neumann and Ulam and soon applied to physics and mathematical science (White & Engelen, 1993). The 'game of life' developed in 1970 by mathematician Conway can be regarded as an explicit CA game, in which the temporal change of a cell depends on its current state and the states of its neighboring cells (Gardner, 1970). It contributed to the wide application of CA design. Recognizing the advantages of CA models, Tobler (1979) first proposed the application of cellular space models to geographic modeling. Furthermore, Wolfram (1984) proved that complex natural phenomena can be modeled by CA models, but did not apply them to the specific cities. However, since then various CA models have been developed to gain insights into the processes and consequences of urban evolution for different countries and regions in the world (Arsanjani et al., 2013; Clarke et al., 1997; He et al., 2008; Li & Yeh, 2002a; Thinh & Vogel, 2005a; Wu & Webster, 1998; Xie, 1996).

CA models are of special interest in modeling urban systems because of several advantages. Firstly, CA is a discrete dynamical system, and its structure offers a capacity for modeling dynamic and complex spatial system (Wolfram, 1984). Secondly, CA can be easily incorporated with GIS and RS because it operates on a lattice, raster-format geographic data (Batty et al., 1999; Couclelis, 1997), and

consequently it can work at high spatial resolution with computational efficiency. Thirdly, the models' results are a set of land-use maps, which are easily be visualized, quantified and analyzed (Jantz et al., 2004). In addition, the process being modeled is entirely represented in transition rules, allowing the link between the patterns and the underlying processes (Torrens, 2000). Furthermore, there is an increasing need for a high level of spatial detail in applications related to decision making processes, and CA models satisfy this need (Torrens, 2000). One of the remarkable advantages of CA is its capacity to represent very complex behaviors only using some simple transition rules (Lorek & Sonnenschein, 1999; White & Engelen, 1993; Yeh & Li, 2002)

These models have two different types of important tasks: simulation and optimization. Simulation aims to develop realistic scenarios under specific conditions, whereas optimization is to provide an optimal solution for planning problem. By combining simulation with optimization, these models can assist planners in predicting the consequences of changes occurring under different conditions (Li, 2011).

A CA based model is a dynamic model using local interactions to simulate the evolution of a system, which is often composed by four elements: the cells, states, the neighborhoods and the transition rules to determine cells' state change (Barredo et al., 2003; White & Engelen, 1997). The original formalism of CA is simple, but can be perceived as too limited when applied in urban simulation (Couclelis, 1997; O'Sullivan, 2001). Many alterations have been made over the years to adapt CA to urban simulation. The major transformations to CA relate primarily to the transition rules and to the neighborhood.

Cells

Cells are the smallest units which must manifest some adjacency or proximity (Li & Yeh, 2000). They are typically represented by a regular grid of two dimensions usually composed of square cells, although some researchers have proposed hexagonal cells to obtain a more homogeneous neighborhood (Iovine et al., 2005). Moreover, the regular cell can be modified by using irregular tessellations such as Voronoi polygons (Shi & Pang, 2000) or land parcels (Stevens & Dragicevic, 2007). Irregular cell may provide a more realistic representation of the objects being modeled (Santé et al., 2010).

The cell size is the area of the landscape each cell will cover. In the application in urban growth modeling, the scale of cells varies significantly. For instance, Li and Yeh (2000) used 100 meters cell size to simulate urban land use pattern for Dongguan city in China. Clarke et al. (1997) used 300 meters cell size for the San Francisco Bay area. However, when applying the model to the Washington/Baltimore region, the cell size of 210, 420, 840 and 1680 meters were adopted respectively (Clarke & Gaydos, 1998). Ménard and Marceau (2005) and Pan et al. (2010) explored the sensitivity of CA model to cell size and highlighted the importance of adjusting cell size to the specific study.

Cell states

Each cell has a finite number of states which characterize the cell. In urban CA model, states can be binary values to represent two land cover types, urban or non-urban (Fuglsang et al., 2013; Li & Yeh, 2004; Zhang et al., 2011). Moreover, the states can also be qualitative values that represent different land use types (Lau & Kam, 2005), and quantitative values that represent urban land development, for example, Li and Yeh (2000) used grey cells to represent the percentages of urban land during the iterations of modeling for more accurate results, Wu (1998a) and Yeh and Li (2002) used the cell states to represent population density. Cell states may also consist of vectors representing a number of attributes (Portugali & Benenson, 1995). Each cell can only take one state at a time, and the state is updated synchronously at each discrete time step according to a set of transition rules and its previous state.

Neighborhood

A neighborhood is a set of one or more locations that are within a specific distance and/or have a relationship to the particular location (Verburg et al., 2004b). A cell's neighborhood is the region that serves as an input to assess the neighborhood effect in the transition rules. This effect is calculated as a function of a cell's own state and the state of the cells within its neighborhood. The neighborhood configuration determines the distribution and number of neighborhood cells that will affect the evolution of each central cell (Ménard & Marceau, 2005). Neighborhood configuration in a CA is generally characterized by neighborhood size and shape (Barredo & Demicheli, 2003). Through sensitivity analysis, Ménard and Marceau (2005) and Kocabas and Dragicevic (2006) demonstrated that neighborhood size and type

significantly affect the performance of CA model employed for land use change modeling.

The traditional neighborhood types for two-dimensional raster based CA models are: Von Neumann neighborhood and rectangular (Moore) neighborhood. The Von Neumann neighborhood consists of four cells which are arranged horizontal and vertical to the central cell. The Moore neighborhood extends the Von Neumann neighborhood by including the diagonal cells, which are commonly used in CA model applications (Al-kheder et al., 2008; Lau & Kam, 2005; Wu & Webster, 1998). Li and Yeh (2000) proposed that the use of a rectangular neighborhood such as Moore might produce significant distortions between cells at different directions. In contrast, the circular neighborhood has no bias in all directions, which was adopted by many studies in order to improve the model's performance (He et al., 2008; White et al., 1997).

Neighborhood size defines the extent of interactions between land use and the dynamics of the system (Caruso et al., 2005). Originally, only direct and diagonally adjacent cells were considered in a neighborhood space in strict CA, such as traditional Von Neumann and Moore neighborhood types. In the case of urban systems, however, neighborhood space may be much larger, since people and institutions can affect their surroundings in a larger space. Thus, it is necessary to extent local neighborhood in order to consider the influence of cells at greater distances (Santé et al., 2010). In practice, some researchers empirically determined the optimal neighborhood size (Verburg et al., 2004b; Zhang et al., 2011), others determined the size based on a calibrated procedure, such as a sensitive analysis (Caruso et al., 2005). Ménard and Marceau (2005) concluded, from the neighborhood configuration in 17 different studies covering nearly 10 years, that the applicable neighborhood radius ranged from 1 to 8, the number of involved cells also varied.

In general, the effect of neighborhood cell decreases with the increasing distance to the central cell. Each cell in the neighborhood should receive a calibrated weight according to its state and the distance to the central cell. Some researchers proposed that neighborhood effect of different cells may be considered as an approximation of distance decay (Barredo et al., 2003; He et al., 2008). A distance decay function is usually introduced in defining neighborhood, so that the effect of a neighborhood cell decreases with the increase in distance between both cells.

Transition rules

The definition of the transition rules of a CA model is the most important part to achieve realistic simulations of land use and land cover change (Verburg et al., 2004b). “They represent the logic of the process which is being modeled, and thus determine the spatial dynamics which result” (White & Engelen, 2000). The traditional transition rules are dependent on the current cell state and its neighborhood effects (Jenerette & Wu, 2001; Yüzer, 2004). In the context of urban growth, however, a variety of factors have significant impacts on urban growth, such as physical suitability for a specific land use, accessibility, socioeconomic factors, urban planning factors, and stochastic disturbance related to the complexity of human system. Consequently, the CA model cannot generate observed urban pattern by using a traditional transition rule without considering various factors. The transition rules involving the effects of different factors, allow for more realistic simulation (Arsanjani et al., 2013; Han et al., 2009; He et al., 2008).

Furthermore, traditional CA models employ only one uniform transition rule for different periods and sub-regions, while the urban growth process may vary over time and space. Therefore, it is necessary to apply different transition rules to the specific characteristics of each period and area. Spatial and temporal varying transition rules can be obtained by calibration (Geertman et al., 2007; Long et al., 2009).

2.3.3 Challenges related to CA modeling

There are several challenges associated with developing a precise CA model to understand urban dynamics. In this dissertation, three key challenges need to be addressed. The first one is associated with developing appropriate transition rules, the second one is related to appropriate method for calibrating and validating the CA models with the increasing number of factors. The last one involves the design and development of scenarios.

2.3.3.1 The definition of transition rules

The definition of the CA rule remains a research issue, despite the emergence of CA as an effective analysis tool in urban growth simulation (Batty, 1998). Transition rules are usually dependent on the specific applications (Li & Yeh, 2002a). According to the methods used in defining the transition rules, Santé et al (2010) classified the existing transition rules into five main types:

- 1) Strictly orthodox transition rules. For example, Jenerette and Wu (2001) and Yüzer (2004) determined the probability of a cell changing as a function of the

neighborhood effect and cell state. It cannot involve the other factors that have significant impacts on urban growth.

- 2) Transition rules based on transition potential. In this type, the key driver of urban development is the transition potential, which is calculated as a function of the current state of cell, its neighborhood and other factors that influence the urban development (Thin & Vogel, 2005b; Wu, 1998a; Wu & Webster, 1998). Various methods have been chosen to calculate the transition potential. Wu & Webster (1998) defined development probabilities of cells using Multi-Criteria Evaluation (MCE), which incorporates multiple factors as a linear weighted sum. Wu (2002) proposed a logistic regression to calculate the transition potential. In addition, transition potential is calculated using more complex functions and more factors. For example, Li and Yeh (2002b) used PCA to identify the factors used in transition rules. He et al. (2008) calculated the transition potential with consideration of the spatial interaction of capital and population.
- 3) Transition rules based on urban shape and form (Clarke et al., 1997; Jantz et al., 2010; Yang & Lo, 2003). A typical example of this type of transition rules is found in SLEUTH model developed by Clarke et al. (1997). SLEUTH is a pattern based model, which simulates urban dynamics through the application of four growth types: spontaneous growth, new spreading center growth, edge growth, and road-influenced growth. Each growth type is determined by an area wide coefficient: diffusion, breed, spread, road growth that reflect the relative contribution of a particular growth type to urban dynamics within a study area. However, the transition rules of SLEUTH cannot allow for the analysis of the causes of the spatial patterns simulated.
- 4) Transition rules based on artificial intelligence methods. Although the aforementioned models are probably the most frequent, a wide variety of urban CA models may be found in the literature based on neural networks (Li & Yeh, 2002a), kernel-based learning method (Liu et al., 2008) and SVM (Yang et al., 2008). They have been proved to simplify CA models but generate more plausible results. However, using of artificial intelligence methods is not so straightforward to achieve a good understanding of the underlying process.
- 5) Transition rules based on fuzzy logic. The aforementioned CA models formulated their transition rules for urban development based on probability theory. The fuzzy logic allows the uncertainty of human behavior to be considered in the simulation and the definition of transition rules through natural language (Al-kheder et al., 2008; Santé et al., 2010). However, fuzzy logic transition rules have difficulties in representing very complex relationships. Furthermore, the choice of fuzzy functions is subjective and largely affects the results.

2.3.3.2 Calibration and validation

Rykiel (1996) defined calibration as “the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set”. Calibration is the basis of their successful implementation because it provides a tool to ensure that models can conduct accurate and reasonable simulation regarding current and future urban growth scenarios (Wu, 2002). The need for stronger calibration techniques for CA model is also noted by Torrens and O’Sullivan (2001).

However, the calibration of CA model is difficult because of the many interacting variables involved (Li & Yeh, 2002a; Pan et al., 2010). There are two traditional calibration methods for CA simulation. One type is based on trial and error method. It does not require strict mathematical methods. It is conducted by running the model many times with different combinations of parameter values. Even though the method can identify the suitable parameter values, it is very computation-intensive especially when many parameters need to be estimated. (Li & Yeh, 2002a; Santé et al., 2010).

Other type is based on statistical techniques. With an increase in the number of parameters and better computational resources, automated calibration procedures have become feasible. A well-defined mathematical function, or a function with a few parameters, can be optimized mathematically. Wu (1998a) proposed a structured procedure based on the Analytic Hierarchy Process (AHP) to identify the parameter values for MCE in a heuristic way. However, the AHP method is overly subjective because of the preferences of decision makers. In addition it cannot identify historical urban development process as the weight values keep constant for the whole study area and period (Cheng & Masser, 2004). The other most widely used method for calibration is logistic regression firstly used by Wu (1998b). An advantage of the logistic regression is its ability to estimate the parameter values by developing statistical relationships between historical land cover change and variables (Arsanjani et al., 2013; Ward et al., 2000). Both of AHP and the logistic regression method are inherently linear and consequently unable to deal with complex relationships among a large number of spatial variables in urban growth process.

Openshaw and Openshaw (1997) argued that techniques from the broader field of artificial or computational intelligence might be used effectively when there are a large number of parameters need to be estimated. Li and Yeh (2002a) proposed ANN to calibrate CA models. In their method, the neural network is used to achieve the optimal parameter values automatically based on the training data. However, the meaning of the parameter values might be difficult to interpret because of the black-box nature of neural network (Straatman et al., 2004). Consequently it is not ideal to reflect the logic of land conversion or spatio-temporal processes (Wu, 2002). More recently, a number of authors studied the application of more efficient methods such as SVM (Yang et al., 2008) and kernel-based method (Liu et al., 2008) for the calibration of CA models. Other automated methods for calibration include the use of

a Genetic Algorithm (GA) to calibrate the parameters of the transition rules (Al-Ahmadi et al., 2009). GA has capabilities in dealing with a lot of complex optimization problems because specific programs are not required (Li et al., 2008). However, it is not clear how either method provides any additional knowledge about the development of the urban system. It is impossible to perform “what-if” experiments on the transitions by modifying the parameter values to reflect different urban development policy (Straatman et al., 2004).

Although various methods have been explored for calibration, there is not general method to calibrate urban CA models because the objectives and structure of these models are different. Wu (2002) argued that the calibration is dependent on the objective of the simulation.

Validation of the CA model is also another challenge to CA applications. Validation is conducted by comparing the simulated results with observed maps in order to assess the performance of CA models with different combination of parameters. Wu (2002) argued that the “measure of model performance itself is a controversial issue”. Many applications used a visual comparison as qualitative validation to confirm the simulated results (Al-Ahmadi et al., 2009; Li & Yeh, 2004; Yang et al., 2008). Mandelbrot (1982) suggested that visual comparison is a very powerful tool for complex fractal forms. The advantage is reflected in its capability to easily highlight locational differences between the simulated results and observed data.

Most studies also explored various indicators to measure the degree of coincidence between two maps, they can be classified into two types: locational and pattern indicators (Jenerette & Wu, 2001). The kappa index is the widely used for measuring the locational agreement between two maps based on cell by cell comparison. More recently, the indicator of figure of merit proposed by Pontius et al. (2007) received more attentions. It allows for assessment of the locational agreement between simulated and real maps in a more realistic way than more common indicators as Kappa index and overall accuracy which are usually calculated using the entire area without excluding the area with fixed land use (Santé et al., 2010).

For a long time, accurate simulation of land use change in terms of locational agreement indicators is considered as a fundamental for CA modeling. For investigating urban dynamics, however, it is also crucial for CA models to successfully reproduce realistic spatial patterns as well as to predict the locations of new developments (Meentemeyer et al., 2013). Furthermore, Jantz and Goetz (2005)

argued that the likelihood that a simulation algorithm matches the exact location of land use change is very low and not necessary. This requires that the model should be validated to identify whether the model can capture the basic features of urban land use, for example, the spatial pattern similarity between simulated and observed urban land use. Wu (2002) used Moran's I index to reveal the pattern of clustering of the same type of use at adjacent cells. Clarke and Gaydos (1998) adopted four indicators (three r-squared fits between the actual and simulated data, modified Lee-Sallee indicator) related to spatial structure to assess the performance of SLEUTH model. As the wide use of spatial metrics, different spatial metrics were adopted to objectively characterize the urban patterns in order to make quantitative comparisons and to determine whether simulated patterns are more complex or compact than the actual ones (Chen et al., 2013; García et al., 2012; Li et al., 2008).

2.3.3.3 Design and development of scenario

Scenarios are one "instrument for strategic thinking and option search" (Xiang & Clarke, 2003). Urban development scenario as a means of optimizing and predicting possible future alternative has been used by planner for several decades (Aguilera et al., 2011; Fuglsang et al., 2013; Song et al., 2006). "At root, land-development scenarios are composed images of an area's land-use patterns that would result from particular land-use plans, policies, and regulations if they were actually adopted and implemented at a certain point of time" (Xiang & Clarke, 2003). Xiang & Clarke (2003) explored five components in land development scenarios: (1) alternatives, which represent the range of potential choices of land-use plans, policies, and regulations. (2) consequences, which represent the impact that each alternative would have on an area's land-development futures; (3) causations, which represent the causal linkage between alternatives and consequences; (4) time frames, which represent the periods between implementation of the alternatives and the consequences; and (5) geographical footprints, which mean "the place-oriented blueprints of alternatives, and the anticipated marks of their ramifications on the geography of an area".

The integration of CA model and GIS has a potential to explore different urban development scenarios under various policies. The simulation serves as not only a matter of visualization but also a bridge between urban growth patterns and decision making (Wu, 1998a). It is not likely that the scenarios will be able to predict the most likely prospect of the future; they will more likely present a range of possible future

alternatives which help manage decisions based on the interpretation of scenarios. The design of scenarios is strongly linked to the current existing concerns of the decision makers of the region addressing the key question. The development of various scenarios becomes increasingly important in urban and regional planning, which can be attributed to:

- 1) Planners can test a set of hypothetical development strategies, matching with a specific goal;
- 2) Planners can consider explicit assumptions to simulate different alternatives;
- 3) Planners can search for ways to achieve specific goals and to inform the decision makers (Song et al., 2006).

Many studies have investigated different aspects of scenarios which are designed under the consideration of different urban development policies in specific areas. For example, Shen et al. (2009) tested two different scenarios of population densities (high and low) to simulate future land use system in Hong Kong. Zhang et al. (2011) investigated three different scenarios (baseline, service oriented center, and manufacturing dominant center) using Markov chain analysis and CA to understand the spatial-temporal dynamics of Shanghai, China. He et al. (2006) simulated the growth of Beijing using different urban land protection policies under the restrictions of water shortage. Long et al. (2012) generated two urban expansion scenarios (baseline and planning-strengthened) using logistic regression based CA model to evaluate the effect of planning on urban development in Beijing, China. Thapa and Murayama (2012) defined three scenarios (spontaneous, environment-protecting, and resources-saving) to optimize spatial patterns of future urban growth in Kathmandu, Nepal. Fuglsang et al. (2013) modeled the growth of Copenhagen metropolitan area under three scenarios (business as usual, growth within limits, new welfare).

Xiang and Clarke (2003) proposed three criterions of good scenarios. First, a good scenario creates surprising and plausible future development. Second, good scenario makes good use of vivid information. Finally, the design of scenarios should be carefully chosen so that the scenarios can interact with the decision makers effectively.

Furthermore, it is important to evaluate the scenarios to investigate the consequences of different scenarios and to inform the planners about the performance of each scenario in achieving different objectives. The scenario evaluation is a process of analyzing possible future events by considering alternative

possible outcomes, which can be challenging and time consuming (Song et al., 2006; Wen et al., 2005). Many researchers argued that scenario evaluation should be a key aspect of land use modeling in order to test and compare different land-use planning policies (Thapa & Murayama, 2012; Zhang et al., 2011). There has been an increasing interest for evaluating urban development scenarios. For example, various spatial metrics have been widely used to evaluate and compare the scenarios, such as edge density, number of patches, area weighted mean shape index, etc (Aguilera et al., 2011; Mitsova et al., 2011; Petrov et al., 2009; Zhang et al., 2011). This can be attributed to their usefulness for quantification and interpretation of land use patterns. They make the processes and patterns of urban development more prominent. Besides this general analysis, only a few researches have been done on the evaluation of scenarios by other more detailed analysis, such as those that use spatial metrics at local scales to better localize changes in land occupation patterns (Aguilera et al., 2011; Thapa & Murayama, 2012).

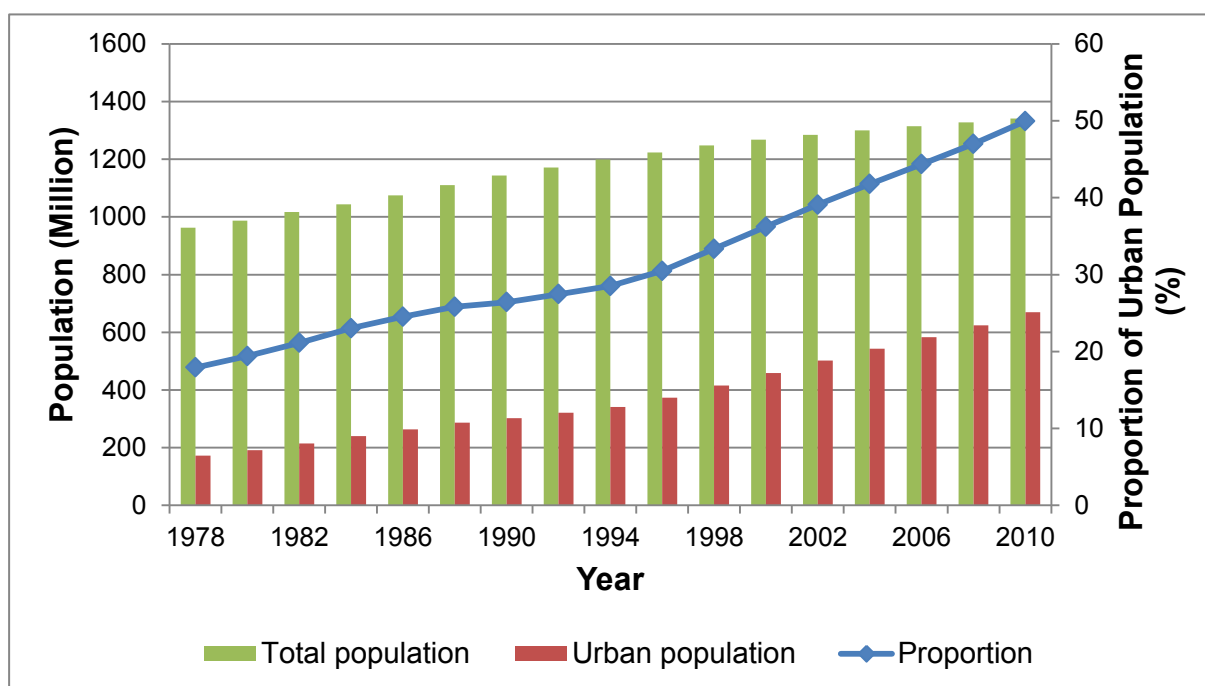
3. Introduction of the study area

This chapter firstly mainly introduces the study area of Xuzhou city in China. Based on the objective of the study, a spatial database is further described, which includes the RS images and other spatial variables. In order to compare with Xuzhou city and to highlight the importance of the study in Xuzhou city, Dortmund city region is also introduced.

3.1 Urbanization process in China

China, as the largest developing country in the world, has been experiencing unprecedented economic growth since the implementation of “Reform and Open Policy” in 1978. Rapid rates of urbanization occurred as a result of its fast growing economic development. Figure 3-1 shows that the urban population rapidly increased from 172.45 million in 1978 to 669.78 million in 2010 with the annual rate of 4.3 %. In 2010, the proportion of urban population in China reached about 50 %. With China’s continuous rapid economic development and government’s promotion of urbanization, it is estimated that about 331.83 million people will be added to China’s urban population by 2050, the proportion will reach 77.3 % (United Nations, 2012). Intensification of economic functions and population growth in urban areas has increased demand for urban developments such as factories and residences.

Figure 3-1: Population dynamics in China from 1978 to 2010



Source: Own illustration; based on United Nations, 2012

Consequently, along with fast economic development and rapid urbanization process, new cities are sprouting up and the existing ones are being restructured and expanded throughout China. The total number of cities increased from 193 in 1978 to 660 in 2008 (National Bureau of Statistics of China, 2009). From 1985 to 2010, built-up areas increased 2.4 fold in China. Meanwhile, a series of development strategies, including “Western Development”, “Revitalization of Northeast”, “Rising of Central China” and so on have been implemented across the country. The land cover patterns of urban areas have undergone a dramatic change.

3.2 Study area

Xuzhou city (between latitudes 33°43′ N and 34°58′ N, longitudes 116°22′ E and 118°40′ E) is situated in the plains of the Yellow River and the Huaihe River. This area has a monsoon-influenced humid subtropical climate, with an average annual temperature of 14.5 °C and annual precipitation within this area varies widely from 800 to 900 mm, all of which are beneficial for agricultural production. Topographically, the Beijing-Hangzhou Grand Canal and old Yellow River are the major rivers in this area. Most of area is flat with a surface elevation ranging from 30 to 40 m.

It has a total administrative area of approximately 11,258 km², with 1,160 km² as the city proper area. It is regarded as a medium-sized metropolitan area in comparison to other cities in China. Xuzhou city is composed of ten county-level divisions, five counties (Peixian, Fengxian, Suining, Pizhou, and Xinyi), and five municipal districts (Quanshan, Gulou, Yunlong, Jiawang, and Tongshan). As shown in Figure 3-2, the five municipal districts are identified as the study area. Traditionally, they are viewed as the central city, in which Quanshan, Gulou and Yunlong are composed of city proper area. Jiawang and Tongshan are composed of fringe and rural areas. Mining and industrial manufacturing have been the source of the strong economic activity of the region. Xuzhou city is well known as one of the most important transportation hubs in China. Jinghu Railway (Beijing to Shanghai), Longhai Railway (Lianyungang to Lanzhou), and some other national main roads provide a good opportunity for development. Benefiting from its industrialization, dramatic changes in local economy have taken place in recent decades. Figure 3-3 shows that the Gross Domestic Product (GDP) of Xuzhou city increased from 2.1 billion RMB in 1979 to 294.2 billion RMB in 2010. Its GDP ranked 37th compared to other cities in China. Furthermore the GDP of central city amounted to more than half of the total GDP of Xuzhou city, while

its population is about 30 % of the total population. Along with this dramatic economic growth, the total population increased by 50.7 % from 6.45 million in 1978 to 9.72 million in 2010, and the proportion of urban population increased from 10.4 % to 53.2 % (Bureau of Statistics of Xuzhou, 2011). As shown in Figure 3-4, the industry structure has been adjusted significantly. The primary industry provides 9.6 % of the total GDP; 50.7 % and 39.7 % are provided by the secondary industry and tertiary industry, respectively. However, the contribution of these to GDP is 44 %, 41.8 % and 14.2 % respectively in 1978 (Bureau of Statistics of Xuzhou, 2011).

Figure 3-2: Location of study area (Xuzhou) and its topography

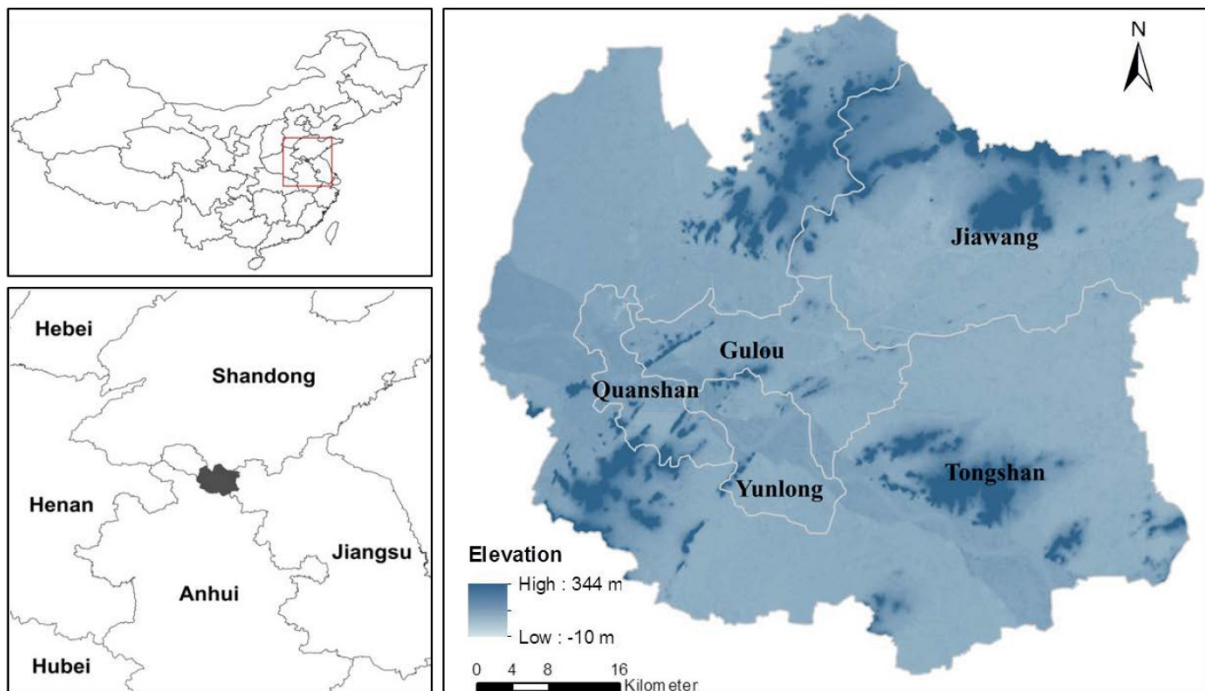
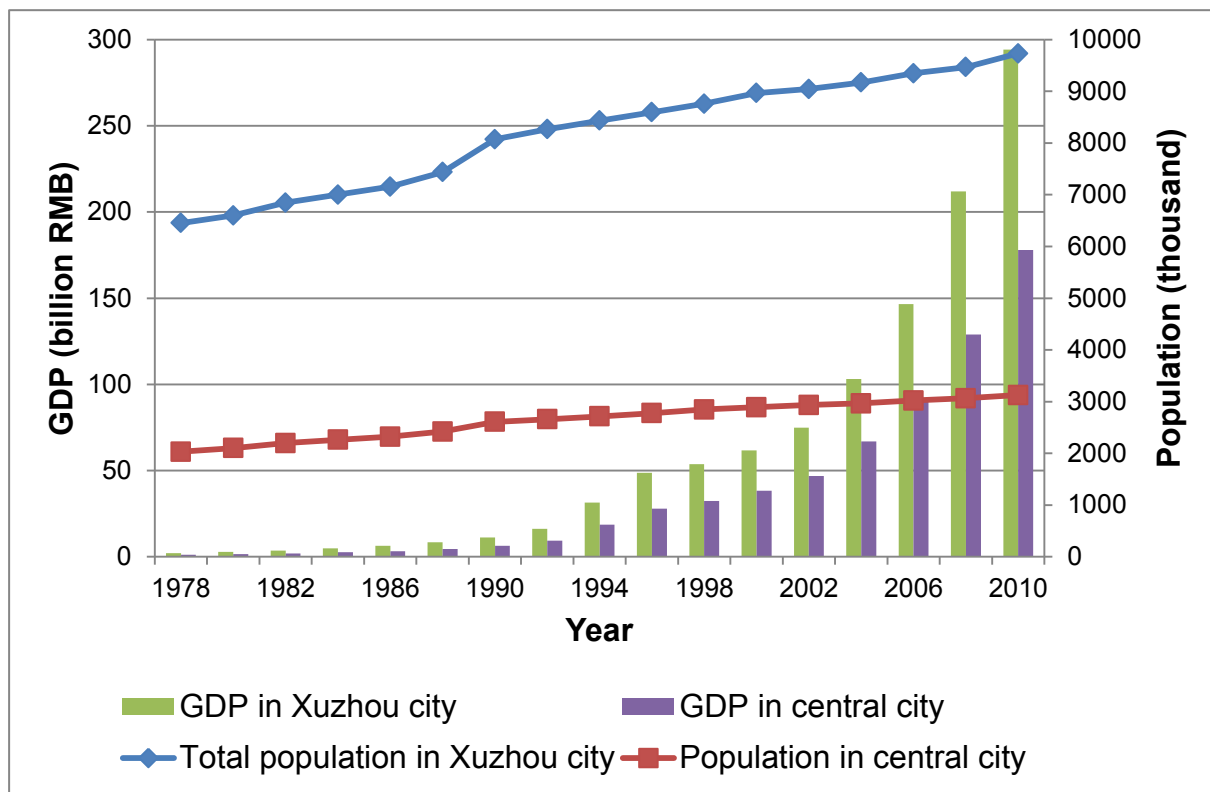
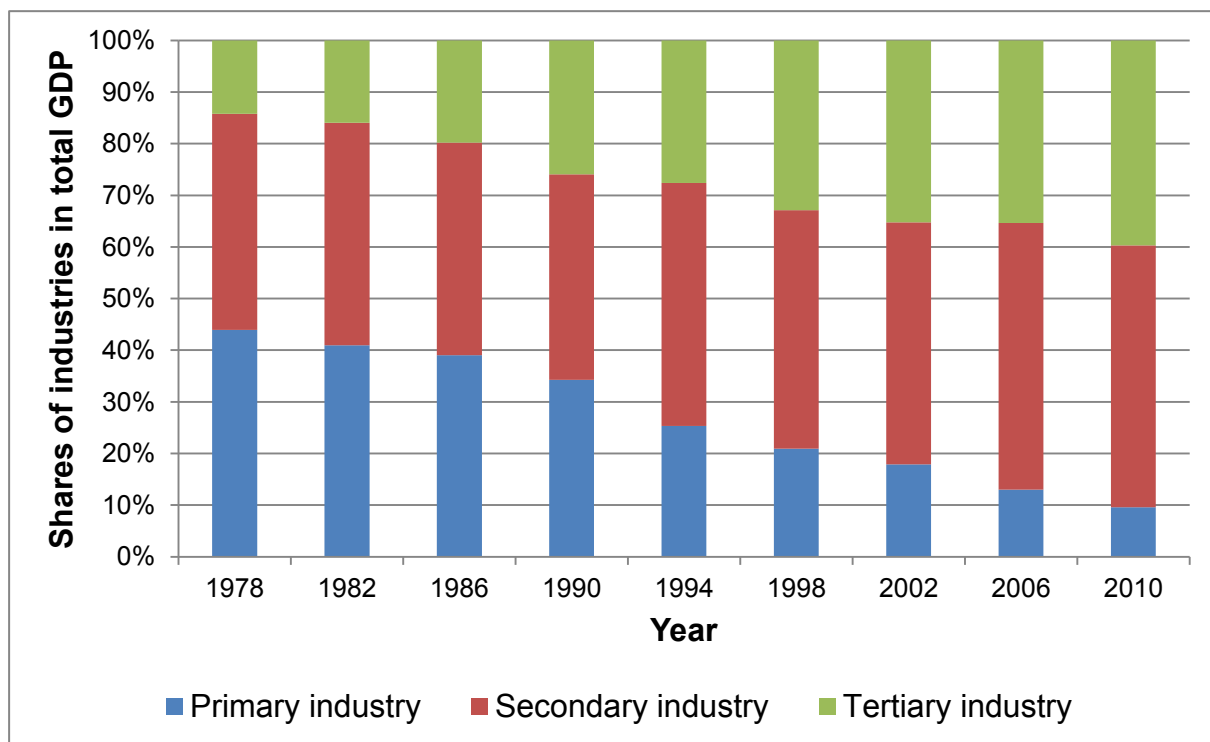


Figure 3-3: GDP and population of Xuzhou city and its central city



Source: Own illustration; based on Bureau of Statistics of Xuzhou, 2011

Figure 3-4: Change in shares of industries in total GDP from 1978 to 2010



Source: Own illustration; based on Bureau of Statistics of Xuzhou, 2011

The major land cover types in Xuzhou city are built-up land, farmland, vegetation, and water body. The farmland is mainly located in the periphery of the city on the plains areas, which accounts for 70.5 % of the total area. The study area covers the five districts, with the area of around 2,897 km² and the population of over 3 million inhabitants in 2010.

In recent decades, studies of urban growth in China have concentrated on a few mega cities, such as Beijing, Shanghai, and Guangzhou, or some economic zones, for example, Pearl River Delta, Yangtze River Delta. Despite their extremely high growth rates and significant importance in China, the study of urban growth in medium sized cities is still necessary due to its larger proportion in the total number of Chinese cities compared with other size cities. Xuzhou is a typical city in China. Its development characteristics and land cover change provide good representatives of the medium sized Chinese cities, because most of them have experienced the same political and socioeconomic development.

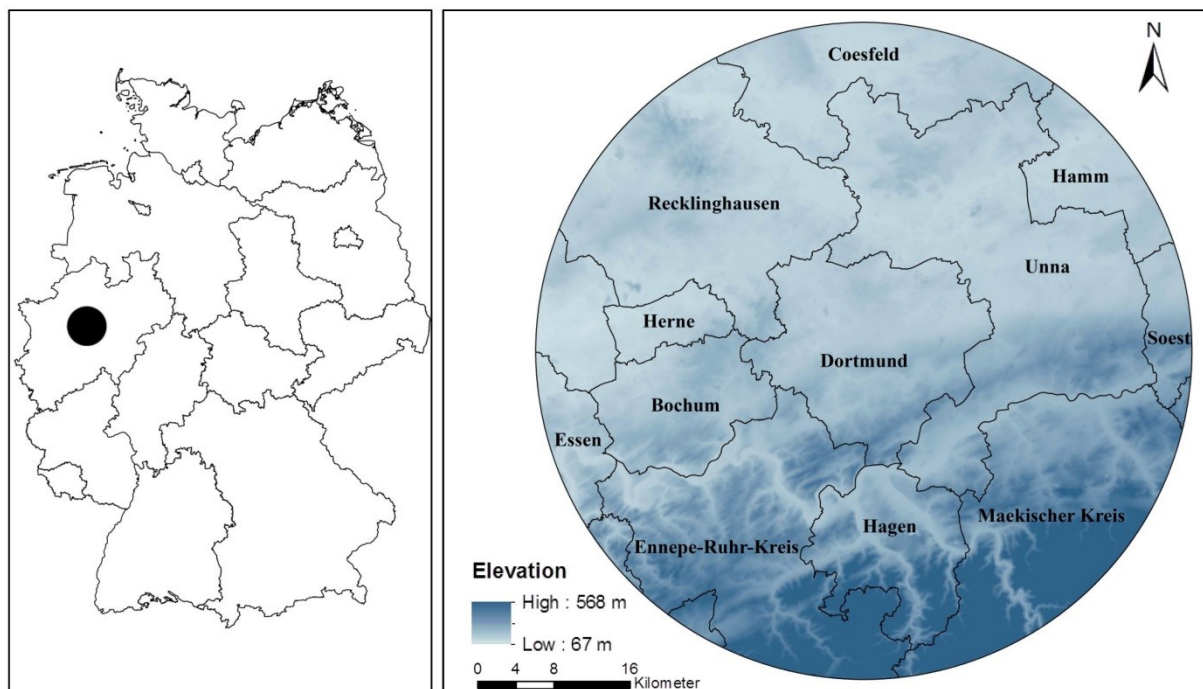
Xuzhou is a typical resource-based city whose development mainly depends on the exploitation of coal. The development of resource-based cities has a negative impact on the ecology and environment. The coal output is from underground mining in Xuzhou, which leads to the serious land subsidence disasters. They result in the significant loss of land resources. Since the exploitation of coal began in 1880, the lands used for coal exploitation and related industries have expanded at unprecedented rates. Based on the authoritative definition offered by the Academy of Macroeconomic Research (AMR) of the Chinese National Development and Reform Commission (NDRC), there are totally 118 resource-based cities in China. In China, a recession in resource-based city occurred in the 1980s and became serious in the early 2000s (Li et al., 2013b). In recent years, with the depletion of coal deposit, the government of Xuzhou began to conduct mining closure program. The era of post-mining will begin, in which the sustainable development is challenging and transition is important. Many different policies are focus on the transition of resource-based cities to achieve sustainable development. From this point of view, Xuzhou is also a representative city for resource-based cities in China.

The accurate analysis of urban growth has become increasingly important not only to better understand the environmental impacts but also for to support the sustainable urban development strategy. Few attentions, however, have been given to the

comparison between land cover change patterns in developing and developed countries. Hence, there is a need to compare and analyze the differences of spatio-temporal urban patterns between developing and developed countries in order to provide valuable information for understanding urbanization process, as well as for supporting sustainable development planning in developing countries.

Therefore, Dortmund region in Germany is selected for the comparison of spatio-temporal pattern with Xuzhou city. It is located in “Ruhr” region. With a population of some five million, Ruhr area is the largest urban agglomeration in Germany, which has a long history of industrial and urban development. During the industrial revolution in Germany since about 1850, the Ruhr became the industrial center of Germany, because of large hard coal deposits and steel production industry (Kretschmann, 2013). The industry had a significant impact on the spatial pattern and the environment of the cities in the Ruhr area. In recent decades, it has undergone serious economic and structural transitions. The decreasing mining activity and shrinking heavy industries have led to considerable transformation processes (Goetzke et al., 2006). Compared to other regions with a similar past, the Ruhr area is a role model when it achieves sustainable development (Kretschmann, 2013).

The study area is defined as a circular area with the center in the city center of Dortmund and a radius of 30 km (Figure 3-5). It covers the whole cities of Dortmund, Bochum, Hagen, and Herne; and a part of cities including Essen, Wuppertal, Gelsenkirchen, and Hamm. It also covers some whole or a part of districts including Unna, Coesfeld, Soest, Maekischer Kreis, Ennepe-Ruhr-Kreis, Mettmann, Hochsauerlandkreis and Recklinghausen. The total area of the study area is 2,830 km². The comparison between Xuzhou city and Dortmund city region provides a support for sustainable land management and urban planning for Xuzhou city in past mining period.

Figure 3-5: Location of Dortmund city region and its topography

3.3 Data

3.3.1 Satellite imagery

Although most developed countries have comprehensive land cover information, the relative lack of geospatial data is a serious situation in developing countries, particularly in China. In addition to the common advantages of remote sensing images, Landsat images with medium spatial resolution and multiple spectral provide an appropriate data source for land cover study because they are free of charge and maximize the possible temporal monitoring period (Patino & Duque, 2013). Table 3-1 lists the acquisition dates and sensors for the satellite images selected. The cloud free remote sensing images as the primary data source for mapping land cover in the study areas were obtained from the U.S. Geological Survey (USGS).

Numerous studies in satellite image based land cover mapping have demonstrated that improved accuracy of the results can be obtained by using more than one date of imagery rather than using single temporal imagery as a basis for classification, because it can increase the potential for spectral differentiation among land cover types (Lillesand, 1994; Lunetta et al., 2006; Oetter et al., 2001). For example, the farmland could represent like the bare soil in some seasons, while in growing seasons, the farmland are spectrally similar to green vegetation because of the crop calendars and phenology. Therefore, besides the images acquired for the study time points, some other images for different seasons were also required to separate farmland from bare soil or vegetation. In order to assess the accuracy of

classification results, a set of reference data were necessary, which included topographic maps, high-resolution aerial photography, and field survey data.

Before being classified, the calculation of reflectance values, atmospheric normalization and geometric correction had to be performed to make the images more interpretable. An improved atmospheric correction technique called COST was used to account for atmospheric transmittance along the path from the sun to the ground surface, which can generate more accurate results compared to Dark Object Subtraction (DOS) model (Chavez, 1988). After atmospheric correction, all remote sensing images need to be geometrically corrected in order to enable correct area measurements, precise location and multi-source integration. All images were georeferenced using well distributed ground control points (GCPs) and topographic maps. A second order polynomial was then used, resulting in the root mean square errors (RMSE) less than 0.75 pixels. The images were resampled to a pixel size of 30 m × 30 m using the nearest neighbor algorithm to maintain the radiometric properties of the original data (Mundia & Aniya, 2005). Image processing was performed using ERDAS IMAGINE 2011 software.

Table 3-1: List of remote sensing images for two study areas

Xuzhou city		Dortmund city region	
Data	Date	Data	Date
Landsat TM (30m)	20.09.1990	Landsat TM (30m)	25.05.1989
Landsat ETM+ (15m)	03.04.2001	Landsat ETM+ (15m)	15.05.2000
Landsat TM (30m)	12.08.2005	Landsat TM (30m)	18.07.2006
Landsat TM (30m)	18.09.2010	Landsat TM (30m)	04.06.2010

3.3.2 GIS data

The urban growth is a complex process which involves the interaction influence of various factors. According to the literature review in chapter 2.2.3 and data availability, the possible variables representing natural, socioeconomic, spatial policies and neighborhood factors were selected in this study, which are listed in Table 3-2.

A DEM at a spatial resolution of 30 m of the study areas was used to represent topography. Slope gradient was derived from the elevation surface.

The influence of the socioeconomic conditions in the region can be best characterized by the access that a location has to socioeconomic center, which has a significant effect on urban growth pattern (He et al., 2006; Li et al., 2013a; Verburg et al., 2004b). In this study, socioeconomic center can be represented by Central

Business District (CBD), district centers, and town centers. These centers can reflect the accessibility effect on land use development at different levels.

Transportation plays an indispensable part in urban growth because a good transportation increases the accessibility of land and decreases the cost of construction (Reilly et al., 2009). Different types of roads have varied strengths of impact or potential to attract new development. In this study, major roads (national, province level roads and city arterial road) and minor roads (the remaining roads) were considered. Because of the infrastructure construction, the traffic system changes all the time. It is difficult to simulate the dynamic process effectively for a long period (1990-2010) in this study. We assumed that the roads dataset remained unchanged during one period, and different datasets were used for different periods in order to take into account the temporal dynamics of roads. For example, the roads network in 2010 was adopted to analyze the effect of roads on urban growth in the period 2005-2010. In this study the accessibilities were calculated as the Euclidean distance using Spatial Analyst in ArcGIS 10.

GDP and population are the main drivers of urban growth. The growth of urban population and economy create urban land demand. More urban land will be required to satisfy further growth of urban population and economy in the future. The population variable was represented by the population density of district-town administrative units because the overall population for the whole study area is more related to the demand of urban land, and has less effect on urban growth allocation. The district units are located in city proper area, which towns are located in the fringe and rural areas. The district-town unit is the smallest geographic unit at which statistical data are available for the public. However, the overall GDP is not considered because its spatial resolution is much coarse than that of the other variables used in this study.

Policy variables affect the urban growth because they serve as constraints or incentives to development. From a practical point of view, the policy variables are expressed by spatially explicit layer designating the specified areas. Owing to the non-availability of master plan for the period of 1990 to 2010, the effects of policy were considered only in terms of natural variables for development. The environmental protection and subsidence areas were defined as the constraints, in where the development should be limited. Furthermore, the master plan for Xuzhou city during period of 2010-2020 was used as a guideline for future development

scenario. A planned land use map was provided in master plan. Each parcel was assigned with a specific land use type: urban and non-urban. Furthermore, the planning regulations related to urban development were obtained from the land use planning guidelines of Xuzhou city.

All the spatial data were registered to the same Universal Transverse Mercator (UTM) coordinate system and sampled to the same cell size of 100 m*100 m, which was sufficient to capture the detailed information about urban dynamics while keeping the volume of computation manageable.

Table 3-2: List of ancillary data

Variable	Year	Description	Sources
Physical factor			
Slope		It is derived from DEM data with spatial resolution of 30 m	Global Land Cover Facility (GLCF)
Socioeconomic factor			
Dis2MajR	2001, 2005, 2010	Distance to major roads	Bureau of Urban Planning of Xuzhou
Dis2MinR	2001, 2005, 2010	Distance to minor roads	Bureau of Urban Planning of Xuzhou
Dis2CBD		Distance to central business district (CBD)	
Dis2Cens		Distance to district centers	
Dis2Town		Distance to town centers	
PopDen	1990, 2001, 2005, 2010	Population density collected at street town level	Bureau of Statistics of Xuzhou
Spatial policy factor			
Subsidence	2000	Layout of potential subsidence areas	Bureau of Land and Resources of Xuzhou
Environment	2000	Layout of environmental protection areas	Bureau of Land and Resources of Xuzhou
Master plan 2010-2020			Bureau of Urban Planning of Xuzhou
Neighborhood factor			
Dis2Urban	1990, 2001, 2005	Distance to existing urban areas	

4. Methodology

The methods presented in this chapter can be categorized into three parts. Chapter 4.1 gives a general land cover classification and change detection procedure which integrates RS and GIS. In addition, buffer analysis and jaggedness degree are introduced for comparing Xuzhou city and Dortmund city region. Focusing on Xuzhou city, Chapter 4.2 presents several spatial metrics that can be used for spatial pattern analysis. Regarding the spatio-temporal dynamics of spatial patterns, GWR is used to investigate the effects of urbanization on urban growth patterns. Logistic regression is further applied to explore the relationship between the urban growth and driving factors. Furthermore, the methods associated with the simulation of urban growth are illustrated, which includes development of CA models, the calibration and validation, and the simulation of future scenarios.

4.1 Mapping and monitoring of land cover change

Continual, historical, and precise information about the land cover change is crucial for urban growth analysis, in which land cover information serves as one of the major input criteria. The land cover change information can be gained from RS data by applying a variety of techniques such as visual interpretation, land cover classification, and change detection. Furthermore, spatio-temporal characteristics can be detected and quantified by the GIS based analysis. In the following sections, firstly the improved RS image classification method is proposed based on the literature review in chapter 2.2.1; then, the land cover change detection is conducted; lastly, the GIS based analysis is presented in order to reveal the spatio-temporal characteristics of Xuzhou city and Dortmund city region.

4.1.1 Remote sensing image classification

Prior to land cover classification, a modified version of the Anderson classification system level I (Anderson et al., 1976) with four land cover categories (built-up land, farmland, vegetation, and water body) was adopted in this study. Though the system was originally developed for the USA, it is the most commonly used land cover system across the world (Dewan & Yamaguchi, 2009b; Yuan et al., 2005). The level I classes proposed by this system can be obtained from Landsat data or high-altitude airphoto, while the other levels (levels II, III and IV) require the use of high, medium or low-altitude photographs. Four separable land cover classes were identified by taking into consideration the spectral characteristics of Landsat images, existing

knowledge of land cover categories within the study areas and the objectives of the study (Table 4-1).

Table 4-1: Land cover classification scheme

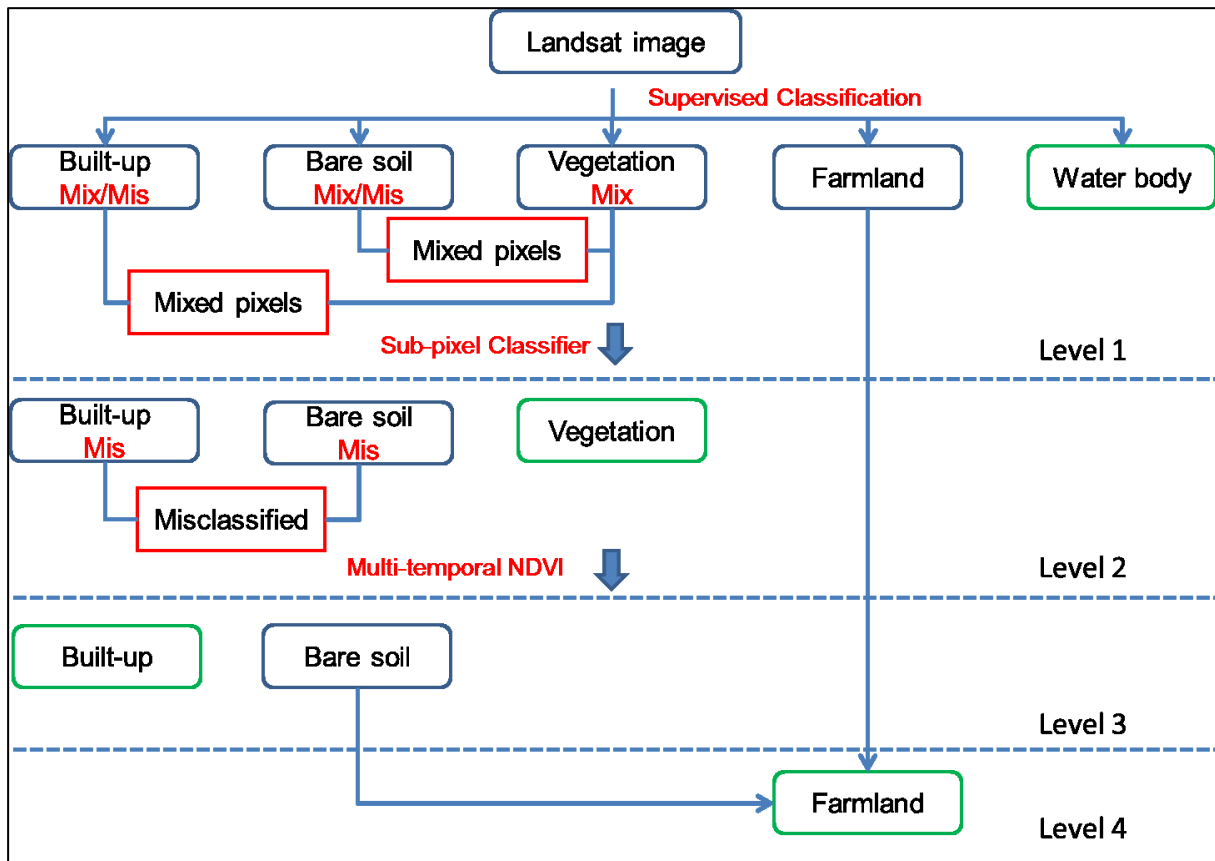
Land cover classes	Description
Built-up land	Residential, commercial services, industrial, transportation, communications, mixed urban or built-up land, other urban or built-up land
Farmland	Crop fields, pasture and bare fields
Vegetation	Deciduous forest land, evergreen forest land, mixed forest land, orchards, groves, vineyards, nurseries, ornamental horticultural area
Water body	Permanent open water, lakes, reservoirs, streams

Source: Own illustration; based on Anderson et al., 1976

MLC was selected to extract land cover information from Landsat data as well as to produce a distance image. In order to consider the influence of seasonal change of farmland, the classified image produced by MLC consisted of five classes: built-up land, farmland, bare soil, vegetation and water body. The distance image represents the Mahalanobis distance between the corresponding pixel in the input continuous raster layer file and signature to which it was classified. In the distance image file, pixels that are most likely to be misclassified have the higher value (Lu & Weng, 2004).

Due to the relatively coarse spatial resolution and spectral similarities of the Landsat images, some pixels were misclassified in the initial classification results after MLC supervised classification. V-I-S model proposed by Ridd (1995) assumes that land cover in urban environments is a linear combination of three components: vegetation, impervious surface, and soil. It provides a suitable way for decomposing urban landscapes and a link for these components to remote sensing spectral characteristics (Lu et al., 2011). Hierarchical classifications are commonly applied in remote sensing image processing. The performance of this method is dependent on the design of the “decision tree”, including the tree structure (number of hierarchy levels and nodes), the choice of the features at each node (spectral or non-spectral) and the decision rules (Setiawan et al., 2006). In this study, a hierarchical classification approach was developed based on the V-I-S model. The hierarchy classification scheme is illustrated in Figure 4-1.

Figure 4-1: Hierarchy classification scheme for land cover mapping based on V-I-S model



As the first step in classification process, distance image was employed to identify the pixels that were the most likely to be misclassified by defining a specific threshold. Expert Classifier was used to correct misclassified land use categories by defining refinement rules and assigning specific thresholds for different classes.

Urban landscape is a complex combination of different land covers, such as farmland, impervious surface, vegetation, and water (Ridd, 1995). Some different land cover classes may be contained in one pixel of satellite image because of the medium spatial resolution of Landsat image; it can cause the difficulty for separating one specific land cover class from other classes using spectral characteristics (Ji & Jensen, 1999). Mixed pixel problem has been regarded as the main reason for low accuracy of classification. In this study, mixed pixel problem was found between non-vegetation (built-up and bare soil) and vegetation categories. Therefore, the hierarchical classification level 1 involved the solution to deal with the mixed pixel problems.

The IMAGINE Subpixel Classifier in Erdas Imagine software provides an efficient way to identify the specific material in each pixel (Civco et al., 2002). It can be

successfully used to identify a specific material when multiple materials are mixed in one pixel. Endmembers of vegetation were firstly selected on the Landsat image through visual interpretation. With the aid of Subpixel classifier, fraction image of vegetation for Landsat image based on selected endmembers was produced, in which the value of each pixel was expressed by the proportion of vegetation in each pixel. A threshold for extracting vegetation pixels was identified from fraction image by visual interpretation. All misclassified pixels caused by mixed pixel problem were reclassified into correct categories by thresholding. At this level, the generated vegetation category was used in the final classification result.

By using sub-pixel classifier, the initially misclassified vegetation pixels were separated from non-vegetation class, but some bare soil pixels were misclassified as built-up due to close spectral similarities between these two types in one temporal image. In these two study areas, the farmland land represents like bare soil because of the crop calendars and phenology. The second hierarchy level involved the separation of built-up class from bare soil class. The season behavior of crop is a fundamental component of successful image interpretation. NDVI values (Eq. 1) derived from multi-temporal images, were used to aid in separation of bare soil and built-up type based on their phenological characteristics. The misclassified built-up samples have high NDVI values during the growing season and low NDVI values during harvest season. There is a significant difference on NDVI between bare soil and built-up land. The refinement rule and threshold within framework of Expert Classifier were defined to reduce the classification errors according to the difference of NDVI values between growing season and ungrowing season.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

where *NIR* corresponds to Landsat band 4, *RED* corresponds to band 3. The index is developed based on the characteristics of green vegetation to significantly absorb wavelengths in the *RED* and significantly reflect in the *NIR* of electromagnetic spectrum (Tucker, 1979).

At the next level, the bare soil class was merged with the initial farmland generated by MLC approach to form a farmland class. Finally, the four land cover categories were generated: built-up, farmland, vegetation, water body.

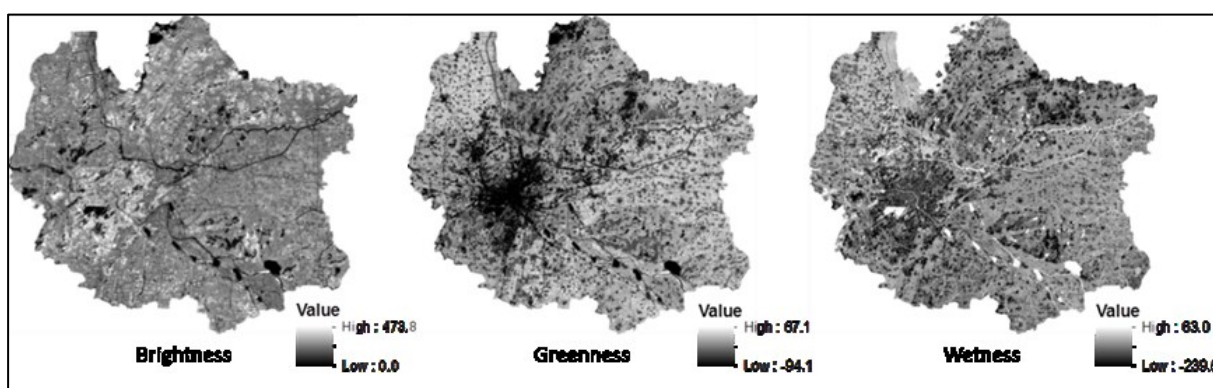
Although application of sub-pixel classifier and multi-temporal images analysis greatly improved the accuracy of MLC classification, some misclassification pixels

were still found in the classified images due to the spectral confusion. The post classification refinement is an effective method to greatly improve the accuracy of results (Dewan & Yamaguchi, 2009a; Harris & Ventura, 1995). Some further data, such as DEM as well as brightness, greenness and wetness components from TCT were incorporated to refine classified results. From the DEM data, the slope value in degree was extracted. In this study, farmland was not expected to be found in the areas with slope higher than 10 degree. Therefore, the farmland pixels with slope higher than 10 degree should be reclassified as vegetation.

Three new bands can be generated by TCT. Brightness shows higher values for surfaces with little or no vegetation; greenness is associated with green vegetation; while wetness is associated with soil moisture, water, and other moist features. We can refine the classification results through defining specific rules in Knowledge Engineer. Figure 4-2 shows TCT results of Landsat TM image of Xuzhou city in 2005. The built-up and bare soil areas have higher values compared to other land cover types in brightness band. In greenness band, the built-up and bore soil land have lower values, while the areas covered by green vegetation have higher values. In wetness band, the water bodies have higher values. Therefore, we can define the specific thresholds to distinguish different land cover classes in each band generated by TCT. In addition, a 3*3 majority filter was applied to remove the salt and pepper appearance in the images. Finally, accurate classified images with four land use categories were generated.

In order to evaluate the performance of the V-I-S based hierarchical classification approach, the classification without this approach was conducted. After the MLC classification, the same post classification refinement method was also used to improve the results.

Figure 4-2: Tasseled cap transformation results of Xuzhou city in 2005



In order to check whether the results are correct for change detection, quantitative accuracy assessment was performed to assess the accuracy for classification results. The most widely used technique to assess the accuracy of land cover maps derived from remote sensing images is the error matrix (Foody, 2002). The error matrix compares classified image with a reference image on class by class basis. Following the recommended minimum sample size of 50 random points for each land cover class by Congalton and Green (1999), a total of 300 random points were generated by using stratified random sampling. Finally, the classified data derived from two methods and reference data were compared and statistically represented in the form of error matrices.

4.1.2 Land cover change detection

Following the land cover classification, change detection analysis was used to analyze patterns of land cover change during the study period. Change detection is the process of identifying differences in the states of an object by observing it at different times (Singh, 1989). Image differencing, principal component analysis and post classification detection are the most widely used methods for change detection (Lu et al., 2004).

Post classification was selected as a change detection method to identify the changes in land covers in different intervals for Xuzhou city and Dortmund city region. It involves independent classification results for each end of the time interval of interest, followed by a segment by segment or pixel by pixel comparison to detect land cover changes (Coppin et al., 2004). The post classification method generated a two way cross matrix, providing “from-to” land cover conversion information. A new thematic map containing different combination of “from-to” change information was also produced for each period. The main advantage of this method lies in the fact that each image is separately classified. This thereby minimizes the differences of sensor characteristics, atmospheric effects, solar illumination angle sensor view angle and vegetation phenology between the dates (Lu et al., 2004).

4.1.3 The analysis of spatio-temporal characteristics of urban growth

Although the land cover change trend of the study areas have been quantitatively characterized by using statistic data of land cover change, it cannot capture the spatio-temporal characteristics of urban growth. In order to address the question of where the urban growth is occurring, GIS based buffer analysis was applied. The

buffer zone areas were established around the existing built-up area by radius of 250 m, 500 m, 1250 m, and 1500 m, respectively.

To quantify the magnitude and pace of urban growth, frequency ratio method was implemented using GIS techniques (Lee & Talib, 2005; Park et al., 2011), which can be computed as the following:

$$FR = \frac{R_a}{R_b} \quad (2)$$

$$R_a = \frac{LC_s}{LC_w} \quad (3)$$

$$R_b = \frac{A_s}{A_w} \quad (4)$$

where LC_s is the new developed area in the single buffer zone, and LC_w is the new developed area in the whole buffer zones. A_s is the area of the single buffer zone, A_w is the area of the whole buffer zones. FR is defined as the ratio of percentage of new developed area in single buffer zone R_a to the percentage of the each buffer zone in the whole buffer zones R_b .

In the case of relationship between new developed built-up area and the buffer zone of 0-250 m around existing built-up area, if the value is larger than 1, it means that the percentage of new developed built-up area in the buffer zone is higher than that of the whole buffer zones, and higher change intensity occurred in this zone, whereas if the value is lower than 1, indicating lower change intensity. A value of 1 is an average value for the whole buffer zones. Therefore it can be used to compare the intensity of built-up change in each buffer zone over various periods.

Besides detecting the land cover change, it is important to measure and analyze temporal change on geometric forms as a basis for understanding spatial patterns and processes. Compactness is an important concept and index which reflects the regional and urban form. To measure and monitor urban compactness we need indicators for capturing the characteristics of land use development. In this study, the jaggedness degree defined by Thinh (2002a), was employed as the measurement of the compactness of study areas.

For any circle, we have the following relationship: $perimeter/SQRT(Area) = 2 \times SQRT(\pi)$. This relationship inspires to use a ratio of the total edge length to the square root of the total area of all individual settlement areas as a measure of the compactness of urban patterns. Let be a_i the area and p_i the circumference of the

polygons of a settlement pattern ($i=1(1)n$). The jaggedness degree was defined as follows (Thinh 2002a, 2003):

$$Jaggedness\ Degree = \frac{\sum_{i=1}^n p_i}{2\sqrt{\pi \sum_{i=1}^n a_i}} \quad (5)$$

4.2 Analysis of urban growth

In this study, the comparison between Xuzhou city and Dortmund city region in both the amount of land cover change and spatio-temporal characteristics of urban growth provides valuable information for understanding the different underlying processes in two study areas. Based on the comparison, the problems threatening the sustainable development in Xuzhou can be identified. Hence, there are wide interests and needs to conduct a comprehensive examination of spatio-temporal change on composition and spatial configuration of urban land cover based on the results generated in the chapter 4.1. Moreover, the underlying cause-effect relationships in urban growth process need to be explored and analyzed. It can provide a better understanding of urban growth process and their impacts on environment in Xuzhou city.

4.2.1 Spatial metrics for quantifying urban spatial pattern

In order to describe and analyze the urban spatial pattern, several landscape metrics were calculated using Fragstats 4 (McGarigal et al., 2012). However, it is difficult to find a one-to-one connection between metric values and pattern. Indeed, most of the metrics describe similar aspect of spatial patterns and they are correlated among themselves (McGarigal et al., 2012). Not all the landscape metrics were required to capture the spatial patterns. Furthermore, the existing studies suggest that agreement does not exist on the selection of the metrics. It seems impossible that a single metric can fully describe a spatial pattern. Thus, the choice of metrics ultimately depends on the purpose of the study and the nature of spatial pattern under investigation. Since the objective was to quantify the spatial characteristics of the urban land, the landscape heterogeneity is represented in two classes: urban and nonurban. Built-up was defined as urban land, while farmland, vegetation and water body were reclassified into non-urban land. According to the objectives of this study, we chose five class-level metrics which are sensitive to the changes in composition, as well as spatial configuration. Table 4-2 provides a description of the spatial metrics used in the study. Different spatial metrics provide different information on the urban growth process.

Class Area describes the total urban areas. NP is a simple quantification of the amount of individual urban patches. It provides information on the amount of new developed patches during certain period. LPI reflects the percentage of the area of the largest urban patch. The LPI value of 100 is obtained when entire urban class consists of a single urban patch. The increase in LPI indicates urban areas become more aggregated and integrated with the urban cores (Pham, 2011). SHAPE measures complexity of urban patches by a perimeter-area proportion (Eq. 6). $SHAPE=1$, when a corresponding patch has a compact square form with a relatively small perimeter relative to the area. If the patches are more complex and fragmented, the perimeter increases and generates a higher fractal dimension (Herold et al., 2005). $SHAPE_AM$ averages the shape index of the patches by weighting patch area so that larger patches weigh more than smaller patches (Eq. 7). This improves the measure of class patch fragmentation at the global level because the structure of smaller patches is often determined more by image pixel size than by characteristics of natural or manmade features found in the landscape (Herold et al., 2003; Milne, 1991).

$$SHAPE = \frac{0.25 * p_{ij}}{\sqrt{a_{ij}}} \quad (6)$$

where p_{ij} represents the perimeter (m) of patch ij . a_{ij} represents the area (m^2) of patch ij . n corresponds the number of patches of class i .

$$SHAPE_AM = \sum_{j=1}^n \left[\frac{0.25 * p_{ij}}{\sqrt{a_{ij}}} \left(\frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \right) \right] \quad (7)$$

ENN is an index to represent average minimum distance between two urban patches. Hence, it can be used to quantify patch isolation, as well as to measure the open space between urban areas. The higher the value of the ENN, the greater isolation the patches are. In order to consider the different influence of patches according to the areas, ENN_AM is calculated by incorporating weighting.

One of the most important issues in spatial metrics is defining the spatial domain of the study as it directly influences the spatial metrics. Spatial domain refers to the geographic extent under analysis. This study adopted the geographic extent of the entire study area and block based sub-divisions for metrics calculation to discover the urban growth pattern at different levels. Firstly the spatial metrics were calculated for the entire study areas in order to provide a general representation of urban spatial patterns. Furthermore, they were further used for each sub-division to better localize

the dynamics of urban spatial patterns. The study area was divided into several sub-regions. The square block, the most commonly used shape for spatial pattern analysis (Luck & Wu, 2002; Weng, 2007), was applied in this study. A preliminary test of the effects of block size on spatial pattern analysis was carried out with the size of 1 km, 2 km, 3 km and 5 km. The block of 2 km was chosen because it retains more details of the spatial pattern than the larger block size does. Furthermore, the block size of 1 km could lead to the situation that no urban patch or only a few urban patches exist in some blocks, which generates the noise in spatial pattern analysis. Therefore, the study area was firstly divided into several square blocks with the size of 2 km×2 km. The selected metrics (NP, LPI, and SHAPE_MN) were then calculated for every block to characterize the spatio-temporal patterns of urban area. After obtaining the multi-temporal metrics values, changes of metrics were calculated using the Eq. 8. Other landscape metrics were not selected because this study was conducted at a local level and these metrics are more suitable for a global scale.

$$C_i = M_{i,t+n} - M_{i,t} \quad (8)$$

where $M_{i,t}$ and $M_{i,t+n}$ are the metrics values in year t and $t + n$ respectively. C_i is the change of metrics in block i .

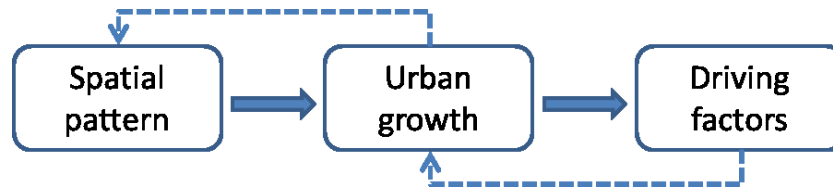
Table 4-2: Description of the spatial metrics used in this study

Landscape metrics	Abbreviation	Description
Class Area	-	The sum area (m ²) of all urban land use patches, divided by 10,000
Number of patches	NP	Total number of urban land use patches.
Largest patch index	LPI	The percentage of the area of the largest urban patch to the total area of the landscape.
Shape index (Area weighted mean shape index/Mean shape index)	SHAPE (SHAPE_AM/ SHAPE_MN)	The index describes the complexity of the patch shape. It uses patch area as a weighting factor. It equals 1 when the patch has a square shape and increases as the irregularity of the shape increases. SHAPE_AM averages the shape index of the patches by weighting patch area so that larger patches weigh more than smaller patches. SHAPE_MN equals the sum of shape index of the patches divided by the number of patches of the same type.
Euclidean distance neighbor distance (Area weighted mean Euclidean distance neighbor distance)	ENN (ENN_AM)	ENN equals the distance (m) to the nearest neighboring patch of the same type, based on shortest edge-edge distance. ENN_AM averages the ENN index of the patches by weighting patch area.

Source: Own illustration; based on McGarigal et al., 2012

4.2.2 Exploring the underlying cause-effect relationships in the urban growth process

By using spatial metrics, historical urban growth patterns can be obtained for better understanding the urban development dynamics in previous section. However, urban growth is a complicated process which involves the spatial and temporal complexity of various natural and socio-economic factors. The spatial models suffer from a lack of knowledge of the historical urban growth process and various factors that contribute to the dynamics of urban areas (Dietzel et al., 2005; Longley & Mesev, 2000). Therefore, it is necessary to analyze the historical urban growth, effects of driving factors underlie urbanization, and their cause-effect relationships. The cause-effect relationships are composed of two aspects which are illustrated in Figure 4-3. The first one is the relationships between spatial patterns and urban growth, and the second focuses on the relationships between urban growth and a set of driving factors.

Figure 4-3: Cause-effect relationships in urbanization process

4.2.2.1 Exploring the effects of urban growth on spatial patterns

To further understand the effects of urban growth on the spatio-temporal patterns, changes of spatial metrics values at block scale were used as dependent variables. The urbanization intensity index (*UII*) was used as an independent variable, which has been recognized as one of the main indicators in measuring the urban growth pace (Wang et al., 2010; Yeh & Huang, 2009). The *UII* value for each block was calculated using Eq. 9.

$$UII_i = \frac{UA_{i,t+n} - UA_{i,t}}{n * TA_i} * 100 \quad (9)$$

where UII_i is the urbanization degree for block i during the time period $t \sim t + n$; and $UA_{i,t}$ and $UA_{i,t+n}$ are the urban area in year t and $t + n$, respectively. TA is the total area of the block i .

In contrast to global models (such as OLS), GWR is conducted using localized points within geographic space. Thus, instead of producing a single average parameter for each relationship, GWR has a potential to produce a set of local parameter estimates that can be mapped to get an insight into the hidden possible causes of this pattern. In other words, it can be used to explore the spatially varying relationships between explanatory variables and spatial pattern by generating a set of local parameter estimates (Brunsdon et al., 1996; Fotheringham et al., 1996; 2001). In addition, GWR model results are mappable and can be combined with GIS, which offers a powerful tool for analyzing the relationships (Tu, 2011).

The GWR model can be expressed as:

$$y_i = a_0(\mu_i, v_i) + \sum_k a_k(\mu_i, v_i)x_{ik} + \varepsilon_i \quad (10)$$

where (μ_i, v_i) represents the coordinate location of the i th point. $a_0(\mu_i, v_i)$ and $a_k(\mu_i, v_i)$ express the intercept and local parameter estimate for independent variable x_{ik} at location i respectively. ε_i is the random error term for location i .

In GWR, parameters for each observation at location i can be estimated by weighting all observations around a specific point i according to their spatial proximity, which is

calculated by Euclidean distance in this study. The observations which are spatially closer to the location i will have a greater impact on the local parameter estimates for the location than those which originate at more distant points. Gaussian distance decay can be used to express the weighting function:

$$w_{ij} = \exp(d_{ij}^2/h^2) \quad (11)$$

where w_{ij} represents the weight of observation j for location i . d_{ij} is the Euclidean distance between points i and j . h is a kernel bandwidth that affects the distance-decay of the weighting function.

In practice, the results obtained from GWR are not sensitive to the choice of kernel type, but they are sensitive to bandwidth (Gao and Li, 2011; Guo et al., 2008). Consequently, when estimating the model it is necessary to determine the optimum bandwidth. There are three choices of the bandwidth method: corrected Akaike Information Criterion (AICc), Cross Validation (CV) and Bandwidth parameter. If the bandwidth is known a priori, bandwidth parameter could be applied. If it is unknown, the first two types allow for using an automatic method to find the optimum bandwidth. In this study, AICc method was used for GWR model. The AICc method finds the bandwidth which minimizes the AICc value. The model with lower AICc value suggests stronger ability of regression model in reflecting reality.

For the comparison purpose, OLS models were also employed to investigate the relationships between spatial patterns and urbanization. Three statistical parameters were used to compare the performance between GWR and OLS: adjusted R^2 , AICc, and Moran's I. Adjusted R^2 and AICc measures provide some indications of the goodness of fit of the corresponding model. Higher adjusted R^2 value indicates that more variances can be explained for the dependent variable. Moran's I is widely used as an indicator of spatial autocorrelation, which ranges from -1 to 1. The larger absolute value of Moran's I indicates that the spatial autocorrelation is more significant. Residuals are the differences between predicted and observed values. Moran's I value was employed to examine spatial autocorrelation based on the residuals, so that their ability to deal with the spatial autocorrelation can be evaluated and compared.

4.2.2.2 Examination of the relationships between driving factors and urban growth

The question of “how can driving factors influence urban growth?” should be addressed in order to understand other aspect of cause-effect relationships operative in urban growth process. Commonly used approaches include linear regression, log-linear regression and logistic regression. The dependent variable of logistic regression could be binary or categorical. The independent variables of logistic regression could be a mixture of continuous and categorical variables. Normality assumption is not needed for logistic regression. Therefore, logistic regression is more suitable for driving factors analysis in this study.

Logistic regression model was used to identify and improve the understanding of a series of variables that affect the dynamics of urban growth, as well as to investigate the temporal dynamics of the effects of these variables. The logistic regression model was expressed as follows:

$$P = \frac{1}{1+e^{-z}} \quad (12)$$

where P is the probability of a cell changing to built-up calculated through the logistic regression procedure. It varies from 0 to 1 on a S-shape curve. z represents the linear combination of independent variables which are regarded as a driving force of urbanization. It can be expressed as follows:

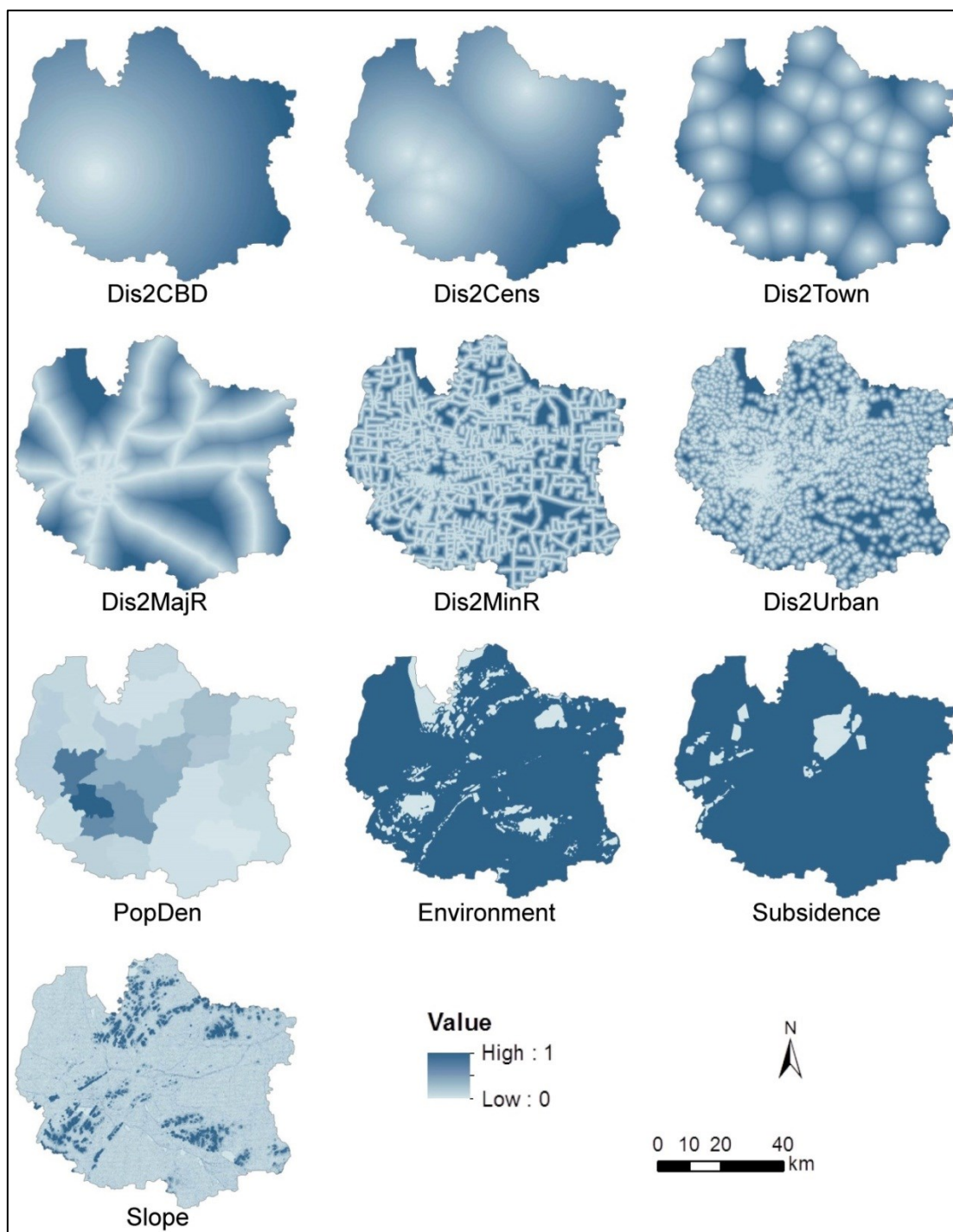
$$z = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n \quad (13)$$

where b_0 is the intercept of the model, b_i ($i=1, 2, \dots, n$) represents the coefficient of the logistic regression model to be estimated, and x_i is an independent variable representing driving factor of urban growth, which can be of interval, ordinal or categorical.

The major interest was to assess the relative importance of variables in determining conversion to urban land uses and to analyze the temporal dynamics of the effects of variables during historical period. Therefore logistic regression model was applied to each time period, the dependent variable value of 1 means non-urban cell has changed its land use to urban during the study period, a value of 0, on the other hand, indicates the cell did not change its use. The coefficient for each variable in Eq. 13 measures the absolute contribution of variable in determining the probability that urban growth. A positive value indicates that the variable will help to increase the probability value and negative value indicates the opposite effect (Cheng & Masser,

2003). However the estimated coefficients of these variables could be misleading in the analysis of urbanization process when the variables are measured in different units. Therefore, all variables should be standardized into the range from 0 to 1 prior to the modeling as shown in Figure 4-4. For natural, socioeconomic and neighborhood factors, linear transformation method was applied to conduct the standardization. For spatial policy factors, the area where urban development is limited was assigned 0 and area that is designated for urban development was assigned 1.

Figure 4-4: Spatial variables for the analysis of urban growth in Xuzhou (2001)



There are a large number of cells for the dependent and independent variables in this study. It is not efficient to handle such a large data in the later statistical analysis. In addition, while using logistic regression to derive the relationship between urban growth and independent variables, the spatial dependence should be considered in order to remove its effects. Otherwise, the parameters estimated by logistic regression have lower precision (Arlinghaus, 1996). Therefore, efficient sampling method is required to reduce the size of samples and remove the spatial dependence

effect. Systematic and random sampling are two frequently used sampling schemes in logistic regression. Systematic sampling can reduce spatial dependence, but it may lose some important information. Conversely, random sampling is capable of representing important information, but does not efficiently reduce spatial dependency (Cheng & Masser, 2003). The issue can be addressed through the integration of systematic and random sampling (Cheng & Masser, 2003; Luo & Wei, 2009). We followed this approach in this study. For each period, 72356 regularly spaced points with 200 m interval were extracted to reduce spatial dependency. After systematic sampling, the size of samples with value 1 (changed from non-urban to urban) was much smaller than the size of samples with value 0 (non-changed). Therefore, to gain unbiased parameter estimation, random sampling was further used to extract the samples from systematic samples in order to obtain equal size of samples with value of 1 and 0. Consequently, the size of samples used in logistic regression were 3816, 3510, 4532, for the periods of 1990-2001, 2001-2005 and 2005-2010, respectively.

Relative Operating Characteristic (ROC) was used as a quantitative measurement to validate the logistic regression model. The ROC method has been recently used in the field of urban growth model to examine the relationship between simulated urban growth and actual one (Arsanjani et al., 2013; Braimoh & Onishi, 2007; Hu & Lo, 2007). ROC assesses how well the pair of maps agrees based on cell by cell comparison (Pontius & Schneider, 2001). The first step in calculating the ROC is to slice the probability map at a series of threshold levels. A threshold refers to the percentage of cells in the probability map need to be reclassified as 1 in preparation for comparison with the actual map. The series of thresholds were specified at an equal interval of 10 %. For each group generated from threshold, the map of urban growth probability was compared against that of actual urban growth (Pontius & Schneider, 2001). The ROC curve was plotted with the true positive rate against the false positive rate for each group. The ROC statistic is the Area Under the Curve (AUC). Eq. 14 uses integral calculus' trapezoidal rule to calculate the area.

$$\text{Area under curve} = \sum_{i=1}^n [x_{i+1} - x_i] \left[y_i + y_{i+1} - \frac{y_i}{2} \right] \quad (14)$$

where x_i represents the rate of false positives for group i , y_i represents the rate of true positives for group i , and n is the number of groups (Pontius & Schneider, 2001).

A ROC value of 1 indicates that the simulated probability map matches perfectly the actual land use map. A ROC value of 0.5 suggests that probability values are assigned at random locations.

4.3 Modeling of urban growth

Based on the urban growth information obtained by applying methods in previous sub-chapters, CA models can be developed to provide an improved ability to analyze urban growth characteristics in strong connection with decision support systems. This sub-chapter describes the method for developing CA model that is designed to enable the simulation of urban growth by integrating various factors. The hybrid calibration method is proposed to make the CA models generate more accurate simulation results. In order to provide a support for decision making process, the future development scenarios are designed and simulated.

4.3.1 Model development

The definition of transition rule plays an important role in CA models. The key element of transition rule is the transition potential which determines the probability of a cell changing to a specific land use (Wu & Webster, 1998). This involves a number of spatial variables that contribute to urban growth. In this study, the transition potential P_{ij} can be practically defined as a function of the global suitability value S_{ij} , neighborhood effects N_{ij} , constraints $CONS_{ij}$ and stochastic perturbation V_{ij} . It can be expressed as follows:

$$P_{ij} = S_{ij} * N_{ij} * CONS_{ij} * V_{ij} \quad (15)$$

The global suitability value represents the intrinsic suitability of urban development. It was calculated as a function of global spatial variables:

$$S_{ij} = f(x_{l,ij}, w_l) \quad (16)$$

where $x_{l,ij}$ ($l = 0, 1, 2, \dots, n$) represents the values of global factors for the cell (i, j) , w_l represents the corresponding weight of the global factor. It is very important to select the best set of the global factors in order to produce the best fit between the simulated maps and the observable reality. After calculating the relationship between historical land transitions and related factors in 4.2.2, a different set of global factors contribute to the changes from non-urban to urban area were identified. In CA model, the transition rule restricts new built-up land to locations within a neighborhood around an existing built-up pixel at each time step. Therefore, the neighborhood was excluded from the global spatial variables.

Neighborhood effect was introduced by many studies to consider the effects of spatial interaction and neighborhood characteristics on urban growth. In this study, this neighborhood score was calculated according to following equation:

$$N_{ij} = \sum_c W_{mn} \times I_{mn} \quad (17)$$

where N_{ij} is the effect of neighborhood cells on the central cell (i, j) within the neighborhood space c ; W_{mn} represents the weight indicating the impact of the interaction between the central cell and cell (m, n) within the neighborhood (Barredo et al., 2003). Following the first law of geography (Tobler, 1970), a distance decay function was applied, so that cells closer to the central cell carry larger weight. I_{mn} represents the state of the cell (m, n) using binary value. $I_{mn}=1$, when the cell is urban land, otherwise $I_{mn}=0$. The neighborhood size, neighborhood type and weighting function have significant effects on the CA model results (Kocabas & Dragicevic, 2006; Pan et al., 2010). Various neighborhood configurations have been applied to models of urban growth. However, most CA models employ one uniform set of generic neighborhood configuration for different period, despite the fact that temporal differences exist in urban patterns and processes. Instead of using stationary neighborhood configuration, different neighborhood configurations were considered in this study to improve the ability to perform more realistic simulations. Through the calibration, optimal ones were identified which enable to generate higher accuracy results. As shown in Figure 4-5, three different neighborhood types (Moore, Moore Circular, and Von Neumann Circular) with different neighborhood size (radius of 1 to 6) were involved. In addition, three different weighting functions (Eq. 18) were applied to define the weights W_{mn} for cells within neighborhood.

$$W_{mn} = \exp(-\beta * D_{mn}) \quad (18)$$

where D_{mn} is the distance between cell (m, n) to the central cell within a neighborhood. β is the exponent of the function. The higher of the value, the more abrupt is the function curve. In this study, β was assigned 0, 0.2 and 0.5, respectively. The function curves are shown in Figure 4-6.

Figure 4-5: Neighborhood types and sizes

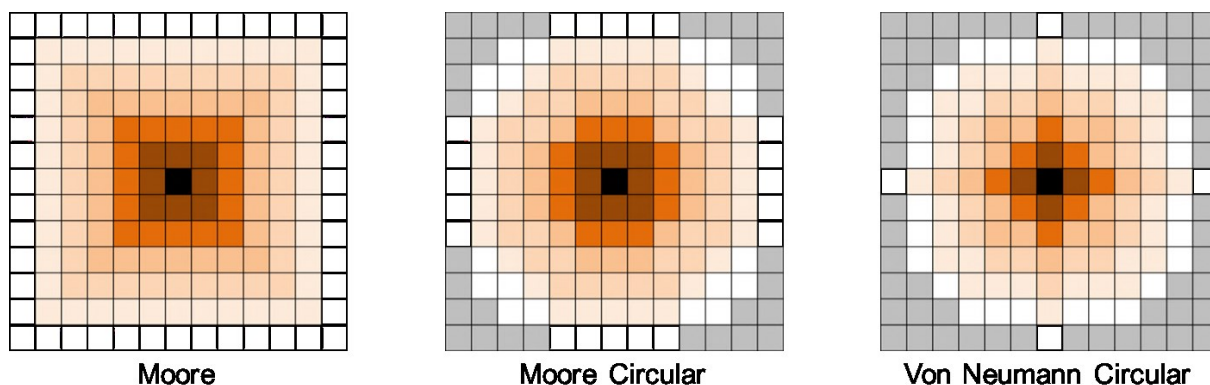
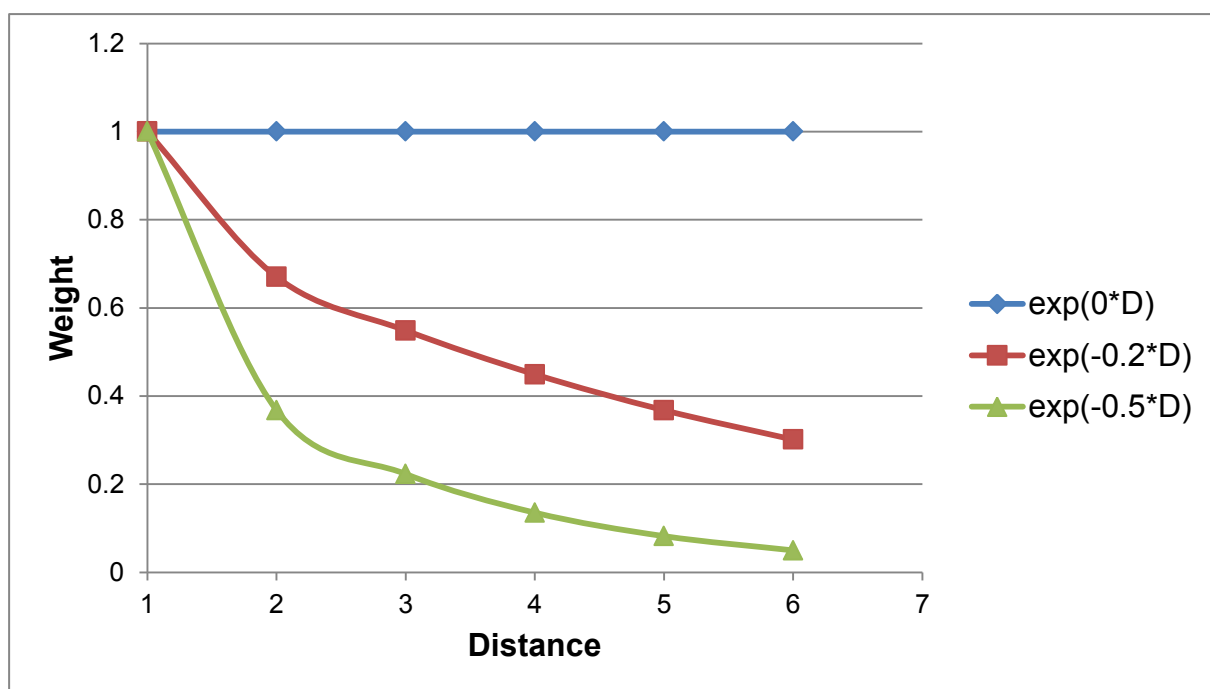


Figure 4-6: Weighting function for neighborhood



The total constraint score was calculated as:

$$CONS_{ij} = \prod_{f=1}^n con_{ij,f} \quad (19)$$

where $CONS_{ij}$ is the total evaluated constraint score representing natural constraints to urban expansion. If $CONS_{ij}=0$, cell (i,j) is constrained by some constraint factors, and the cell cannot be converted to urban land use. Otherwise, $CONS_{ij}=1$. $con_{ij,f}$ represents the binary value of constraint factor f for the cell (i,j) . In this study, water body is considered as the constraint areas.

Principally, land conversion is allocated according to the potential score. However, considering the complex elements which participate in the urban growth in China, simulations of the development are subject to a high degree of uncertainty. From a practical point of view, the related complexity of urban systems could be modeled as

some degree of stochasticity (Barredo et al., 2003). Thus, a stochastic disturbance parameter was introduced into the model. It was calculated with Eq. 20:

$$V = 1 + (-\ln(rand))^a \quad (20)$$

where *rand* is a random value within the range from 0 to 1, and *a* is random variable which is used to control the degree of stochasticity. A higher value of *a* represents more random degree involved in this model.

Once the transition potential is calculated, decision rules need to be identified to spatially allocate the new urban area in order to simulate the historical and future urban growth process. At each iteration, the new urban pixels are allocated by selecting the non-urban pixels with the higher transition potential values. The non-urban pixels with lower values remain unchanged. The iteration continued until the total urban expansion area is reached.

4.3.2 Model calibration and validation

The aim of calibration is to estimate the transition rule parameters that allow for the accurate simulation of the past urban growth (Santé et al., 2010). However, the calibration of cellular automata model is difficult because of the many interacting variables involved (Pan et al., 2010). Because the logistic regression model is essential static, it is not able to reveal the path-dependent and self-organization development that is typical for urban growth. In this study, therefore, the weights of global suitability variables, neighborhood size, neighborhood types, weighting function, and random variables need to be calibrated. As discussion in 2.3.3, there are many calibration methods, choosing an appropriate method for the study in question is challenging. An advantage of the logistic regression is its ability to estimate the weights of various spatial factors by developing statistical relationships between historical urban growth and spatial factors (Arsanjani et al., 2013; Ward et al., 2000). It can avoid subjectivity in determining the weights involved in transition rules of the CA model. However, it does not include all the relevant variables and cannot explain temporal dynamics of relationships (Hu and Lo, 2007). The global factors which keep constant during each simulation period are involved into the logistic regression model. While the neighborhood effect and the random variable change with the running of the CA model. It is impossible to estimate these parameters using the logistic regression model. The trial and error method is a more rigorous calibration method. But its time cost for calibrating all parameters is not acceptable because trial and error method is implemented by running CA model

many times with different parameter values. In this study, the hybrid method consisting of logistic regression and trial and error was used for the calibration in this study.

Validation is conducted by comparing the simulated results generated from calibrated CA models with observed maps in order to assess the simulation ability of CA models for different periods. Various indicators have been introduced to measure the goodness-of-fit between the simulated and the observed urban land use maps. They can be classified into two types: locational and pattern indicators (Jenerette & Wu, 2001). The former one provides a frequent way to conduct the comparison on the basis of cell by cell, while the latter focuses on similarity of urban spatial patterns between simulated and observed maps. The calibration and validation of the CA model should depend on the specific objective of the CA model (Wu, 2002). With the consideration of the simulation purpose which is to make the simulated urban growth as close as the actual one in terms of location and pattern, a mixed measure based on the cell by cell and spatial pattern analysis was chosen in this study. The figure of merit (Eq. 21) (Pontius et al., 2007), and the relative difference of spatial metrics (Eq. 22) were computed to evaluate the fit of goodness between simulated and observed maps.

The figure of merit is the ratio of the intersection of the observed developed and simulated developed to the union of the observed developed and predicted developed (Pontius et al., 2008). The figure of merit can range from 0% to 100%. A higher value of figure of merit indicates a higher agreement in terms of cell by cell comparison. The figure of merit is calculated using the following equation (Pontius et al., 2008):

$$\text{Figure of merit} = \frac{B}{A+B+C+D} \quad (21)$$

where A is the area of error due to observed developed and simulated as persistence, B is the area of correct due to observed developed and simulated as developed, C represents the area of error due to observed developed and simulated as incorrect gaining category, and D is the area of error due to observed persistence and simulated as developed. Because the CA model only simulates the change of states from non-urban to urban, the value of C should be equal to 0.

The pattern similarity was incorporated, which was estimated through the comparison of spatial metrics between simulated patterns and observed ones. A total of four

spatial metrics were selected to represent the spatial pattern from different aspects. These metrics are: NP, LPI, SHAPE_AM and ENN_AM. The relative difference Rd can be calculated as follows:

$$Rd(\%) = \frac{1}{4} \times \sum_i \left| \frac{M_{s,i} - M_{o,i}}{M_{o,i}} \right| \times 100 \quad (22)$$

where $M_{s,i}$ and $M_{o,i}$ are the values of spatial metric i calculated from the simulated and observed urban land use maps, respectively. A smaller absolute value of Rd indicates that the simulated urban spatial pattern is closer to the observable pattern.

The calibration objectives can be expressed as following:

$$\text{Figure of merit } (w_1, w_2, \dots, w_n) \rightarrow \text{Max} \quad (23)$$

$$Rd (w_1, w_2, \dots, w_n) \rightarrow \text{Min} \quad (24)$$

4.3.3 Simulation of the future scenarios

In addition to the simulation of realistic urban growth, the CA model provides a means for simulation different scenarios under the different urban land use planning policies. Scenario-based analysis can help in further understanding the driving factors of urban growth and in assessing the potential impact of urbanization on the environment, consequently, provide a support for urban planning and decision making. Scenario simulation is a process of analyzing possible future development by considering alternative possible outcomes. It is a tool for balancing land use changes with sustainable growth, examining the emerging spatial patterns of the scenarios, and facilitating decision making (Munshi et al., 2014; Thapa & Murayama, 2012).

4.3.3.1 Design of the scenarios

The design of scenarios should be based on the three criteria of scenarios proposed by Xiang and Clarke (2003) and strongly linked to the current existing concerns of the policy makers of the region addressing the key question as well as the historical urban growth trend. In recent years, there has been an increasing interest for developing sustainable urban form. A compact development is necessary in order to improve sustainability. Although there is a strong agreement on this statement, a debate between compact city and dispersed city has never stopped. Both of positive and negative effects of each type of city have been reported. In order to provide an insight into the different urban development strategies, five urban growth scenarios were designed towards 2020 and were named according to the

main themes that result from the scenarios (Figure 4-7). The land demand during this period was estimated according to the urban plan of Xuzhou.

1. The business as usual scenario (BUS) assumes that the future urban growth follows historical trend without any adjustment when environmental and developmental conditions are similar to the ones observed from the historical data. However the expanded road network will be involved. This scenario provides an insight into the spatial consequence of urban growth under the same conditions as those used to simulate the urban growth from 2005 to 2010.

2. The planning-strengthened scenario (PSS) assumes that the future urban growth strictly follows the master plan of Xuzhou city. The plan influences new developed urban allocation, as it establishes the legal regulatory framework for future land use. The master planning for Xuzhou city 2020 emphasizes to protect farmland and discourage the urban development in environmental protection areas and to achieve balanced development. This scenario provides a better understanding of the impact of planning on urban growth. The alternative also reflects maximum protection of environmentally sensitive land.

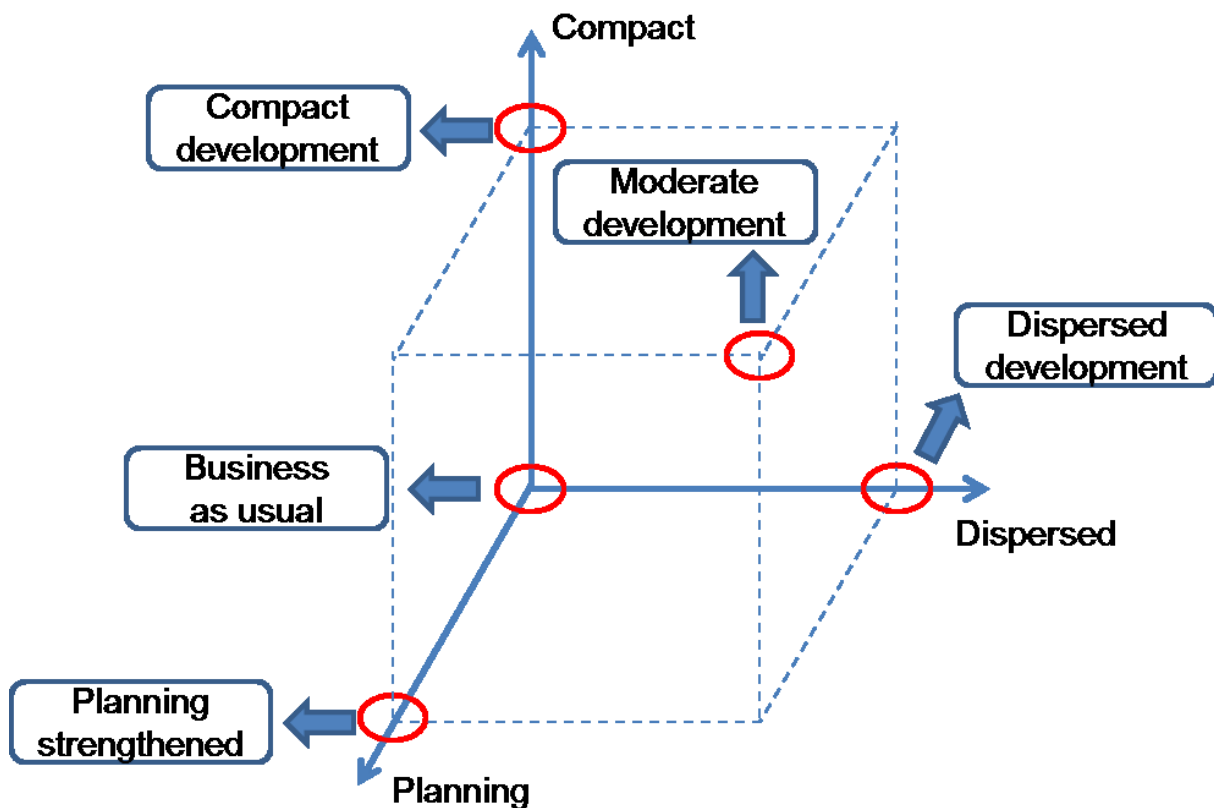
3. Considering the urban development challenges, we established the compact development scenario (CDS) that aims to prevent sprawl-like development and to create a more compact city. The compact development is crucial for less pressure on other land cover types, being more efficient in the use of natural resources and sustainability. It is not only associated with high density, the centralization but also plays an important role in forming a compact city. This scenario takes into consideration the fact and urban development policy which includes three aspects when implementing this scenario. First, the development is mainly concentrated around the existing city center, providing a more compact urban form. In other words, development would be allocated in areas with good access to the city center to support the use of other means of transportation than by car (Fuglsang et al., 2013); Second, in order to increase land use efficiency, a major development policy is implemented to increase the development of high-density residential and to decrease the development of low-density residential, which can reduce the per capita demand for the occupied land. Additionally, the urban growth allocation should be strictly limited to the environmental considerations.

4. Contrary, the dispersed development scenario (DDS) was developed to simulate the future urban pattern with an increase of urban sprawl but without any effective

urban planning against this trend. Urban sprawl is a worldwide phenomenon and it leads to an outwards spreading of the city and to a growth in lower density areas. Due to the rapid economic growth and widespread of private vehicles, people desire to move to the low density settlements in order to avoid the congestion and large pollution in the city center, as well as to pursue a better living environment. In addition, the cost of housing outside the city center could be lower. Hence, the aim of the scenario is to encourage developments of new urban patches and urban infrastructure outside the city center. This scenario reflects a lesser degree of environmental protection.

5. The debate concerning sustainable urban form could move towards more moderate position where agreements are easier to achieve. The master planning 2020 of Xuzhou focuses on balancing city core, fringe and rural development. The focus of development will be shifted from the city center to the whole Xuzhou region. In this respect, development in the form of polycentric development is increasingly considered as the best way for urban sustainability (Bontje, 2004; Catalán et al., 2008). Meanwhile the demand of residents for better living environment is also enhanced. Considering this fact and the urban development policy, the moderate development scenario (MDS) was designed. Closer link between the former city center and several developed regions in fringe area is established. In addition, due to the fact that the rural settlements in Xuzhou are small in size but numerous and scattered, coordinating urban and rural development is also involved in this scenario not only for intensive land use but also for economic growth in rural areas. Therefore, the scenario aims to promote the endogenous potential of city center, suburban center, and rural area and the cooperation between them in order to achieve a physically and functionally connected region.

Figure 4-7: Different development scenarios



4.3.3.2 Identification of parameters

The flexibility in parameters allows the CA model to explore different urban development scenarios. The spatial distribution characteristics can be controlled by parameter settings. In this study, global suitability values were calculated by the logistic regression. As mentioned in previous section, an advantage of the logistic regression is its ability to objectively analyze relationships between historical urban growth and factors. However, it is not an optimal way to simulate different scenarios by changing coefficients of the logistic regression according to the scenarios. In contrast, MCE is an important means of analysis in spatial decision support systems, as it allows weighted value to be assigned to spatial layers, and the sum of these values produces a final suitability map. However, determining factor weights is a complicated task in MCE. AHP originally developed by Saaty (1980) is one of the most commonly used approaches when analyzing complex decision problems. It can be used to derive behavior-oriented transition rules (Wu, 1998b). Basically, the pair-wise comparison of the relative importance is conducted to arrive at a scale of preference among a set of alternatives (Malczewski, 1999). A detailed analytic process is presented below.

The relative importance of variables is first compared using Saaty's 1-9 scale (Table 4-3). A pairwise comparison matrix A is then obtained:

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & 1 \end{bmatrix}, (i, j = 1, 2, \dots, n) \quad (25)$$

where $a_{ji} = 1/a_{ij}$. Then A is normalized as a matrix B :

$$B = [b_{ij}], (i, j = 1, 2, \dots, n) \quad (26)$$

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}, (i, j = 1, 2, \dots, n) \quad (27)$$

Each weight value is calculated as:

$$w_i = \frac{\sum_{j=1}^n b_{ij}}{\sum_{i=1}^n \sum_{j=1}^n b_{ij}}, (i, j = 1, 2, \dots, n) \quad (28)$$

The relationships between the λ_{max} and corresponding eigenvector W of the matrix B is presented as follows:

$$BW = \lambda_{max}W \quad (29)$$

$$W = (w_1, w_2, \dots, w_n)^T \quad (30)$$

$$\lambda_{max} = \sum_{i=1}^n \frac{(BW)_i}{nw_i}, (i, j = 1, 2, \dots, n) \quad (31)$$

where $(BW)_i$ is the i -th value of the vector BW .

Additionally, an index of consistency known as the Consistency Ratio (CR) is used to check judgment inconsistencies.

$$CR = \frac{CI}{RI} \quad (32)$$

where the Random Index (RI) is the average of the resulting consistency index depending on the order of the matrix. A CR less than 0.1 indicates that the matrix can be considered as having an acceptable consistency (Satty, 1980). Otherwise, the matrix should be reconsidered and revised. The Consistency Index (CI) can be calculated as following:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (33)$$

Table 4-3: Scale for pairwise comparison

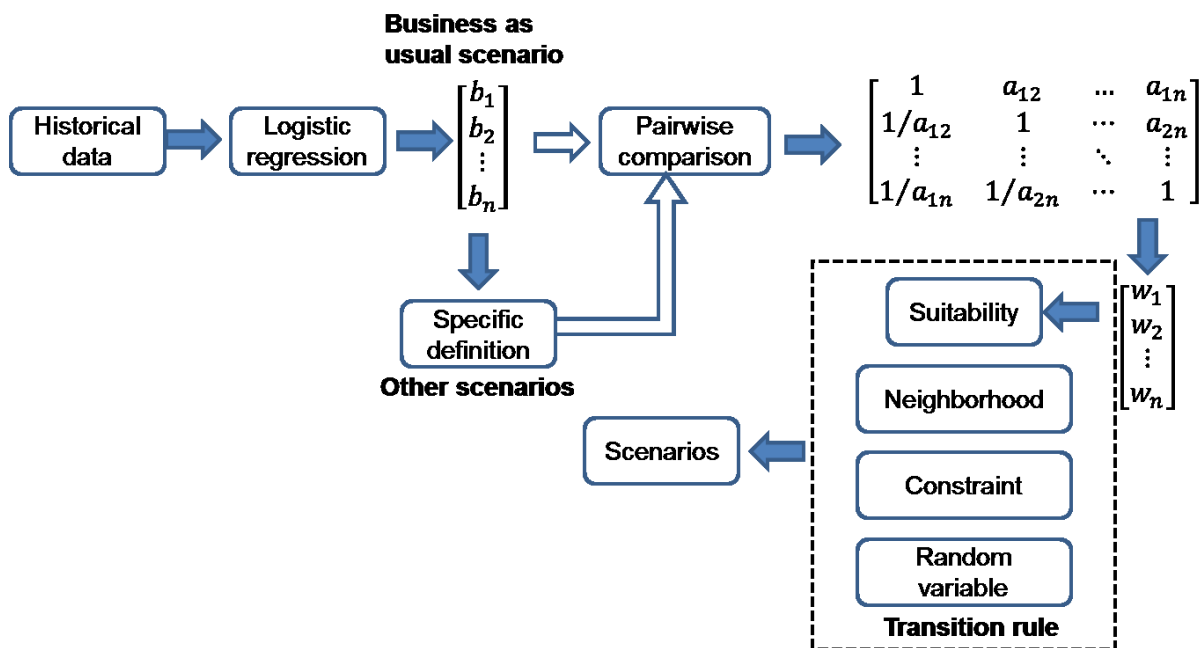
Intensity of importance	Description
1	Equal importance
3	Weak importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments

Source: Saaty & Vargas, 2001

By using AHP, the weights of global factors are identified and imported into the CA model for calculating global suitability value. AHP provides a comprehensive and rational framework for structural conceptualization of decision making, in which the relative importance of several variables can be compared (Vaz et al., 2012). Hence, the integration of MCE and AHP benefited this study in that it has capability to link scenario simulation with decision making processes and to translate the qualitative descriptions of scenarios into quantitative spatial analysis.

However, the weight of each global factor in AHP is usually identified by direct subjective assessment because preferences of decision makers determine the relative importance of each factor. In order to incorporate more realistic behavior into the simulation, the historical urban growth trend needs to be considered in decision making process. Therefore, the logistic regression coefficients for the period of 2005-2010 in CA model were used to identify the relative importance of each global factor in AHP for further modification. Figure 4-8 shows the integrated approach for modeling different development scenarios. When simulating business as usual scenario, the relative importance derived from logistic regression kept unchanged. While simulating other scenarios, the relative importance needed to be modified according to the initial relative importance of each factor in 2005-2010 and specific definition of each scenario. Furthermore, the neighborhood configurations and random variables also needed to be modified.

Figure 4-8: Multiple scenarios modeling approach



4.3.3.3 Evaluation and comparison of the scenarios

Scenario-based urban growth analysis can help in further understanding the driving factors of urban growth and in assessing the potential impact of urbanization on the environment. For the evaluation and comparison of the five scenarios, a set of spatial metrics were selected to quantify the urban growth pattern of each scenario at two scales: global and local scales. For the global level, NP, LPI, and SHAPE_AM, ENN_AM were calculated using Fragstats 4 (McGarigal et al., 2012). However, this result provides a general description of urban growth pattern at global level. The spatial metric is scale-dependent. The scale used is the entire study area. In order to discover and locate differences of the scenarios in urban growth pattern, local scale was used to conduct spatial metrics analysis. This study divided the study area into several 2 km × 2 km blocks. Class Area, NP, and SHAPE_MN were calculated for every block to characterize the urban spatial pattern in each scenario.

5. Results and discussion

In the previous chapters, the attempt was made to illustrate how important is the monitoring and analysis of urban growth and how to conduct this work by adopting related methods. In order to evaluate the performance of the proposed methods described in previous chapter as well as to provide a better understanding of the urban growth in Xuzhou city, the methods have been applied based on the available data. The chapter presents and discusses the major findings of this study.

5.1 Land cover change

5.1.1 Classification accuracy

The efficiency of the V-I-S based hierarchical classification approach for land cover classification was analyzed in comparison with a traditional classification approach based on MLC and post classification refinement. A total of 300 samples were used for accuracy assessment.

The assessment results of traditional classification were generated for two study areas (Tables 5-1 and 5-2). The overall accuracies range from 82.7 % to 84.0 % for Xuzhou city and from 80.0 % to 85.0 % for Dortmund city region. The results show a strong confusion among different land cover classes, as indicated by low accuracy values. This could be related to the fact that the traditional method cannot solve the problems caused by mixed pixel and spectral similarity.

Table 5-1: Accuracy assessment of Xuzhou land cover maps produced using traditional approach (%)

Land cover class	1990		2001		2005		2010	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Built-up	73.4	81.0	77.3	81.0	78.8	80.0	80.6	80.6
Farmland	86.7	83.0	87.7	83.8	89.5	82.2	86.8	82.0
Vegetation	78.0	76.5	77.8	82.4	75.9	88.0	77.2	88.0
Water body	88.2	90.0	86.0	86.0	86.5	90.0	84.0	84.0
Overall accuracy	82.7		83.3		84.0		83.0	

Table 5-2: Accuracy assessment of Dortmund city region land cover maps produced using traditional approach (%)

Land cover class	1989		2000		2006		2010	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Built-up	75.8	77.0	73.9	75.0	76.3	78.4	76.6	74.7
Farmland	86.8	84.6	83.5	83.5	82.0	81.3	76.6	78.2
Vegetation	84.4	90.3	84.4	80.6	80.6	84.4	78.1	82.0
Water body	93.6	88.0	86.5	90.0	91.3	84.0	88.2	90.0
Overall accuracy	85.0		82.0		81.7		80.0	

The classification results generated by V-I-S based hierarchical classification approach are presented in Tables 5-3 and 5-4. They have higher accuracies than the traditional approach in all classes. Over accuracy of more than 89 % is achieved. The overall accuracies are found to be improved by 6.0-7.7 % for Xuzhou city and 5.3-9.3 % for Dortmund city region, respectively, using the hierarchical classification method. Both the producer's and user's accuracy are consistently higher than the corresponding accuracies of the traditional approach.

Table 5-3: Accuracy assessment of Xuzhou city land cover maps produced using V-I-S based hierarchical classification approach (%)

Land cover class	1990		2001		2005		2010	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Built-up	87.7	89.3	90.6	89.2	89.9	88.6	87.2	90.7
Farmland	92.3	93.0	90.6	94.0	93.8	92.3	81.1	90.4
Vegetation	86.0	89.6	88.2	88.2	85.2	92.0	83.0	88.0
Water body	97.8	90.0	95.7	88.0	95.9	94.0	93.3	84.0
Overall accuracy	90.0		91.0		91.7		89.0	

Table 5-4: Accuracy assessment of Dortmund city region land cover maps produced using V-I-S based hierarchical classification approach (%)

Land cover class	1989		2000		2006		2010	
	Producer's	User's	Producer's	User's	Producer's	User's	Producer's	User's
Built-up	85.9	87.3	86.7	91.5	91.9	90.1	90.9	89.7
Farmland	91.4	92.2	93.7	91.2	90.3	91.7	89.8	89.0
Vegetation	88.0	91.7	89.4	90.8	88.2	92.3	83.3	87.3
Water body	97.8	88.0	95.8	92.0	95.6	86.0	93.9	92.0
Overall accuracy	90.3		91.3		91.0		89.3	

The comparison of results demonstrates that the V-I-S based hierarchical classification approach is effective in extracting land cover information from Landsat images especially in urban areas. The accuracies meet the minimum USGS total accuracy set out by Anderson et al. (1976), hence the classified results can be used as data source for post classification comparison and further analysis.

5.1.2 Land cover classification

The multi-temporal land cover classification maps for two study areas are shown in Figures 5-1 and 5-2. The individual class area for the study years are summarized in Tables 5-5 and 5-6.

From the overall trend, intense land cover change occurred in Xuzhou city was mainly characterized by a significant increase in built-up land, and a gradual decrease in farmland and vegetation. The area of water body increased rapidly due to the waterlogged subsidence in coal mining areas during 1990-2005. Because of

the reclamation of subsidence, some of them were used as farmland, which led to the decrease of water body in 2010. The built-up land, as the largest growth type, increased from 174.6 km² in 1990 to 566.9 km² in 2010. Furthermore, the annual rate of growth in built-up land increased (Figure 5-3), which indicates Xuzhou city experienced rapid urban growth process with the accelerating speed over the study period. The economic reform started in China since late 1970s. After the initial period of around 10 years from centralized planning to market-oriented economic system, the economy of Xuzhou city was moving into the fast lane. Rapid development required more built-up land and industrial workers than ever before, which also led to relatively high urbanization speed. The incredible pressure of rapid urbanization on non-urban land was reflected by the high loss in farmland and vegetation land. A large amount of non-urban land was converted into built-up land. The farmland and vegetation decreased by 327.8 km² and 109.5 km², respectively.

Compared to Xuzhou city, Dortmund city region in Germany showed different land cover change trends. The built-up area increased at a lower speed. In 1989, built-up area was 588.1 km², representing 20.77 % of the total area, and increased to 738.9 km² in 2010. It has been observed that growth speed of built-up land was slower than that in Xuzhou city. Moreover, the annual growth rate decreased from 8.30 km² to 5.85 km² over time, which indicates that the speed of development slowed down. Meanwhile, the corresponding reduction in farmland and vegetation land also slowed down. The trends in land cover change for the three important classes, built-up, farmland and vegetation areas are shown in Figure 5-4.

Figure 5-1: Classified land cover maps of Xuzhou city from 1990 to 2010

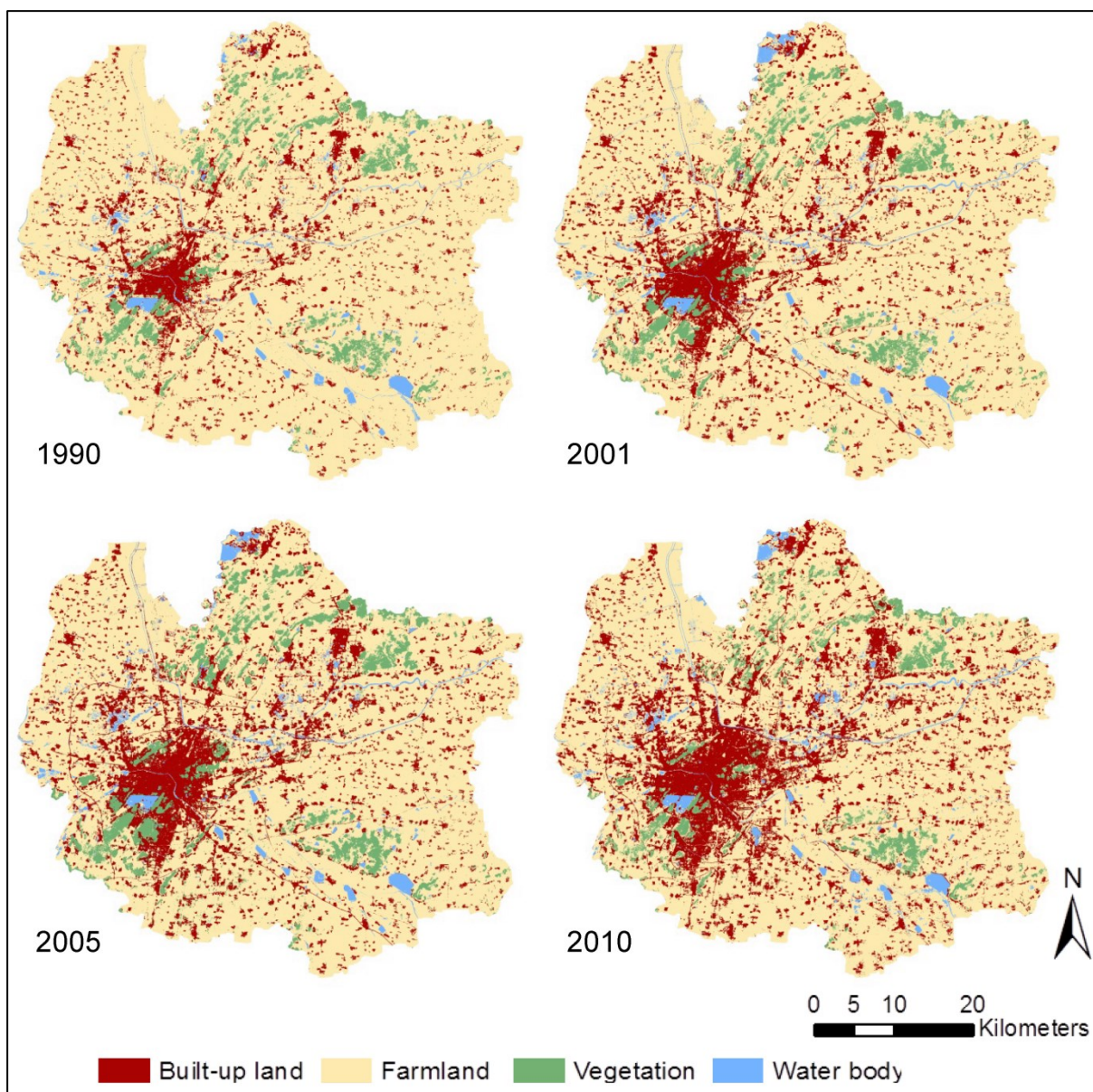
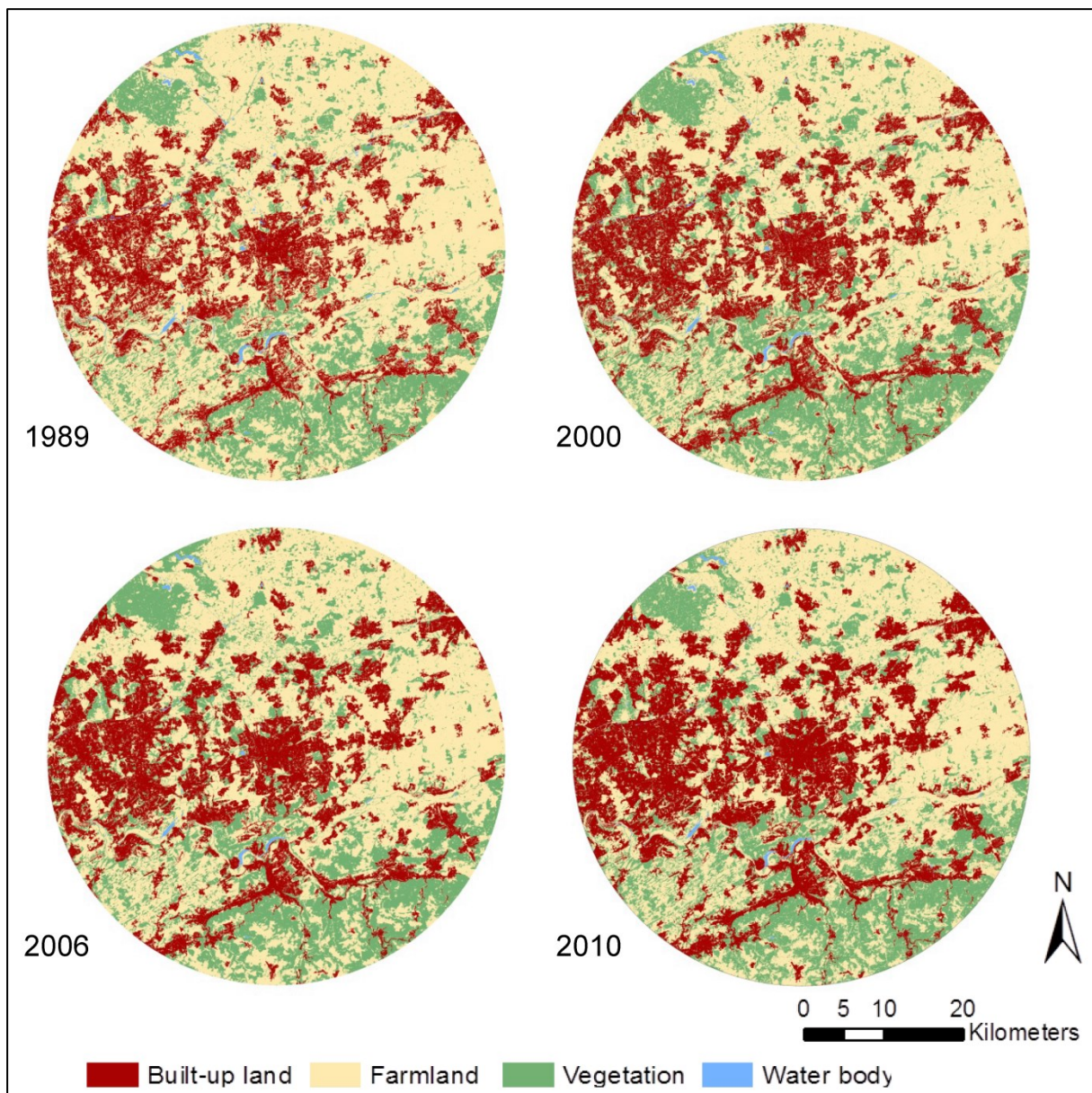


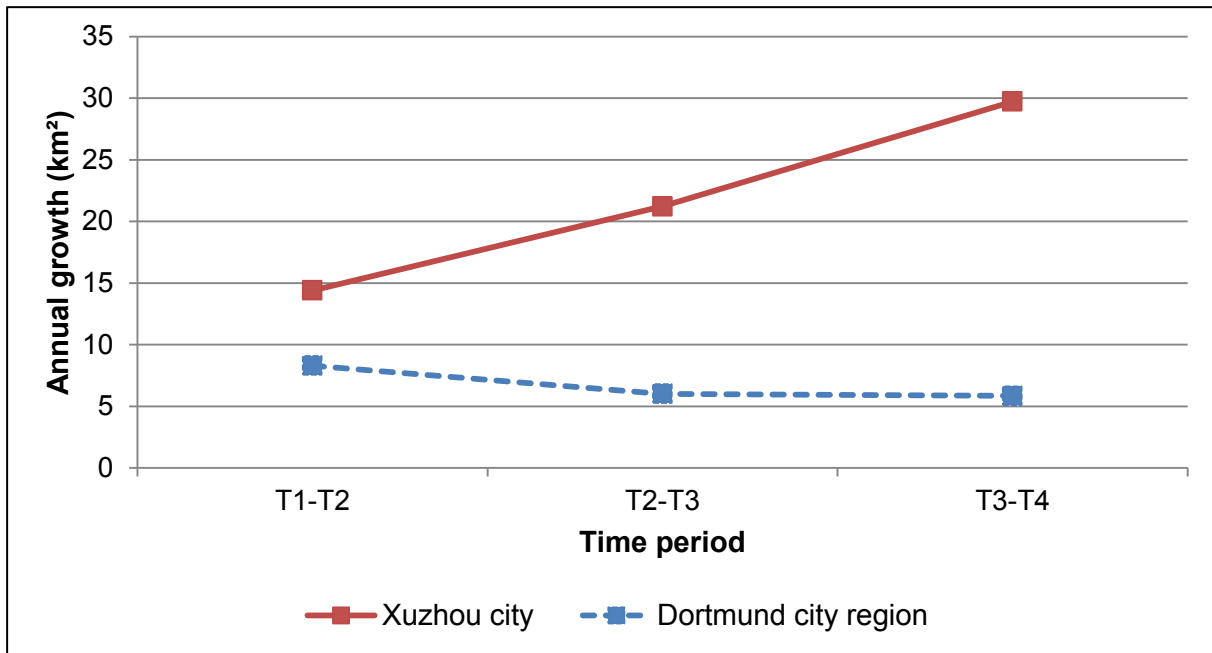
Table 5-5: Land cover statistical data of Xuzhou city

Classes	1990		2001		2005		2010	
	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)
Built-up	174.6	6.03	333.4	11.50	418.3	14.44	566.9	19.57
Farmland	2430.2	83.88	2303.4	79.51	2230.3	76.98	2102.4	72.57
Vegetation	253.6	8.75	192.3	6.64	151.8	5.24	144.1	4.97
Water	38.9	1.34	68.1	2.35	96.8	3.34	83.8	2.89

Figure 5-2: Classified land cover maps of Dortmund city region from 1989 to 2010**Table 5-6: Land cover statistical data of Dortmund city region**

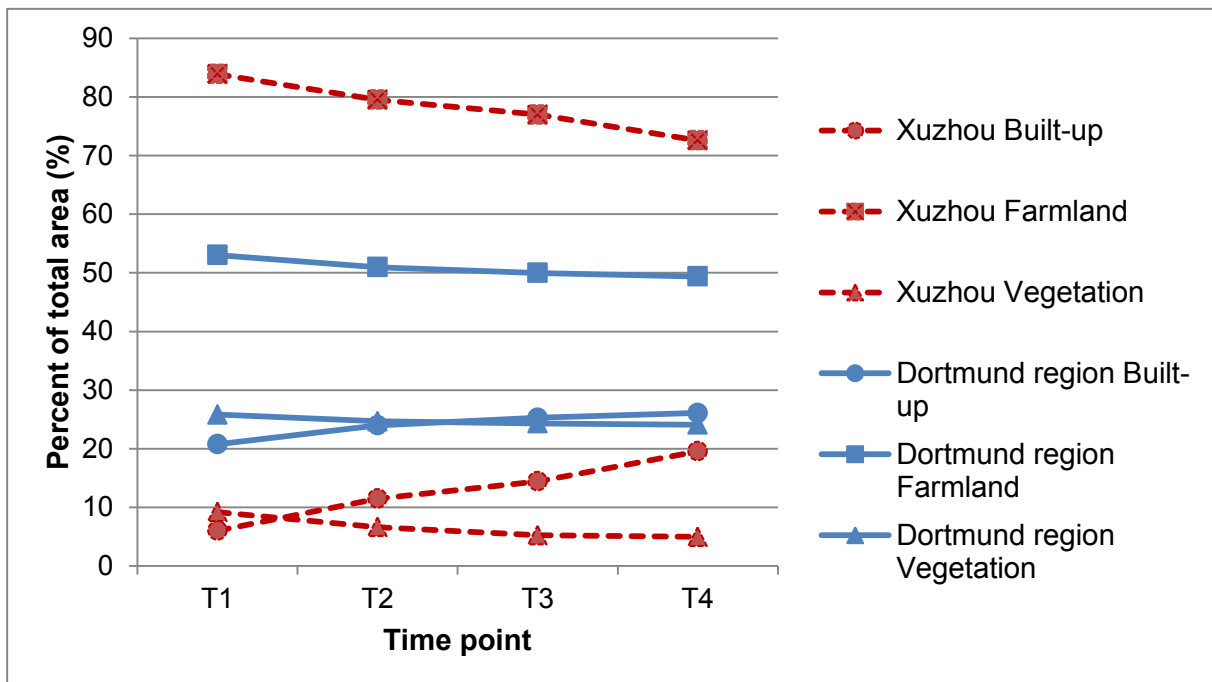
Classes	1989		2000		2006		2010	
	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)	Area (km ²)	Percent (%)
Built-up	588.1	20.77	679.4	24.00	715.5	25.27	738.9	26.10
Farmland	1501.4	53.03	1442.4	50.95	1415.3	49.99	1398.3	49.39
Vegetation	730.8	25.82	698.4	24.67	688.8	24.33	682.2	24.10
Water	10.8	0.38	10.9	0.38	11.5	0.41	11.7	0.41

Figure 5-3: Annual growth of built-up class



Note: Xuzhou city (T1: 1990; T2: 2001; T3: 2005; T4: 2010). Dortmund city region (T1: 1989; T2: 2000; T3: 2006; T4: 2010)

Figure 5-4: Area percentage of built-up, farmland, and vegetation classes



5.1.3 Land cover change in Xuzhou city and Dortmund city region

To further evaluate the results of land cover conversions, the post classification comparison of change detection was carried out using GIS, producing matrices of land cover changes and change maps.

The matrices of land cover changes during the study period of two areas (Tables 5-7 and 5-8) show a summary of the major land cover conversions. The unchanged

pixels are located along the major diagonal of the matrix. The results for Xuzhou indicate that a total of 392.3 km² of land was converted into built-up land accounting for about 67.6 % of the total land cover change area during 1990-2010. As indicated, the majority of built-up land came from conversion of farmland to urban uses. In particular, 74.2 %, 97.3 %, and 97.2 % of the increase in built-up land were converted from farmland in the periods 1990-2001, 2001-2005, and 2005-2010, respectively. It reflects the conflict between the increasing demand for built-up land and limited land resources.

In Dortmund city region, the matrices (Table 5-8) show that 198.8 km² land experienced change between 1989 to 2010, of which the urban conversion accounts for 75.9 %. This indicates that built-up development is the main component of land cover change within both Xuzhou city and Dortmund city region. Furthermore, major changes are also observed from farmland to built-up land. Approximately 86.0 %, 84.8 %, and 64.5 % of new developed built-up land were acquired by converting areas that were previously farmland in the periods 1989-2000, 2000-2006 and 2006-2010, respectively. The situation is similar with the corresponding conversions in Xuzhou city.

Table 5-7: Matrices of land cover changes in Xuzhou city from 1990 to 2010 (unit: km²)

	Class	Built-up	Farmland	Vegetation	Water body
		1990			
2001	Built-up	168.9	119.5	45	0
	Farmland	1.6	2285	16.4	0.5
	Vegetation	1	1.8	189.5	0
	Water body	3.1	23.9	2.7	38.4
		2001			
2005	Built-up	325.4	83.9	9.1	0
	Farmland	1.2	2198.8	26.5	3.8
	Vegetation	2.8	0.6	148.4	0
	Water body	4	20.2	8.3	64.3
		2005			
2010	Built-up	414.8	145.1	7	0
	Farmland	0.7	2073.7	13.6	14.4
	Vegetation	2.3	1.1	131.2	9.5
	Water body	0.5	10.4	0	72.9

Table 5-8: Matrices of land cover changes in Dortmund city region from 1989 to 2010 (unit: km²)

	Class	Built-up	Farmland	Vegetation	Water body
		1989			
2000	Built-up	584.8	79.4	15.2	0
	Farmland	0.9	1421.5	19.5	0.5
	Vegetation	2.4	0.3	695.7	0
	Water body	0	0.2	0.4	10.3
		2000			
2006	Built-up	678.1	31.4	6	0
	Farmland	0.8	1409.1	5.2	0.2
	Vegetation	0.5	1.4	686.9	0
	Water body	0	0.5	0.3	10.7
		2006			
2010	Built-up	713.6	16.2	8.7	0.4
	Farmland	1.1	1395.2	2	0
	Vegetation	0.8	3.3	677.6	0.5
	Water body	0	0.6	0.5	10.6

Although above statistics generated the similar “from-to” information in both two study areas, they reveal few insights into the question of where land cover changes are occurring. Figures 5-5 and 5-6 show the location of major land cover conversions for the two study areas for understanding the spatial pattern of change during the study period.

In Xuzhou city, the built-up land growth was observed in different forms. Fringe area has experienced rapid urbanization which is indicated by the rapid increase in built-up land in this area. Meanwhile, some land was developed to built-up land beyond the existing developed areas. In addition, infill growth is also observed. In Dortmund city region, however, the majority of changes from other land to built-up land were concentrated along the periphery of existing built-up areas as well as in the areas that have already been developed. Although urbanization is generally driven by population and economic growth (Hu & Lo, 2007; Li et al., 2013a), the urban growth pattern in the study areas were associated with other factors such as accessibility to the city center.

Figure 5-5: Spatial distribution of built-up land growth in Xuzhou city between 1990 and 2010

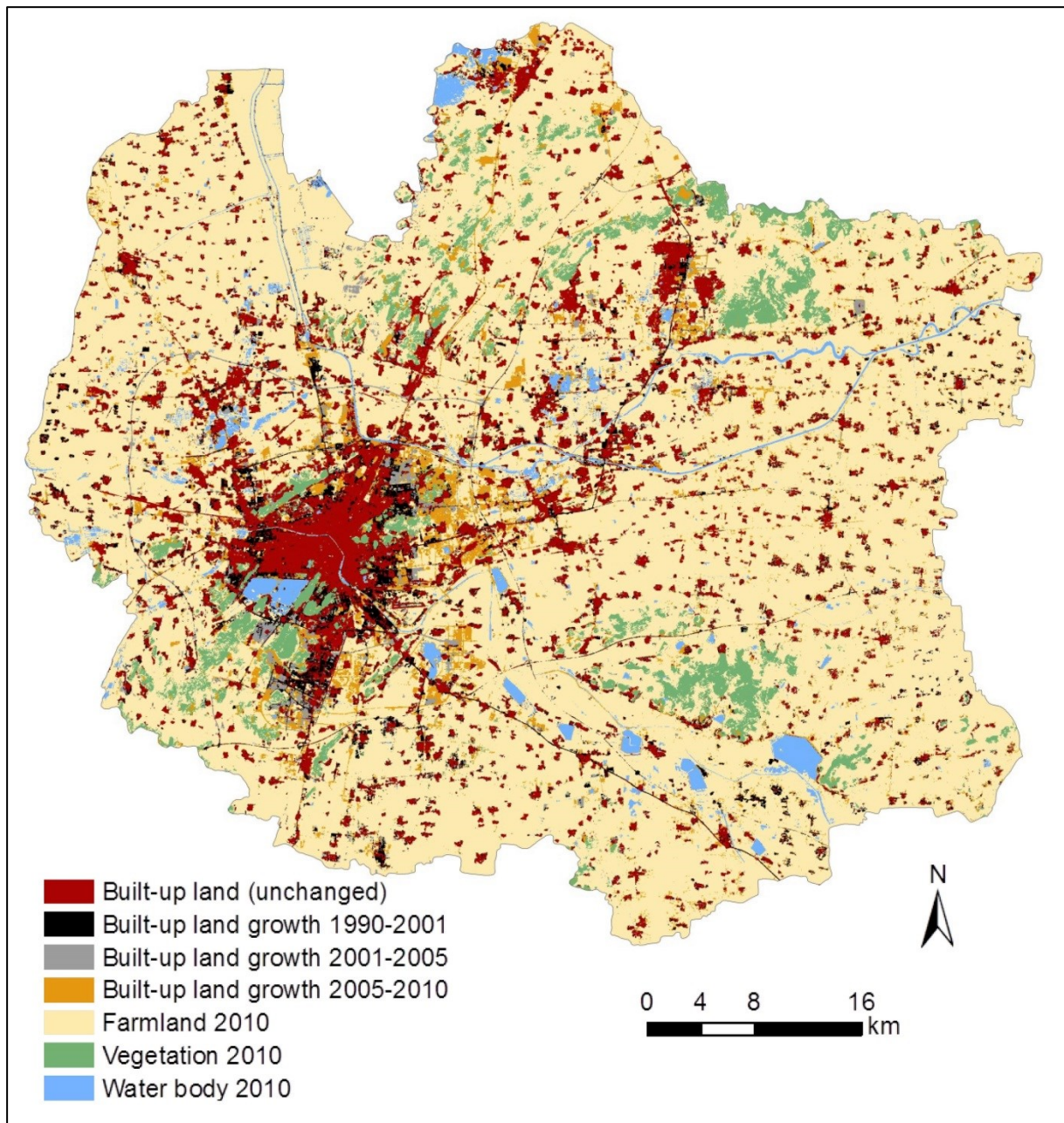
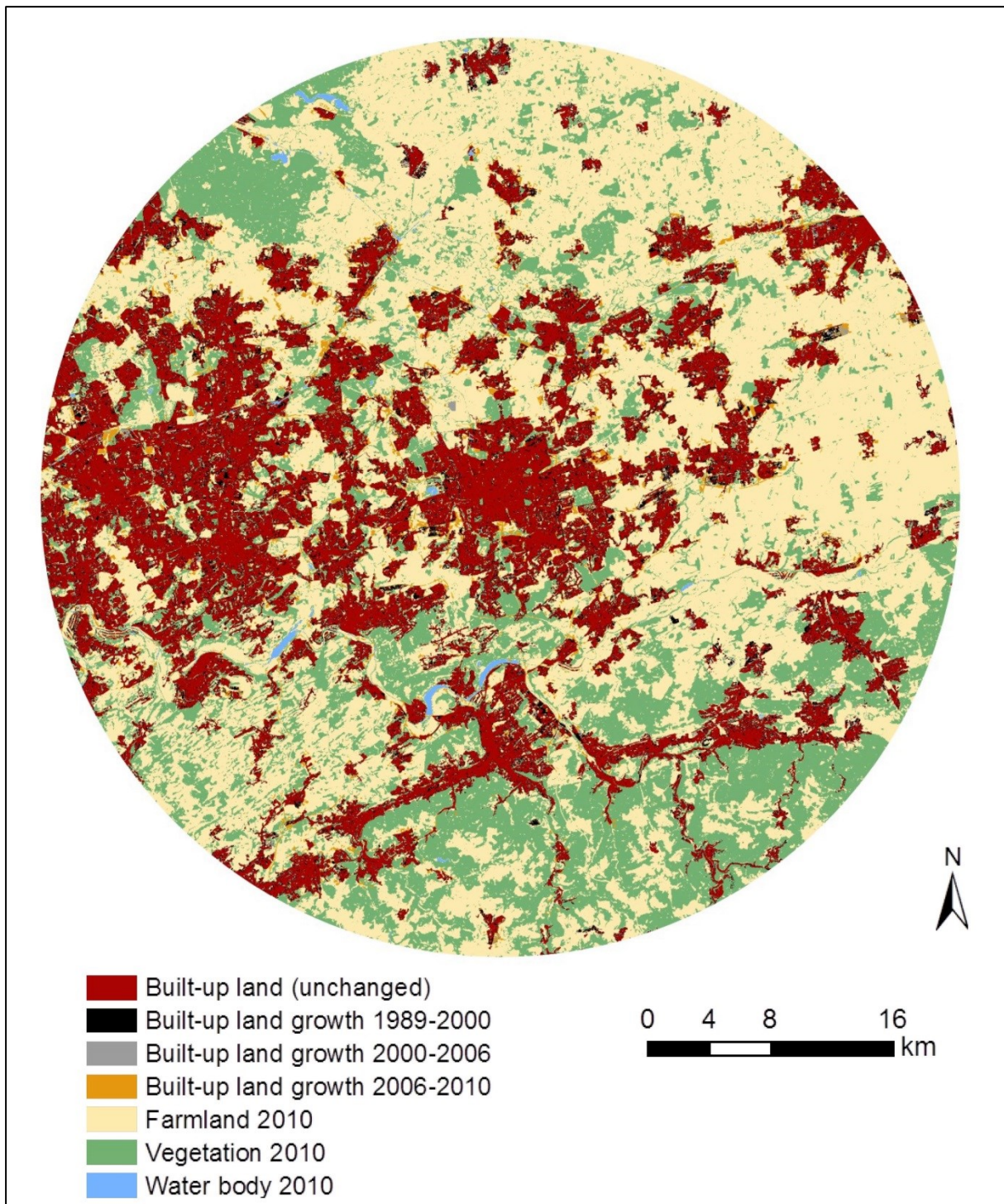


Figure 5-6: Spatial distribution of built-up land growth in Dortmund city region between 1990 and 2010



5.1.4 Spatio-temporal characteristics of urban growth

The previous section gave a general overview of the land cover and the changes that occurred in the study areas. In this section, changes of built-up land were addressed in both spatial and temporal in order to capture the spatio-temporal dynamics of built-up land and provide an insight into the differences of urban growth characteristics between Xuzhou city and Dortmund city region.

The relationships between urban growth and distance from the existing built-up area were explored using buffer analysis. Figures 5-7 and 5-8 present the percentage of new developed area in each buffer zone to that in the whole buffer zones (R_a). By using FR indicator, the results of buffer analysis for the new developed built-up land in two study areas are shown in Figures 5-9 and 5-10, in which urban expansion and its temporal dynamics are reflected.

Figure 5-7: Change in R_a with distance to the existing built-up over Xuzhou city in different periods

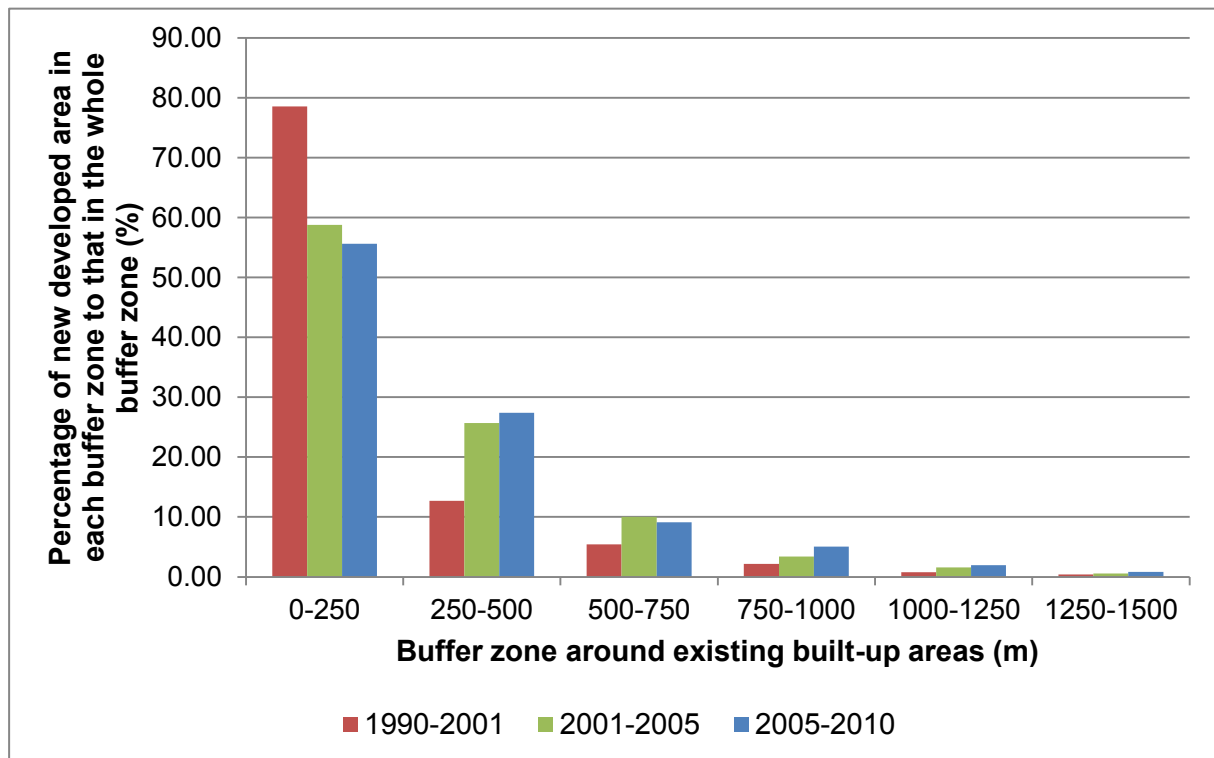


Figure 5-8: Change in R_d with distance to the existing built-up over Dortmund city region in different periods

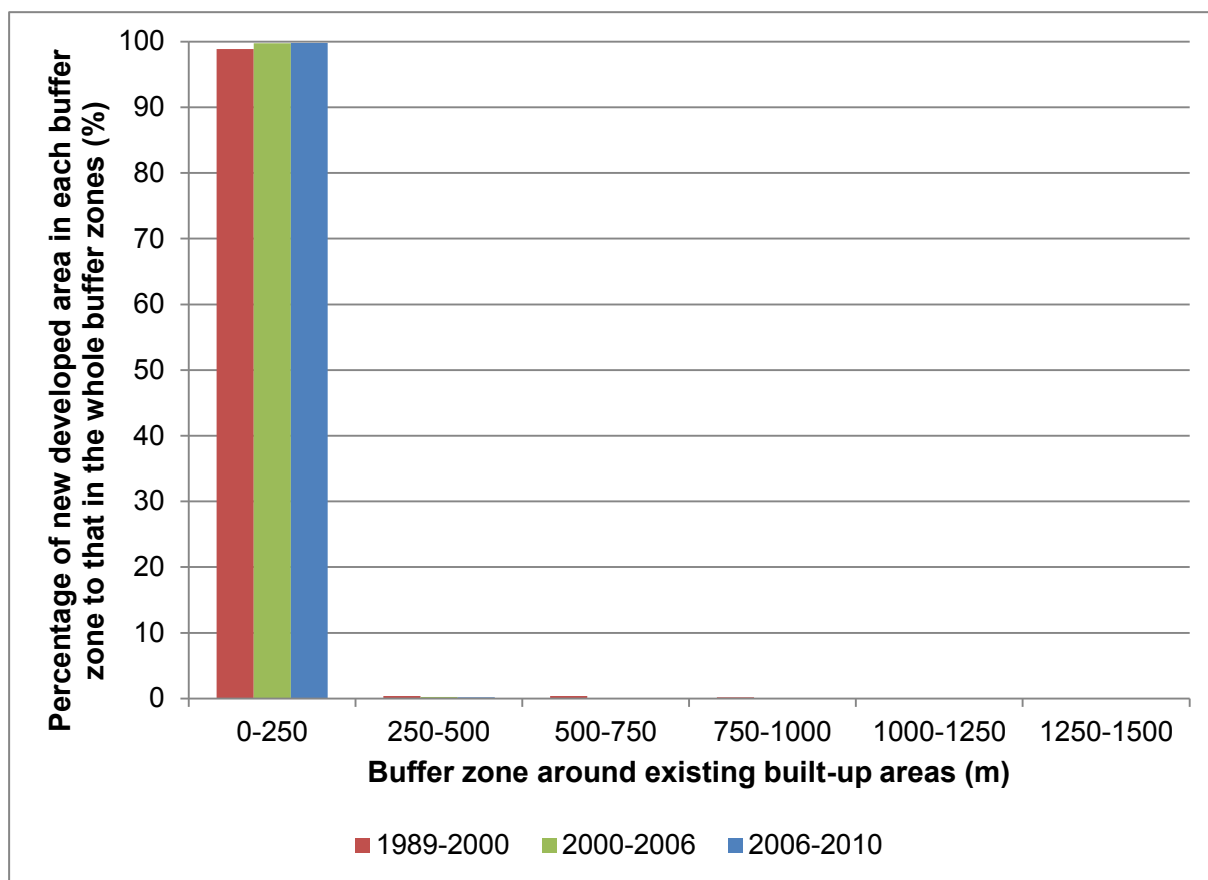


Figure 5-9: Change in FR with distance to the existing built-up over Xuzhou city in different periods

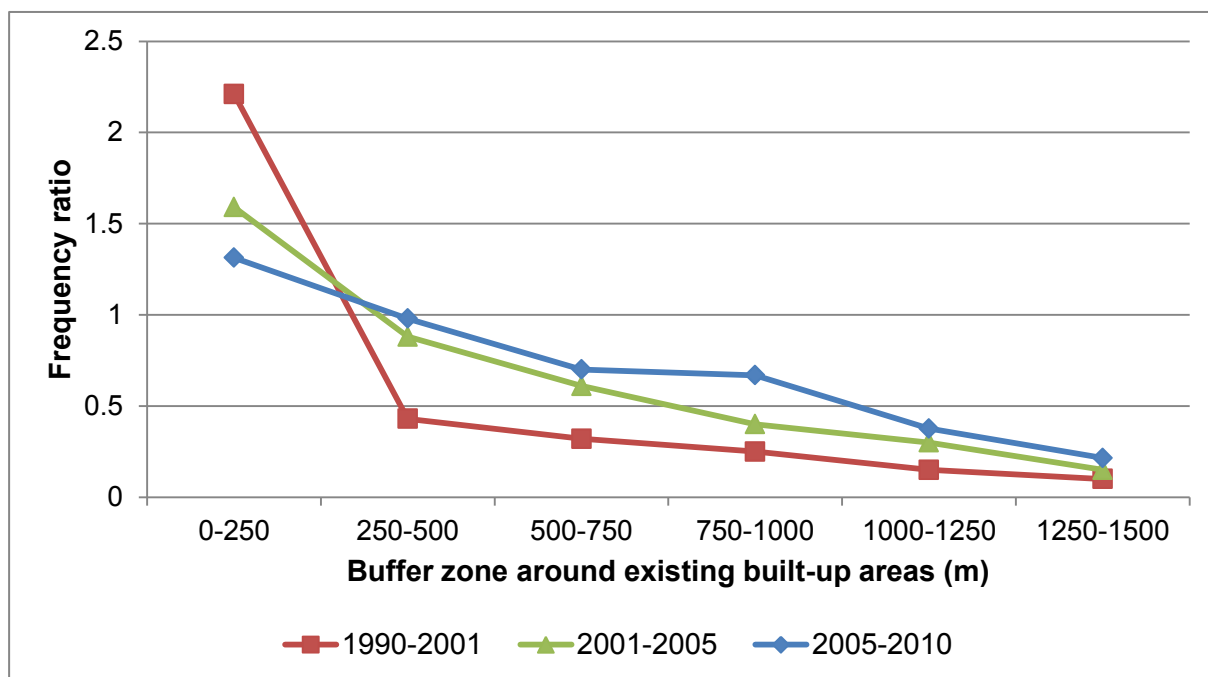
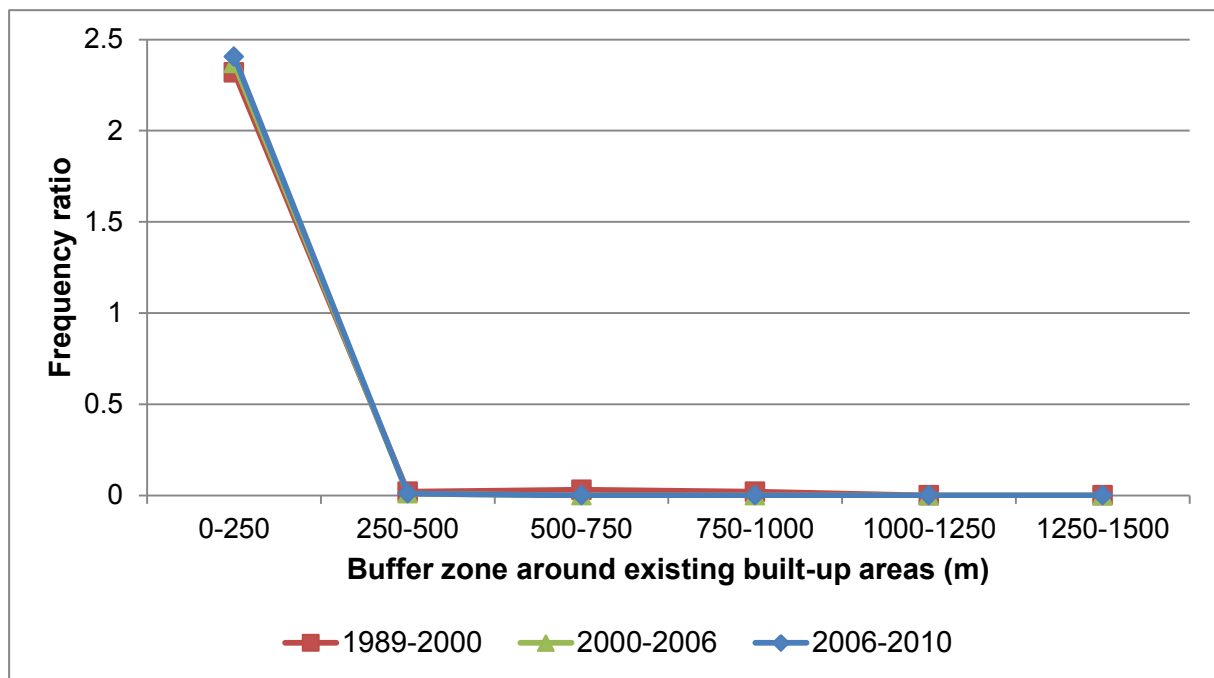


Figure 5-10: Change in FR with distance to the existing built-up over Dortmund city region in different periods



In Xuzhou city, overall, the new built-up area mainly focused on the first buffer zone around the existing built-up area with the frequency ratio larger than 1, and as the distance to the existing built-up increased, the frequency of built-up growth decreased until it reached 0 (see Figure 5-9). However, the characteristics of spatial pattern of built-up change varied over time.

For the period of 1990-2001, Figure 5-9 shows a rapid decline in the buffer zones from 0 to 500 m with a peak value of 2.21, which suggests that the area experienced the high intensity change from other land to built-up land. Furthermore, according to Figure 5-7, the new developed built-up land in the first buffer zone accounted for 78.54 % of new developed land occurred in the whole buffer zones, which implies that the urbanization in Xuzhou during this period was mainly concentrated within 250 m from the existing built-up area. At 500 m, the curves kept a gradual and smooth downtrend with low FR value as the distance increased. The result shows that there existed significant correlation between distance to the existing built-up area and development of built-up land. Compared with the first period mentioned above, the curves for the periods of 2001-2005 and 2005-2010 present a significant change in intensity and magnitude of urbanization, which involved dramatic reduction in frequency ratio value and share of new built-up land within 250 m, while higher FR and proportion values in the outer buffer zone. The differences imply that the active area for high intensity development has been expanded to a larger zone, and the

effect of distance to the existing built-up on new developed land became weakened during this period. Thus, this finding can be considered as an indication of sprawling urban development.

For Dortmund city region, the results of buffer analysis (Figures 5-8 and 5-10) reflect that the spatio-temporal patterns of built-up growth have similar characteristics both in terms of magnitude and intensity during the period from 1989 to 2010 with high-initial peak values, followed by decline. The peaks of FR curves were observed in the range from 0 to 250 m around the existing built-up area, owning higher peak values than those of Xuzhou city. Beyond 250 m, however, the FR value rapidly declined to approach 0. This indicates that the intensity of land cover change remained at high level near the existing built-up land over study periods. In addition, more than 90 % of the new developed built-up land in the first buffer shown in Figure 5-8 suggests that the new developed land is mainly distributed very close to existing built-up areas. This trend was getting strengthened over time, which was reflected by the slight increase in proportional value of new built-up land in 0-250 m from 1989 to 2010.

Comparing the buffer analysis results of the two study areas, they shared certain common characteristics. The development of new built-up areas was related to the distance to the existing built-up area. The shorter the distance was to the existing built-up area, the higher the intensity of land cover change. However, the curve of FR values for different periods and study areas reflects different spatio-temporal characteristics. In general, for Dortmund city region, the area close the existing built-up land experienced a higher intensity of urbanization, and a larger proportion of new developed built-up land was concentrated in first buffer zone compared with Xuzhou city. Furthermore, there are other significant differences in variance of share of new developed built-up land over time. The share of new built-up land in the first buffer zone decreased over time in Xuzhou city, whereas a slight increase in share value was observed in Dortmund city region. These differences in spatio-temporal characteristics of built-up change show the different urbanization processes the two study areas experienced.

To further explore the differences between the two study areas, we used the jaggedness degree to quantify and compare the urban forms and development patterns. The jaggedness degree (Table 5-9) shows very distinct spatial differences between these two study areas, which enables a more detailed view of how urban form varied. The jaggedness degree for Dortmund city region was much lower at

each time point compared with contemporary jaggedness degree for Xuzhou city, indicating relatively compact urban form for Dortmund city region. The higher jaggedness degree for Xuzhou city means that it had a more dispersed urban form. The urban form of Xuzhou city was characterized by dispersed built-up areas around the main city center, most of which were small-sized rural settlement areas.

Moreover, the temporal changes in jaggedness degrees represent two different urban development trends. The slight decrease in jaggedness degrees during study period indicates that Dortmund city region underwent compact development, which is also reflected by the buffer analysis that most of new developed built-up land occurred around the existing built-up land. Dortmund city region experienced effective growth to produce big and dense city cores for providing the necessary services and management facilities for its inhabitants. Whereas the situation is just opposite in Xuzhou city; an increase in jaggedness degrees for Xuzhou city suggests that it had dispersed development trend. A jump on value from T2 (2001) to T3 (2005) shows the increased sprawling development trend, which can be explained by the fact of rapid urbanization and increasing new dispersed built-up land.

Table 5-9: Jaggedness degrees of the two study areas

Study area	T1	T2	T3	T4
Xuzhou city	55.95	56.73	58.5	59.83
Dortmund city region	29.72	29.36	29.34	29.15

5.2 Analysis of urban growth

5.2.1 Urban spatial pattern

To further describe and analyze urban growth process of Xuzhou city, a set of spatial metrics were used to quantify the spatial-temporal patterns of urban growth. Table 5-10 presents statistical data of temporal change of six different spatial metrics from 1990 to 2010.

Overall, the change of metrics reveals the spatial-temporal pattern of urban change during study period. The allocation of urban area includes both the developing outward from the original city core and the growth of new individual urban patches, which are illustrated by the increases in the both of LPI and NP. Some individual urban patches continued to grow together to form a larger patch, the connection of individual urban patches is increasing, according to the decreasing ENN value. It also implies the significant loss of open space between urban patches. As the increasingly rapid urbanization process, Xuzhou's diffuse sprawling development and fragmented

growth of existing urban area are illustrated by the continuous increases in SHAPE_AM, and NP.

Temporally, rapid urbanization in Xuzhou went through three periods, the urban growth pattern in each period can be obtained and interpreted through the temporal change of spatial metrics.

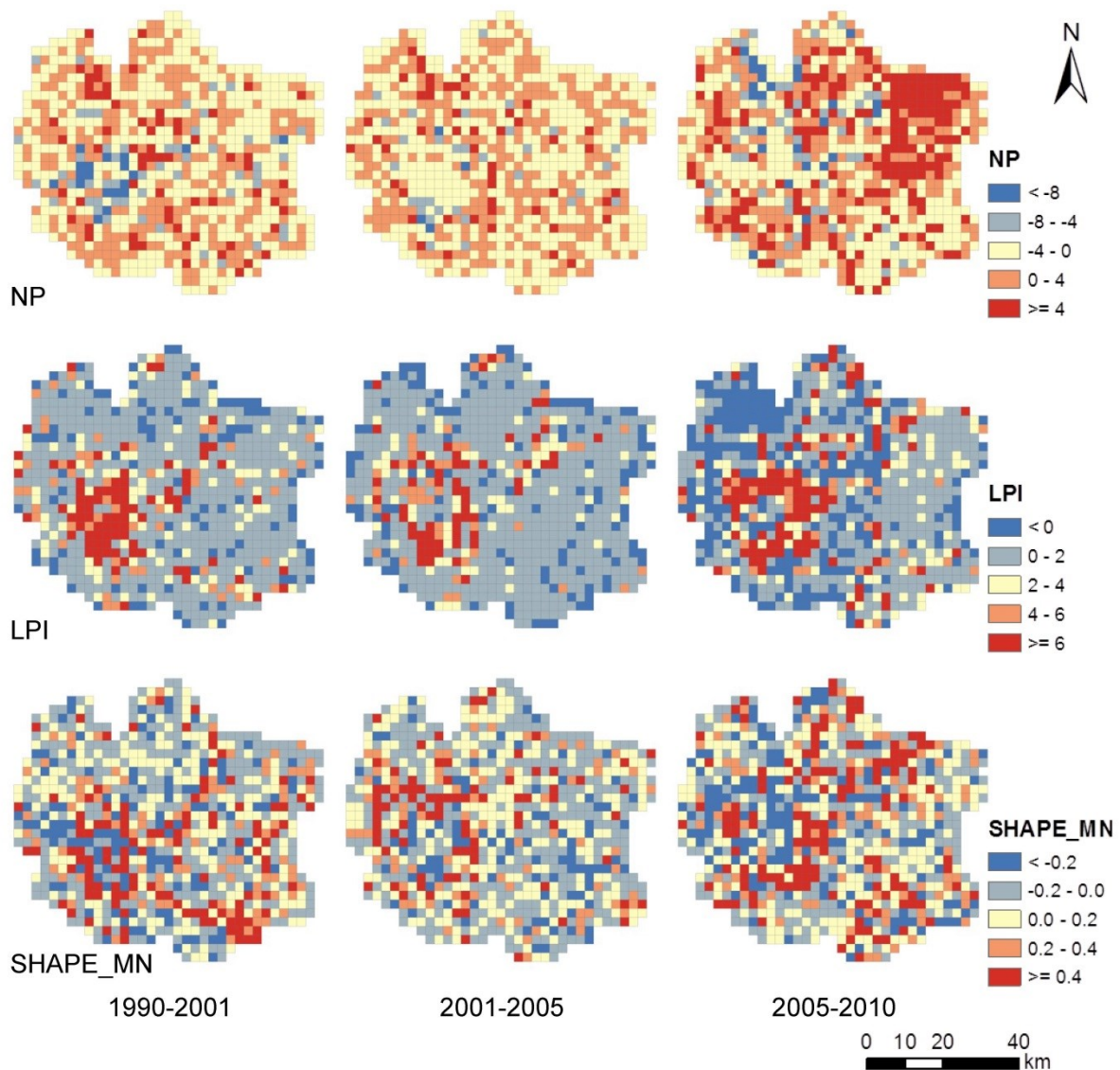
In the period of 1990-2001, the rapid development around the city core led to the increase in the size of the main urban area, which is illustrated by an increase in LPI. The relatively complete infrastructure and transportation around city center provided a good opportunity for development. The development in this period was characterized by concentric expansion. For the period of 2001-2005, a larger proportion of urban expansion in Xuzhou was focused on the development of new urban patches, rather than the expansion of the existing urban patches. A dispersal of new development on isolated areas separated from other areas by vacant land can be observed on the urban-rural fringe area. It indicates urban expand through leapfrog expansion. We assumed that the potential of further urbanization in city center is exhausted after the rapid development during 1990-2001. The vacant land left for development around the main city received more attention. Consequently, the massive construction of infrastructure, and factories formed many new urban patches, which have been a key factor contributing to the rapid expansion of urban areas. In addition, compared to the period of 1990-2001, the continuous complex urban form development slowed down in the period of 2001-2005, as evidently indicated by the slight increase in SHAPE_AM, although the number of new patches significantly increased. This is partly due to the relatively small size of these new developed urban patches. Smaller patches weigh less than larger patches according to the definition of SHAPE_AM. As opposed to focusing on the development of new patches in 2001-2005, the continued growth in Xuzhou focused on the extension of historical urban cores and the increasing connection of recent individual urban patches already close to the center, which are indicated by the significant increase in LPI, and the slight increase in NP. As a result, only a few new urban patches were established. The existing individual urban patches grew together to decrease the distance between patches, becoming more connected with central urban patches, which can be confirmed by the decreasing ENN value. The most of new urban areas expanded rapidly along the east and south-east development axes to form new development centers, which were attributed to the improved infrastructure and

transportation. Furthermore, the more significant increase in SHAPE_AM compared to two other periods exhibited diffuse sprawl urban development pattern which were explained by the fact that historical urban patches grew together to form larger but more complicated patches.

Table 5-10: Statistical summary of spatial metrics calculated for Xuzhou city

Date	NP	LPI	SHAPE_AM	ENN_AM
1990	2345	1.8253	3.42	297.01
2001	2412	3.7846	5.21	275.01
2005	2489	4.6318	5.73	261.87
2010	2509	7.07	8.46	246.36

Figure 5-11: Changes of spatial metrics across Xuzhou city for 1990-2001 (left column) 2001-2005 (central column), and 2005-2010 (right column)



The changes of spatial metrics values at local scale are shown in Figure 5-11. The results indicate that the variations of spatial metrics have spatio-temporal

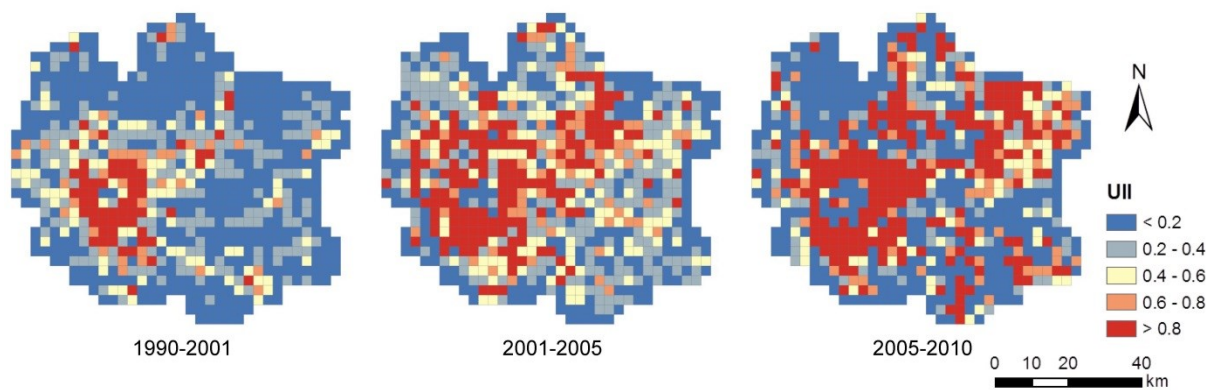
heterogeneities. Moreover, the changes can be related to the urbanization intensity. The areas with intensive urbanization experienced more significant variations of the urban spatial patterns. For example, most of blocks with significant changes of spatial metrics are found in the area around the city core.

5.2.2 The cause-effect relationships in the urban growth process

5.2.2.1 The effects of urbanization on urban growth patterns

Spatial patterns of urbanization intensity index are illustrated in Figure 5-12. Specifically, city core witnessed the most significant urban growth. However, as the continuous development of the city core, the fringe area also experienced rapid urbanization as indicated by the Figure 5-12.

Figure 5-12: Urbanization intensity patterns in Xuzhou city for 1990-2001 (left), 2001-2005 (central), and 2005-2010 (right)



In order to explore the effects of urbanization on urban growth patterns, OLS and GWR were used in this study. OLS models took the entire region as a whole to explore the effects of urbanization on spatial pattern changes. The results only provide a statistical average parameter for the whole study area, but when the GWR results were mapped, the variables changes throughout the study area. The Adjusted R^2 and AICc values generated by GWR and OLS models for different periods are shown in Table 5-11. In all cases for different periods, the results obtained by GWR are characterized by higher R^2 and lower AICc values compared with corresponding OLS models. The comparison of these two indicators suggests that GWR models perform better than OLS models in investigating the relationships between urban spatial patterns and urbanization. The results obtained from GWR indicate that the transformations of spatial patterns are significantly associated with urbanization process.

Moreover, Table 5-11 also summarizes the Moran's I statistics on the models residuals from GWR and OLS. Significant positive spatial autocorrelations are found

in all OLS models, which are characterized by higher Moran's I values ranging from 0.225 to 0.574. In contrast, the Moran's I values of GWR models range from 0.011 to 0.090, which indicates that GWR models can improve the reliability of relationships by effectively reducing spatial autocorrelations in residuals.

Table 5-11: Comparison between GWR and OLS models

		Adjusted R ²		AICc		Moran's I	
		GWR	OLS	GWR	OLS	GWR	OLS
1990-2001	NP	0.447	0.223	3960.9	5067.6	0.013	0.283
	LPI	0.677	0.270	4627.0	5722.7	0.025	0.484
	SHAPE_MN	0.342	0.074	721.7	839.5	0.015	0.250
2001-2005	NP	0.415	0.083	3642.0	5689.6	0.052	0.381
	LPI	0.653	0.250	3676.6	4723.1	0.011	0.261
	SHAPE_MN	0.313	0.061	392.4	680.8	0.090	0.388
2005-2010	NP	0.488	0.011	4702.2	7033.5	0.057	0.401
	LPI	0.744	0.542	4951.3	6024.4	0.069	0.574
	SHAPE_MN	0.529	0.285	1095.9	2223.7	0.017	0.225

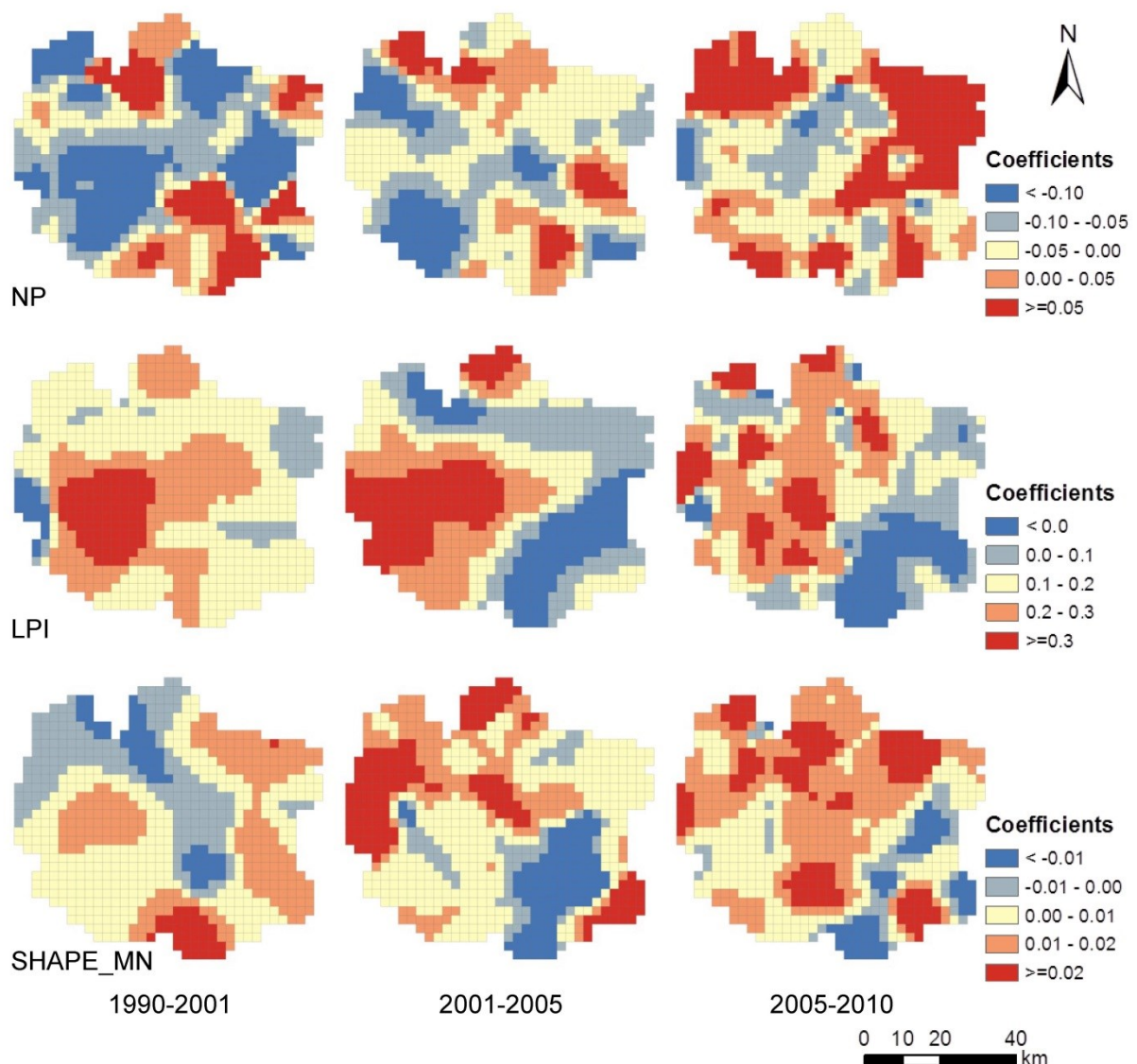
As shown in Figure 5-13, the spatially varying coefficients indicate that the relationships between the variations of four spatial metrics values and urbanization intensity index varied spatially across the study area.

Both the positive and negative correlations between the variations of NP and urbanization are identified. In 1990-2001, the significant negative correlation with the coefficients smaller than -0.05 is observed in a large part of Xuzhou city, implying that the accelerating urbanization could result in degradation of NP. The negative relationship is also found in the city core, which indicates the aggregation development in the city core. The temporal changes of effects of urbanization were also investigated in this study. Along with the urbanization process, the area with the negative effects of urbanization on NP is declining. Especially in the period of 2005-2010, the variation NP in the fringe and rural areas received the significant positive effects of urbanization, which suggests that the newly developed urban land is fragmented. The rapid urbanization led to the development of new urban patches, instead of the expansion of existing urban patches.

The spatio-temporally varying effects of urbanization on the variation of LPI are also explored. Regarding the period of 1990-2001 and 2001-2005, urbanization had a significant positive impact on the increase of LPI in city core, as evidenced by the coefficient higher than 0.3. It indicates that the development focused on the expansion of the existing core urban patches along with the urbanization process. This could be explained by the good accessibility to the importance facilities in core

urban patches. However, the negative correlation played an important role in the dynamics of LPI in less urbanized area since 2001, which implies that the increase of LPI was negatively related with urbanization intensity. This is also consistent with the positive effect of urbanization on NP. The significant increase in NP resulted in the decrease of LPI along with urbanization process. Compared to the two former periods, the areas which received strong impact from urbanization were smaller in size and more fragmentation, while the other areas in the city core received less significant impact during 2005-2010. The city core was developed to almost its full capacity after the rapid urbanization in former two periods.

Figure 5-13: Spatial distributions of the coefficients obtained from GWR



As shown in Figure 5-13, the effects of urbanization on the variations of SHAPE_MN value varied over study area during the study period. The areas with more significant positive effects were larger during 2005-2010, which indicates that accelerating urbanization could lead to more complex patterns in most of study area than other

periods. As a new development center in 2005-2010, the eastern area of Xuzhou city experienced a significant increase in SHAPE_MN caused by urbanization. In the same area, however, urbanization had negative impacts on the variation of complexity during the previous periods.

In summary, the results generated from GWR suggests that the historical urban growth patterns in Xuzhou city can, in considerable part, be explained by urbanization process with relatively high levels of explanation of the spatial variability. This corresponds with the findings in literature related to other cities in the world (Yeh & Huang, 2009; Weng, 2007; Luck & Wu, 2002). Moreover, the research extends these previous studies by investigating spatio-temporally varying effects of urbanization instead of global qualitative effects.

By combining GWR models with temporal analysis, this study identifies how the processes of urbanization differentially influenced the urban spatial patterns. The significant correlations were found around the city core and fringe area in 1990-2001. This can be due to locations closer to the city center offering more opportunities to access socioeconomic resources. In the city core, the landscape is dominated by a well-connected urban land after the rapid urbanization. In contrast, the expanded urban land in fringe area is always highly fragmented and complex in shape (Su et al, 2011). Therefore the most significant effects of urbanization are located in the fringe area rather than in the city core especially in 2005-2010. Furthermore, the temporal changes of effects of urbanization were also investigated in this study. The effects of urbanization on the variations of spatial patterns varied over the study period, which can be explained by the socioeconomic processes and the consequence of urban development policy. During the period 1990-2001, urbanization mainly occurred in the city core. Due to the lack of space for further development in the city core, the urbanization gradually slowed down. In contrast, the urban fringes were those places where rapid urbanization occurred since 2001. As a result, the influences of urbanization on fragmentation and irregularity varied significantly over time in the fringe area. Therefore, there is a relay-race effect of the changes of spatial patterns in response to urbanization: the former urban core gradually became stabilized with the city fringes experiencing the rapid variation of spatial patterns (Weng, 2007). In addition, the urban growth was focused more on the development of new city centers in the period of 2005-2010.

5.2.2.2 The effects of driving factors on urban growth

The relationships between spatial variables and urban growth were explored through logistic regression. Before performing logistic regression, a correlation analysis was first implemented for the spatial variables. The results indicate that Dis2CBD and Dis2Cens are significantly correlated variables with the Pearson correlation coefficients of 0.680, 0.702 and 0.654, respectively. They are redundant and may cause multicollinearity. In order to exclude redundant variable and select optimum set of variables, logistic regression was estimated for two possible variables sets, which considered all variables excluding Dis2Cens (Variables set 1) or Dis2CBD (Variables set 2). By involving the independent variables in logistic regression models, Dis2Town is not significant, while the other variables are significant at 0.01 level. According to the significance test, it is necessary to construct a modified model which excludes the variable considered to be insignificant. The results of the logistic regression models with the all independent variables are illustrated in Table 5-12. When using ROC values to compare the performance of different combinations of spatial variables, the model involving Dis2CBD generated the best results for 1990-2001. While regarding the 2001-2005 and 2005-2010, the combinations including Dis2Cens achieved higher ROC values. Therefore, the variables set 1 was identified as the optimal variables set for explaining urban growth in 1990-2001, and set 2 for the rest of study periods, respectively.

Table 5-12: Logistic regression models results for three periods

	1990-2001		2001-2005		2005-2010	
	Variables set 1	Variables set 2	Variables set 1	Variables set 2	Variables set 1	Variables set 2
Dis2CBD	-1.468	-	-1.223	-	-0.948	-
Dis2Cens	-	-1.250	-	-1.716	-	-2.303
Dis2MajR	-1.166	-1.254	-1.070	-1.091	-1.578	-1.306
Dis2MinR	-0.830	-0.768	-0.938	-0.903	-0.757	-0.644
Dis2Urban	-3.347	-3.552	-3.142	-3.135	-3.012	-3.062
PopDen	1.432	1.432	0.421	0.399	-0.547	-0.314
Slope	-2.273	-2.164	-2.151	-2.027	-0.600	-0.623
Subsidence	0.460	0.457	0.513	0.498	0.209	0.157
Environment	0.272	0.329	0.237	0.315	0.137	0.148
ROC (%)	87.7	86.4	87.1	87.5	87.6	88.5

The interpretation of the multi-temporal calibrated results is crucial for analyzing the urbanization process in Xuzhou from 1990 to 2010. The study suggests that the historical urban growth patterns in Xuzhou city can be affected by distance to CBD,

distance to district centers, distance to roads, slope, population density, neighborhood effect, spatial policy, etc. This corresponds with findings from other cities in the world (Braimoh & Onishi, 2007; Clarke et al., 1997; Weng, 2007). ROC values of 87.7 %, 87.5 %, and 88.5 % for three periods were obtained, which imply a high degree of spatial consistency between the actual urban patterns and simulated results using the variables and their estimated coefficients. Importantly, a set of coefficients in Table 5-12 presented not only the relative importance of each variable in urban growth process, but also the temporal dynamic of effect of each variable on urban growth over study periods. It can be used to explain the urban growth and identify the effects of driving factors underlying urbanization.

Among the variables, neighborhood had the strongest negative effect on urban growth probability indicating urban growth was more likely to take place around the existing urban area. This is consistent with previous findings (Braimoh & Onishi, 2007; Hu & Lo, 2007; Li et al., 2013a). This result can be explained by the fact that areas close to the existing urban areas have lower development costs and better accessibility to urban infrastructure (Verburg et al., 2004a). The slight decrease in the absolute coefficient value from 3.347 to 3.062 indicates the decreasing effect of neighborhood on the urban growth, which can be mainly reflected by the fact of construction in fringe area and increased sprawling development trend. Consequently, more and more discontinuous urban land was located further away from the existing urban area. This is also explained by the buffer analysis. The development within high density of built-up area in main city was constrained, while more and more new urbanized areas were found in fringe area.

The coefficients of distance to socioeconomic centers suggest that the variables had the negative effects on urban growth probability. The areas which have great accessibility to these centers had more probability of development. It is worth noting that the optimal variable regarding the distance to socioeconomic centers varied from Dis2CBD to Dis2Cens along with the urbanization process. Furthermore, the absolute value of coefficient increased dramatically from 1.250 to 2.303 during 2000-2010. The significant variation may have been due to the implementation of polycentric development. The available land for further urbanization in city center was extremely reduced and mostly exhausted after the rapid development during 1990-2001. In order to promote regional economic integration as well as to avoid the “big pancake” form generated by the limitless expansion of the city core, which could

result in a series of problems, such as air pollution, traffic jams, loss of green space, increased “heat island” effect (He et al., 2006), the polycentric development has been proposed as a new planning policy to guide the future development in Xuzhou. Within the framework of the policy, the development in the city core was constrained; in contrast, development in the fringe around the separated district centers was promoted. The similar trends can also be observed in some big cities in China, such as Shanghai and Hangzhou, in which the linkages between former city cores and new developed regions are getting closer to promote regional economic integration and high efficiency of land use (Cui & Shi, 2012; Wu & Zhang, 2012).

The Dis2MajR is another significant factor. Areas with good accessibility to major roads are more easily selected for urban development (Luo & Wei, 2009). However, the slight decrease and increase in the coefficient of this factor was found in this study, which can be partly attributed to the shift of development focus from city core to outside the city core. In the period of 1990-2001, concentric development played an important role in shaping the urban growth pattern. The city core continued to expand along with the existing major roads. However, with the implementation of new planning policy since 2001, new developed area was found in fringe area to improve the infrastructures and facilities conditions for further development. New roads were constructed to improve the accessibility. After the improvement of living and working condition, the new built-up areas were developed near the roads for good accessibility, which led to increase of effect of this factor on urban growth.

The dramatic variation of effect of population density on urbanization patterns was found in this study. During the period of 1990-2001, the population density was positively correlated with the urban growth probability, which suggests the development focused on the existing city core with large population density. The relatively complete infrastructure and transportation in the city core provided a good opportunity for development. For the period of 2001-2010, urban growth in Xuzhou was focused on the development of new urban patches which were in the fringe area, rather than the expansion of the city core. The vacant land with low population density in the fringe area received more attention. Therefore, PopDen had a negative effect on urban growth.

Slope is a main natural constraint (Aspinall, 2004), which has a negative effect on urban growth. However, the result shows that the effect of this factor on urban growth decreased over time, especially in the period of 2005-2010. The weakened influence

can be explained by the following facts: (1). Due to the limited suitable construction areas located on flat land and protection of farmland, the vacant land left for future development is limited and located on the steep slopes. Some areas with higher slope value were selected as developed land. (2). The improvement of construction technology provides an effective way to conduct construction projects on the steep land with less cost compared to before (Ye et al., 2011). This trend is more likely to continue in the future to balance the conflict between protection of farmland and increasing demand of urban area. However, this phenomenon also suggests an increasing pressure for development in the mountainous areas which are regarded as ecologically valuable zones. Moreover, the policy factors (Subsidence and Environment) have slight effects on urban growth during the study period, indicating the lack of consideration of environment protection and scientific land use management along with the rapid urbanization process.

5.3 Urban growth simulation

5.3.1 Calibration results and historical urban growth simulation

The calibration of the CA model was conducted by using the hybrid method. The spatial variables in chapter 5.2.2.2 except Dis2Urban were calibrated using logistic regression. Neighborhood configurations including neighborhood type, function, and size, as well as random variable were estimated by “trial and error” approach.

The specific procedure of calibration and validation followed three steps. Take the period of 1990-2001 as an example:

- 1) The historical urban growth (1 = changed and 0 = no change) was set as a dependent variable, and the global factors after standardization were set as independent variables. Based on the historical urban development trends, the weights for the global factors were accurately determined using a binary logistic regression model.
- 2) The neighborhood configurations were calibrated through the trial and error method by running the model many times with different neighborhood configurations, while the random variable was set as 0, and held constant. The figure of merit value was calculated for each simulated result to measure the overall performance of the model (Figure 5-14). The results show that the model with neighborhood type of Von Neumann Circular and exponent value of -0.5 generated the simulation result with the highest value. Therefore, they were used for further simulation.
- 3) Various simulations were performed using random variables in the range 0-3 with 0.1 increment and different neighborhood sizes. Figure of merit value was calculated at each neighborhood size and random variable (Figure 5-15(a)). Because of the involvement of random variable, each simulation generated different result with different value of figure of merit. However, the stochastic CA can maintain stability in spatial pattern (Yeh & Li, 2006). A range of random

variables (0.8-2.0) were selected to ensure that CA model can generate relatively high figure of merit values. Focusing on this range, Rd value was calculated for each simulation result (Figure 5-15(b)). The result indicates that random variable and neighborhood size should be set with values of 1.8 and 1 respectively so as to fit the observed urban land use map in terms of location and pattern.

Figure 5-14: Variation of figure of merit value response to neighborhood configuration variation. (a) The figure of merit value calculated for different exponent values and sizes using Moore type, (b) The figure of merit value calculated for different exponent values and sizes using Moore Circular type, (c) The figure of merit value calculated for different exponent values and sizes using Von Neumann Circular type and (d) The figure of merit value calculated for different neighborhood types and sizes when exponent is set as -0.5

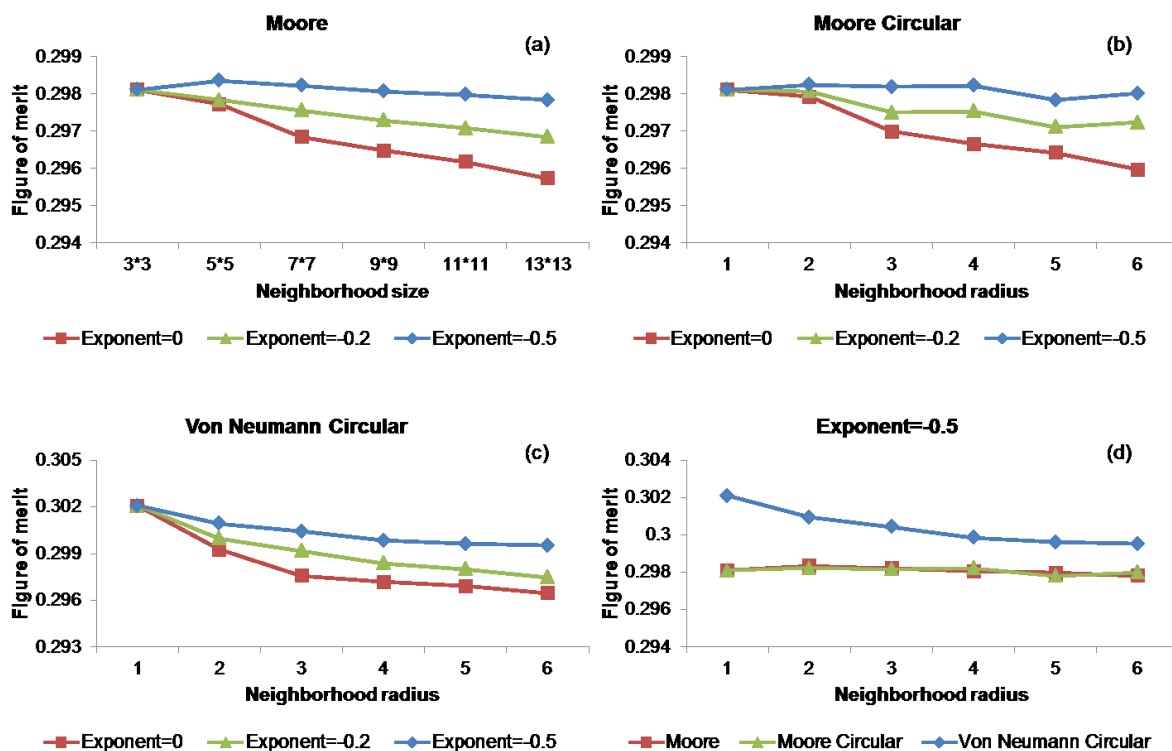
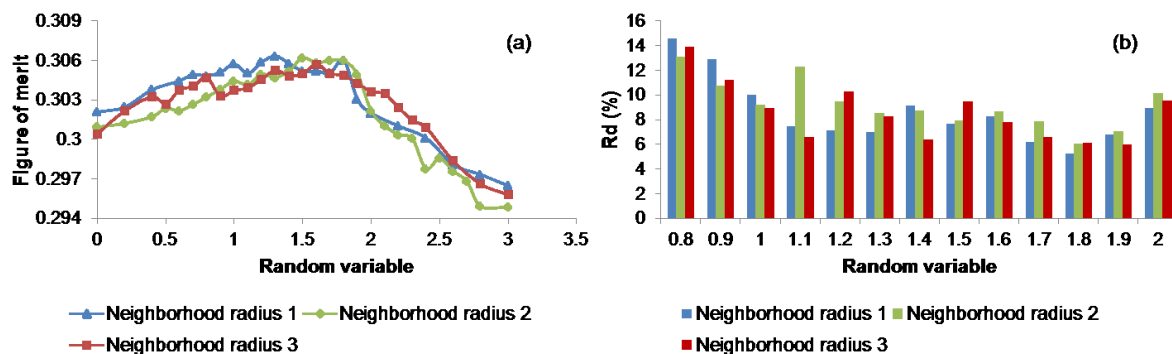


Figure 5-15: Variation of figure of merit and Rd values response to neighborhood size and random variable variation. (a) The figure of merit value calculated for different neighborhood sizes and random variables and (b) The Rd value calculated for different neighborhood sizes and random variables



The same procedure was used to calibrate the cellular automata models for other periods. The estimated parameters for the periods of 1990-2001, 2001-2005 and 2005-2010 are listed in Table 5-13.

Table 5-13: Calibration results of the CA model during 1990-2001, 2001-2005 and 2005-2010

	Parameters	1990-2001	2001-2005	2005-2010
Global suitability factors	Dis2CBD	-1.422	-	-
	Dis2Cens	-	-1.697	-1.964
	Dis2MajR	-1.295	-1.114	-1.470
	Dis2MinR	-0.975	-1.002	-0.843
	Slope	-1.636	-1.392	-0.375
	Popden	0.846	0.254	-0.310
	Subsidence	0.413	0.435	0.343
	Environment	0.363	0.328	0.239
Neighborhood configurations	Type	Von Neumann Circular	Von Neumann Circular	Von Neumann Circular
	Function	$\exp(-0.5*D)$	$\exp(-0.5*D)$	$\exp(-0.5*D)$
	Size	1	2	2
Random	Variable	1.8	2.0	2.1

The temporal changes of relative importance of global suitability factors are discussed in chapter 5.2.2.2. Besides the global suitability factors, the temporally varying neighborhood configurations and random variables provide an insight into the urbanization process. Previous studies have confirmed that neighborhood effect plays an important role in urban growth patterns (Hu & Lo, 2007; Li & Yeh, 2000). However, the result differs from that found in previous studies (Li et al., 2013a; Reilly et al., 2009), which only considered the variation of the weight of neighborhood factor, while the variation of neighborhood configuration was ignored. In this study, a better understanding of neighborhood factor was obtained by estimating the neighborhood configuration. The trial and error method was used to reveal the variation in neighborhood configuration along with urbanization process.

The simulation most fits the observed pattern when the Von Neumann Circular was used. This could be attributed to the significant distortions between cells at different directions (Li & Yeh, 2000). The weighting assignment for each cell in neighborhood is done by the weighting function. The parameter β controls the shape of the weighting function curve. The simulated maps most fit the observed ones when β is set as 0.5. Thus, the steeper weighting function of $\exp(-0.5*D)$ rather than commonly

used average weighting function was determined. Compared to other weighting functions, the distant cell received a smaller weight. Although large neighborhood size is widely used in many studies without calibration, the relatively smaller size is identified through the calibration in this study. It indicates that neighborhood effect only focused on the area close to the existing urban area. Especially during the period of 1990-2001, the neighborhood size of 1 suggests that only adjacent cells were involved into the calculation of neighborhood effects. The increase of neighborhood size during 2001-2005 indicates that urban growth tended to take place in locations further away from developed areas.

The random variable was further calibrated by running the model with different random variables and comparing the simulated results with the observed urban land use. The random variable reflects the complexity of urbanization process. The stochastic implementation produces “leap-frog” growth of urban land uses (Barredo et al., 2003). This was set as 1.8, 2.0, and 2.1 for different study periods respectively following trial and error approach. The value allows of generating a sufficient number of new “seed” cells of urban land use in new location such as fringe and rural areas, which will be subsequently developed. Therefore non-continuous growth of urban land use is produced. The increase in the random variable suggests that the stochastic level involved in urban growth became higher. The more random factors were involved into the urbanization process to create a more dispersed urban pattern.

The calibrated CA model was then used to simulate urban growth in Xuzhou during the periods of 1990-2001, 2001-2005, and 2005-2010, respectively. The observed and simulated maps are shown in Figure 5-16. A visual comparison during the study period shows that the results produced by the CA models matched well with the actual urban extent. However generating the correct location of each simulated land use cell is very difficult due to the path dependence and uncertainty factor (Brown et al., 2005). The assessment of error in CA modeling is important for understanding the results of simulation. As shown in Figure 5-17, the actual urban development map was overlaid with simulation map to identify the four groups of cells (observed change simulated as persistence, observed persistence simulated as change, observed change simulated as change, observed persistence simulated as persistence). Owing to the transition rules of CA models, such rules can in effect evenly locate new urban cells mainly in the city core and around the edge of initial

urban patches. As a result, some of simulated urban cells in the city core were located where no changes from non-urban to urban land uses took place. While some real developed cells in fringe and rural areas were underestimated by models. The errors found in simulation results also reveal that some errors are caused by issues not related to the model, such as the complexity of urban growth. Urban growth process usually have some unpredictable features because of the complexity of nature. Although the uncertainty of urban growth can be represented by incorporating random variable, as demonstrated by Yeh and Li (2006), each simulation will generate different result when the inputs are the same because of the involvement of random variable. However, major uncertainties caused by random variable only existed in the fringe and rural areas, which can partly explain the errors in simulating new isolated urban cells outside the city core. Furthermore, some errors are observed due to the difficulties in considering all driving factors. The number of variables used in CA simulation will affect its outcome (Yeh & Li, 2006). For example, the urban simulated as non-urban in the city core was mainly located in the southern and eastern part, where the development policies acted as an accelerating factor to promote more new development. However it was not involved into the transition rules, which made the accurate simulation of urban growth more difficult.

In addition to the description of visual comparison, the quantitative validation methods are required to quantify the degree of error of the simulation results. Figure 5-18 presents a summary of the error analysis according to Figure 5-17. The value represents the number of cells at the resolution of 100 m. The union sections of observed change simulated as persistence and observed change simulated as change represent the area of change according to the reference maps, and the union sections of observed change simulated as change and observed persistence simulated as change are the area of change according to the simulation maps. Table 5-14 presents the simulation accuracy at cell level. The figure of merit was calculated based on the quantitative error analysis. It enables to assess the cell to cell coincidence between simulated and actual maps in a more realistic way than more common metrics as Kappa index which are usually calculated using the entire area with fixed land use (Santé, 2010). As presented by the figure of merit, 30.6 %, 33.2 %, and 27.7 % of overlap in the observed change and the predicted change is found in 2001, 2005, and 2010 respectively. The models for 2001 and 2005 produced more matches with the actual maps. However the model for 2010 is the one that produced less matches, which could be partly attributed to the urbanization process

during this period as discussed in the previous sections. New development areas were promoted by planning policies, which cannot be involved in the transition rules. In addition, the increase in stochasticity of development indicated by random variables also influenced the performance of the CA model. The overall agreement between the simulated and observed maps are shown by the relatively higher values of overall accuracy, which ranges from 94.4 % to 97.1 %

Besides the matching the exact location of urban land use change, the generating urban patterns similar to actual urban spatial patterns is also an important objective of CA models. Spatial metrics were used to objectively characterize the spatial pattern observed in the visual analysis in order to make quantitative comparison and to determine whether simulated patterns are similar to the actual patterns. Table 5-15 shows the spatial metrics values for the multi-temporal simulations results. Figure 5-19 used the relative difference of the spatial metrics values between the simulated and observed maps to further evaluate the performance of the CA models at pattern level. According to the analyzed spatial metrics, the models produced the urban spatial patterns substantially close to the observed ones. When looking at the Rd value calculated for the different spatial metrics, however, the models had relatively larger error in the simulated NP. The CA models generated lower number of patches, which were larger and more clustered than those in observed patterns. The isolated cells can be developed only by involving the random variables in this model, such that some of small new patches cannot be generated. Although fewer patches generated by CA models, the lower Rd values of SHAPE_AM and ENN_AM indicate that the compaction and isolation were similar to the observed ones.

The validation results shown above reveal that the CA models for three time points have the ability to produce the multi-temporal simulation results which can be considered to be in line with the observed maps in terms of location and pattern similarity.

Figure 5-16: Simulation results of urban growth in 2001-2010. (a) Actual and (b) simulated

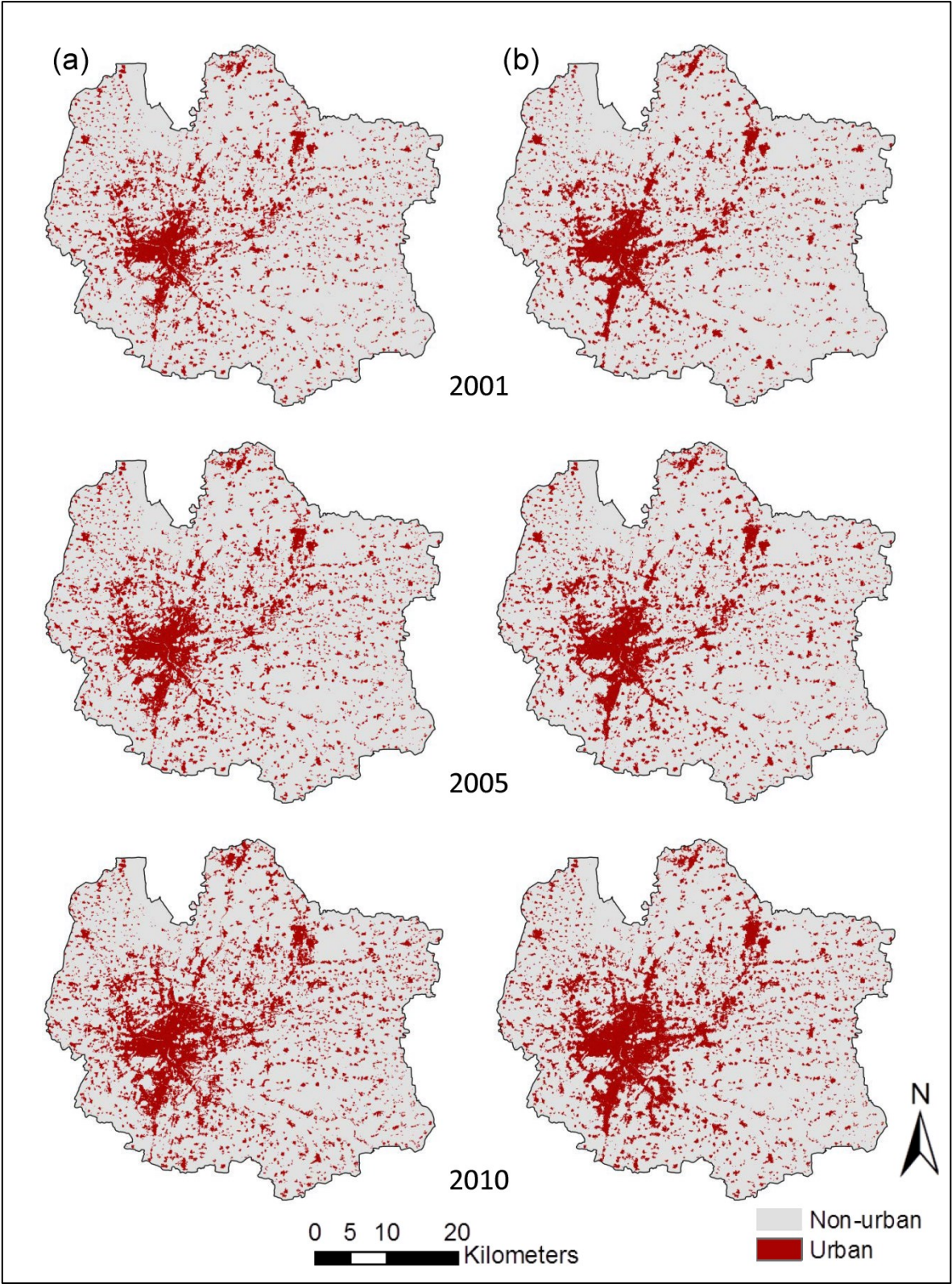


Figure 5-17: Spatial distribution of corrects and errors of the simulation results

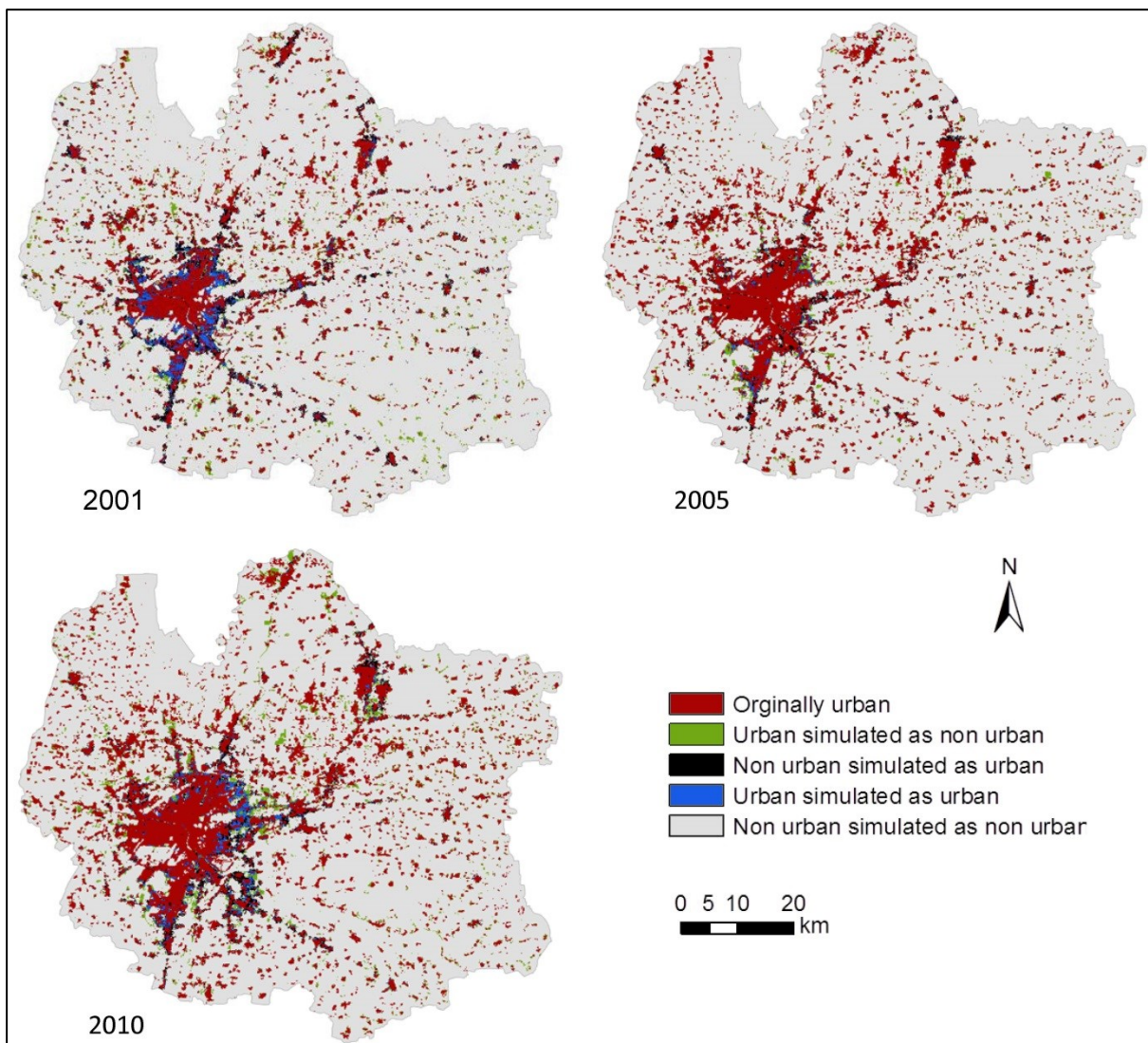


Figure 5-18: Quantities of correct and errors values in the model validation

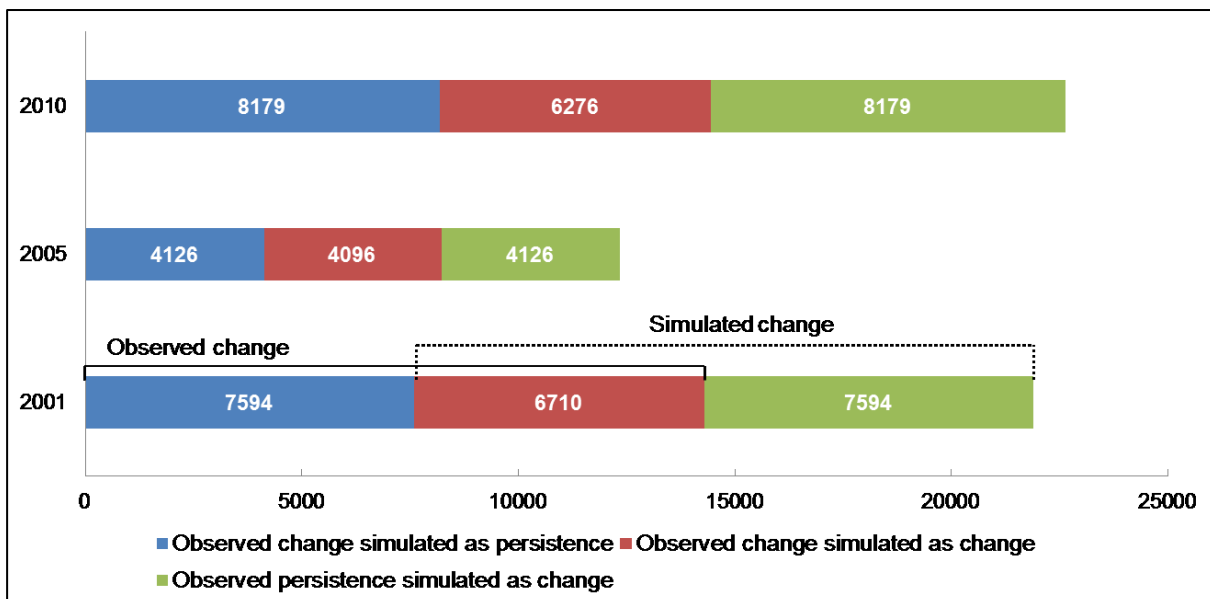
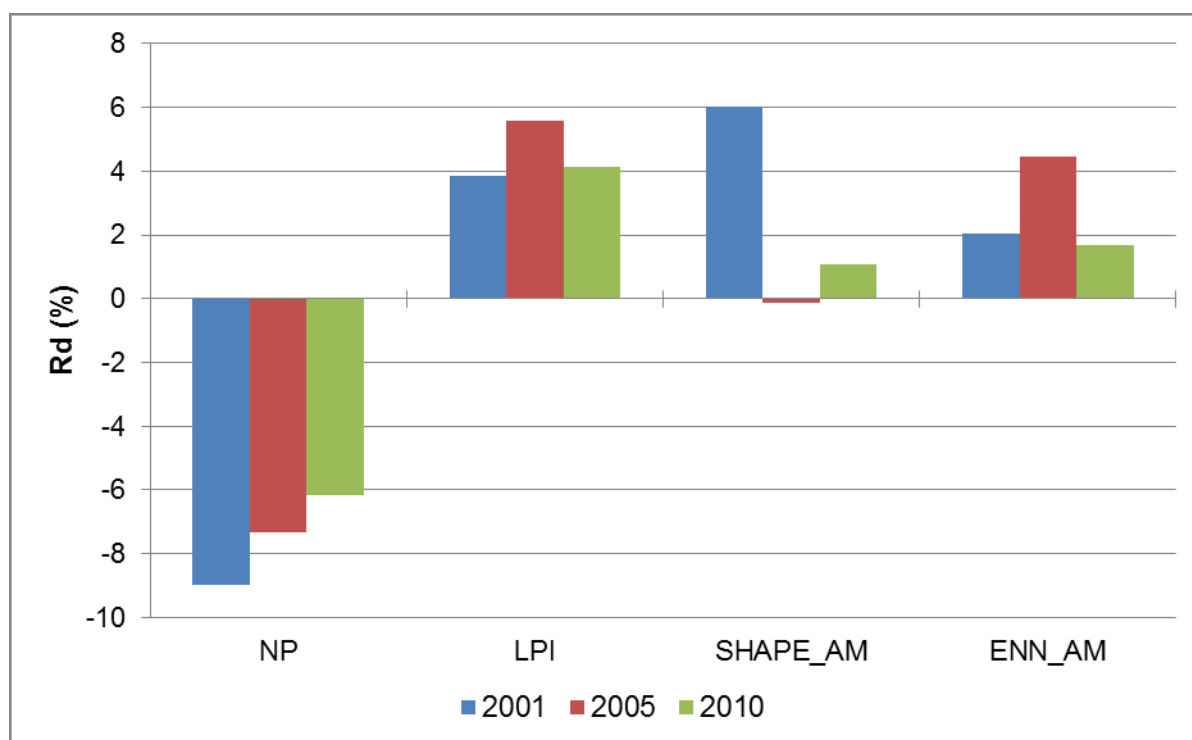


Table 5-14: Quantitative assesment of accuracy based on cell by cell comparison (%)

Year	Figure of merit	Overall accuracy
2001	30.6	94.8
2005	33.2	97.1
2010	27.7	94.4

Table 5-15: Simulated and observed spatial metrics for urban land use

		NP	LPI	SHAPE_AM	ENN_AM
2001	Observed	2412	3.78	5.21	275.01
	Simulated	2195	3.93	5.53	280.63
2005	Observed	2489	4.63	5.73	261.87
	Simulated	2307	4.89	5.72	273.57
2010	Observed	2509	7.07	8.46	246.36
	Simulated	2354	7.36	8.56	250.48

Figure 5-19: Validation of CA models in terms of spatial metrics

5.3.2 Future development scenarios

In addition to the simulation of historical urban growth, the combination of the different parameters enabled to produce a series of maps showing the future scenarios for Xuzhou city from 2010 to 2020. Through the transformation from logistic regression to MCE, the parameters of global factors in CA models for business as usual scenario were defined by AHP. In order to evaluate the performance of the transformation method and to check whether the weights of global factors were identified correctly, ROC values were calculated to assess the

goodness of fit between the suitability maps generated by logistic regression and MCE. The high values of 0.93, 0.91, and 0.94 were obtained, which verify the accuracy of this method.

Furthermore, the parameters of CA model were modified according to the story-line of each scenario and the weights of business as usual. As illustrated in Figure 5-20, the elements of the story-line of each urban growth scenario were defined through the AHP process, in which the value represents the relative importance of global factors used for each scenario. Under the CDS scenarios, Dis2CBD was considered to represent the distance to socioeconomic centers, while Dis2Cens was used for other scenarios instead of the Dis2CBD. A summary of the neighborhood configurations and random variables, and constraints for each scenario is given in Table 5-16.

Figure 5-20: Relative importance of global factors for each scenario

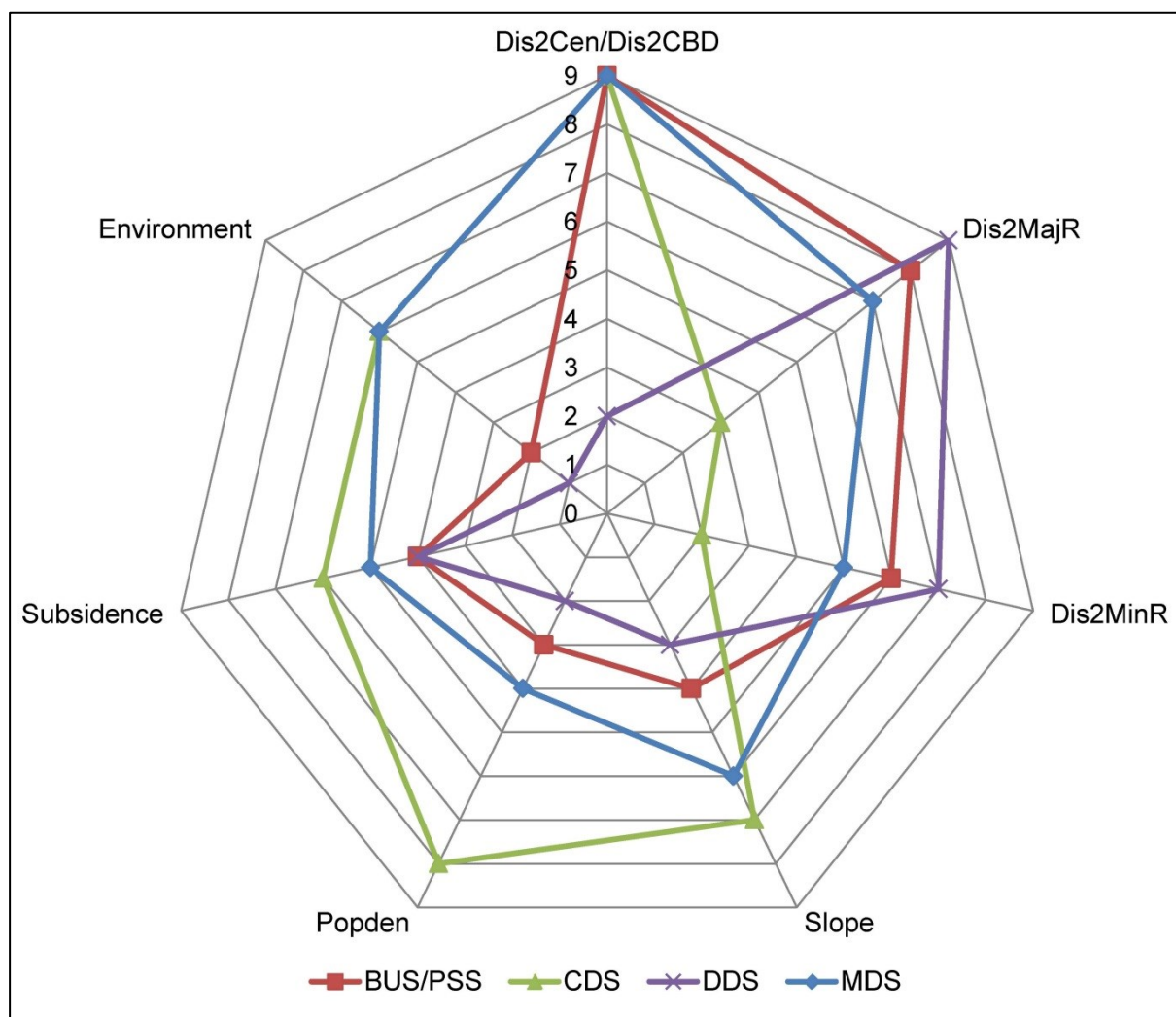


Table 5-16: The configurations of CA model for each scenario

		BUS	PSS	CDS	DDS	MDS
Neighborhood configurations	Type	Von Neumann Circular	Von Neumann Circular	Von Neumann Circular	Von Neumann Circular	Von Neumann Circular
	Size	2	2	1	3	1
	Exponent value	-0.5	-0.5	-	0	-
Stochastic perturbation	Random variable	2.1	2.1	1.5	3.0	1.5
Constraint	Nature	water	water	water	water	water
	Policy	-	Master planning	-	-	Mater planning

Using the modeling configuration, the input map of 2010, we performed simulations under the five scenarios aiming to project alternative spatio-temporal patterns of urban growth in 2020. Figure 5-21 shows the simulated spatial patterns of urban land use in 2020. Although these scenarios are simple, they are rooted in some facts of Xuzhou urban development patterns and spatial policies. Because of the incorporation of AHP and MCE, the scenarios have a potential to connect urban growth modeling with decision making process, which is important for the future development. Although all scenarios have the same urban land area as that of the 2010-2020 urban planning, the urban growth patterns differed. We can visualize how the different policy options and development constraints led to differences in urban spatial pattern for each scenario.

Due to the fact that the historical trend continues without any additional policy intervention, the urban growth consistently agglomerates the small urban patches around the city center by 2020. Meanwhile, the urban land sprawls significantly in fringe and rural areas.

The urban master plan of 2010-2020 aims at solving the environmental problem, achieving coordinative development of urban-rural area and promoting regional economic integration. As expected, the PSS generates several new development hotspots, which are located in both fringe and rural areas. A large part of urban development is focused within the urban growth zones that are defined in master plan of Xuzhou city. However, some new scattered patches are also observed because other parameters kept same with the historical simulation models.

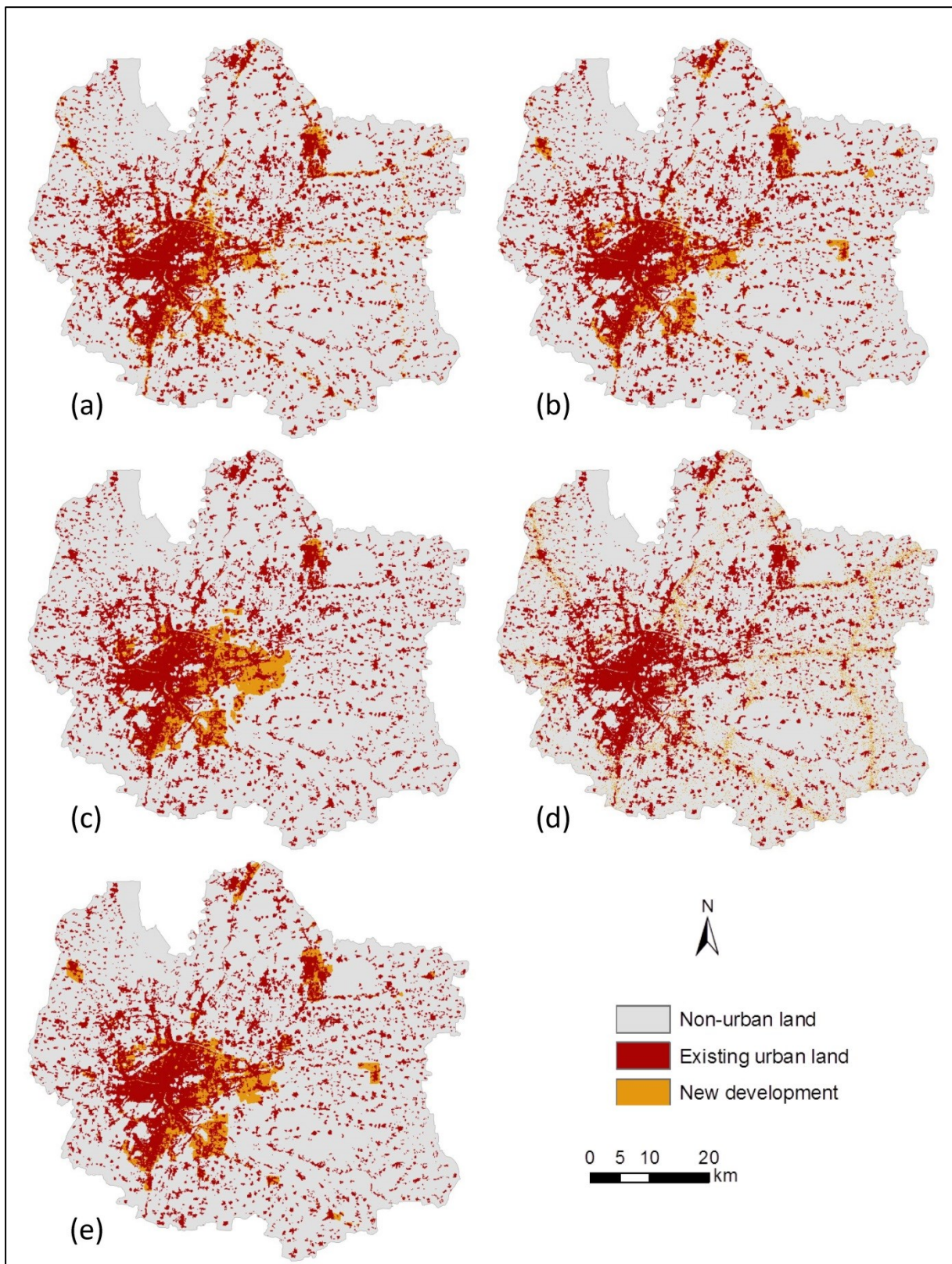
Under CDS scenario, due to the fact that we did not use constraints within the urban area, changes occur within the city core, thereby making it denser. This indicates that

green urban area and leisure facilities change to urban land use where the model finds them suitable for development. In addition, some new urban land tends to cluster around the city center, while new development far from the city center is rather scarce. It can be interpreted as the shift to a more efficient in land use which encourages the infill and edge growth, without developing new scattered urban patches.

In the DDS scenario, accessibility seems to control the spatial pattern of urban land to a large extent. Most of new urban land scatters in the fringe and rural areas along the main road in order to achieve a good accessibility. However, new urban development seldom occurs in the city core where the rapid urban growth is observed under CDS which indicates that the open spaces within the urban core are remaining. The urban land presents a large sprawl in fringe and rural areas. The growth pattern extends over adjacent and environmentally sensitive areas such as environment protection areas, subsidence areas by 2020 which suggests that introducing environmental constraints is an effective way to exclude the development of the environmentally sensitive area.

Compared to other scenario, MDS scenario is characterized by the compact polycentric development. The pressure of land conversion is constantly high due to the large population and rapid economic development in the city core. Instead of the concentrated development around the city center in compact development scenario, several hotspots with relatively larger size are promoted in fringe and rural areas when considering the benefits of dispersed development and the coordination development between urban and rural areas. The spatial distribution of the new hotspots is based on the master plan of Xuzhou city. Within each hotspot area, the new development provides a more compact urban area, with higher degree of urban coherence.

Figure 5-21: The alternative urban maps of Xuzhou city for 2020 under different scenarios: (a) business as usual scenario (BUS), (b) planning strengthened scenario (PSS), (c) compact development scenario (CDS), (d) dispersed development scenario (DDS), and (e) moderate development scenario (MDS)

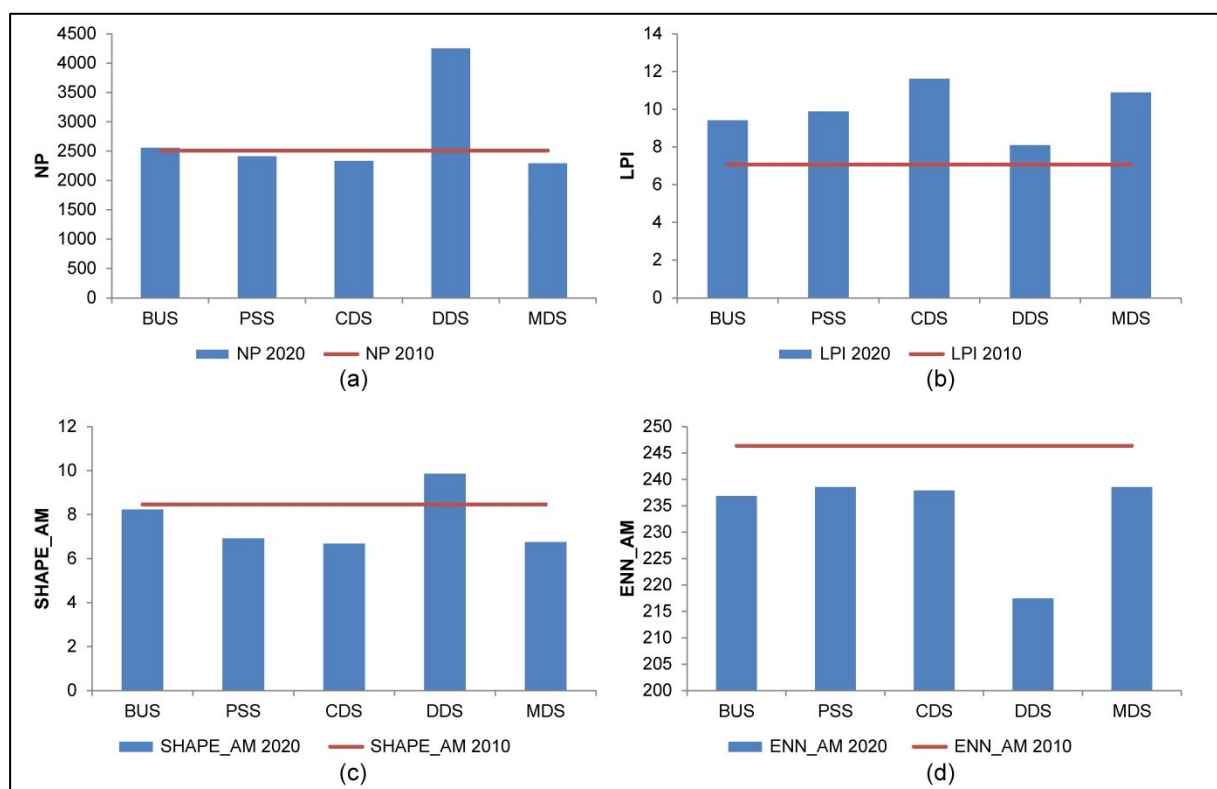


To further evaluate and compare these scenarios, NP, LPI, SHAPE_AM and ENN_AM were used to further clarify the differences between the five scenarios by

quantifying the spatial pattern under each scenario. In order to capture the urban growth patterns during the period of 2010-2020, the observed urban pattern in 2010 was also involved in the comparison. The evaluation of the different urban development scenarios can lead to an important insight into how different future strategies affect urban development.

When looking at these comparison results in Figure 5-22, we can gain the insight into the differences of the spatial patterns among different scenarios at global levels. The spatial patterns of scenarios differed from that of the observed urban pattern in 2010 due to the urbanization. If we look at the binary comparisons between scenarios in 2020 and observed spatial pattern in 2010 at local level, the urban growth pattern under each scenario can be discovered and located. In addition, the role of the transition rule can be better understood.

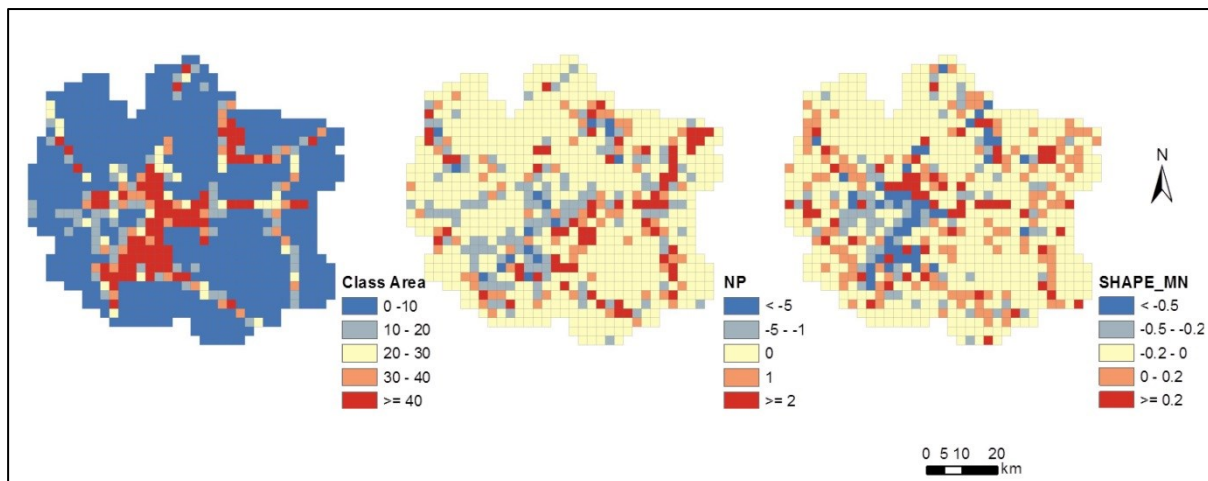
Figure 5-22: Spatial metrics values of urban land use under different scenarios and observed urban spatial pattern in 2010: (a) NP value, (b) LPI value, (c) SHAPEAM value, and (d) ENN_AM value



Under the BUS scenario, the increases in NP and LPI values are observed, which illustrate that urban growth in Xuzhou is focused on the development of new urban patches, as well as the expansion of the existing urban patches. The urban pattern becomes compact as reflected by the slight decrease in SHAPE_AM. As evidenced by the decrease in ENN_AM value, the individual urban patches get close to each other, becoming more connected with the city core. This is also reflected by the

binary comparison in Figure 5-23, Xuzhou city expands outside its historical core. Furthermore, urban growth is constantly moving toward the urban fringe in the eastern part of Xuzhou city. Some of new urban land is situated adjacent to or near major roads with scattered and irregular patches.

Figure 5-23: Binary comparison between BUS senario and observed urban spatial pattern 2010 in Class Area, NP, and SHAPE_MN values



In contrast to the historical urban growth trend, the PSS, CDS, and MDS scenarios have fewer urban patches compared to historical urban spatial pattern in 2010. Under these scenarios, the individual patches tend to be aggregated with increasing connection with previous individual urban patches already close to the city center and district centers, which is indicated by the decreases in NP and the increases in LPI values. The SHAPE_AM values decline suggests that urban pattern become more compact by locating continued growth in diffuse sprawl urban areas. Among these scenarios, the PSS scenario has highest NP, lowest LPI, highest SHAPE_AM and ENN_AM values, which are more similar to the BUS scenario compared to other scenarios. It is also confirmed by the small number of blocks with significant increase in NP and SHAPE_MN values in Figure 5-24. By 2020, some of the sprawl areas develop into compact urban land by infill of vacant land between the existing urban patches. It is clear that in this scenario, some areas would become more attractive, since they are enforced as hotspots in fringe and rural areas that are potential for future urban development and the evolution of compact centers. Around the hotspots, the fragmentation and diffuse urban development slows down as evidenced by the significant decreases in NP and SHAPE_MN values. Despite the strict implementation of master plan of Xuzhou city leads to the slowing down of the urban diffuse sprawl around the hotspots, it does not change the urban spatial pattern significantly, which could be explained by the fact that only master plan is involved

without considering other factors that have significant impacts on urban growth pattern.

Figure 5-24: Binary comparison between PSS senario and observed urban spatial pattern 2010 in Class Area, NP, and SHAPE_MN values

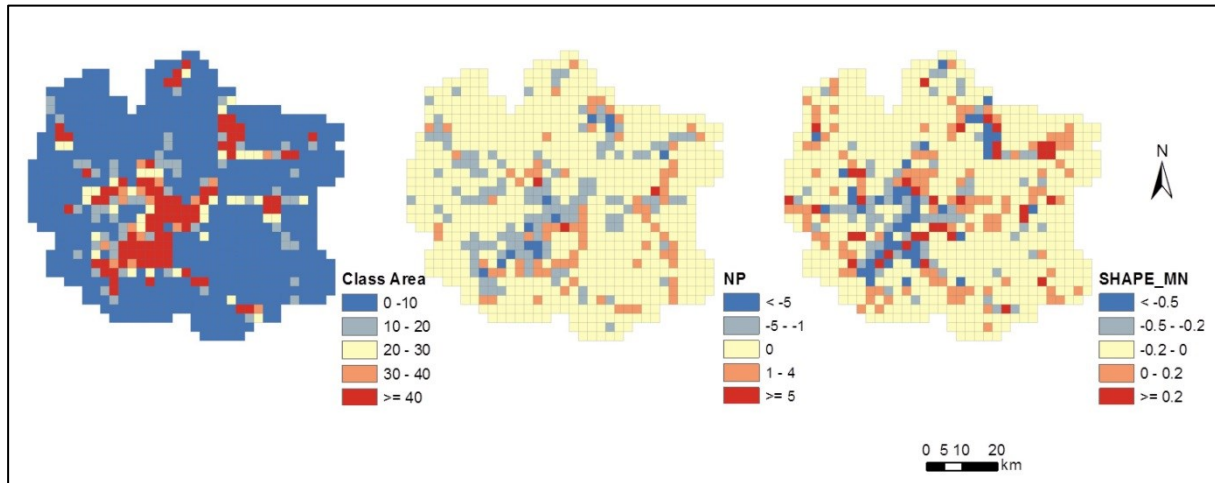
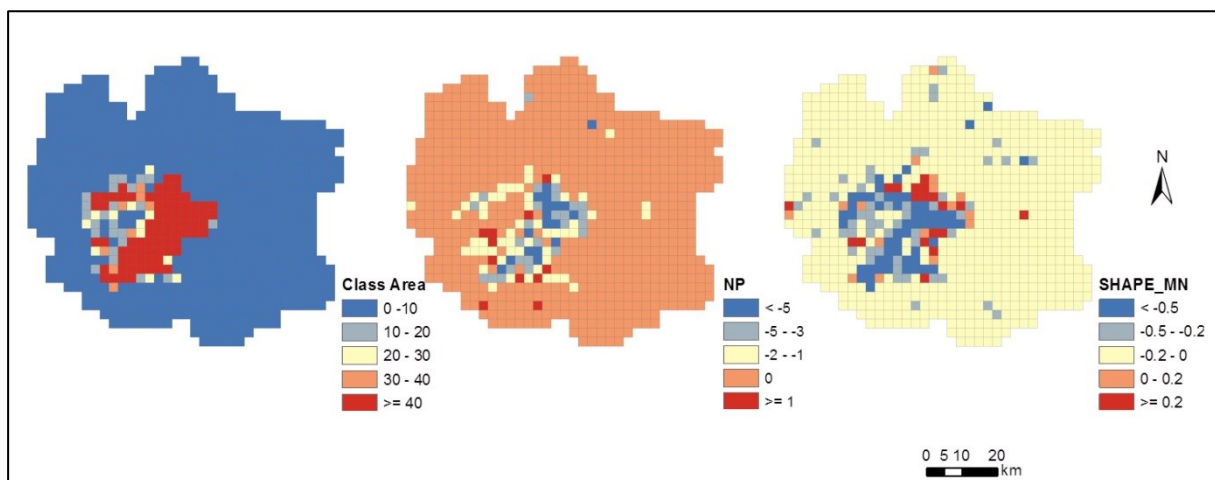


Figure 5-25: Binary comparison between CDS senario and observed urban spatial pattern 2010 in Class Area, NP, and SHAPE_MN values

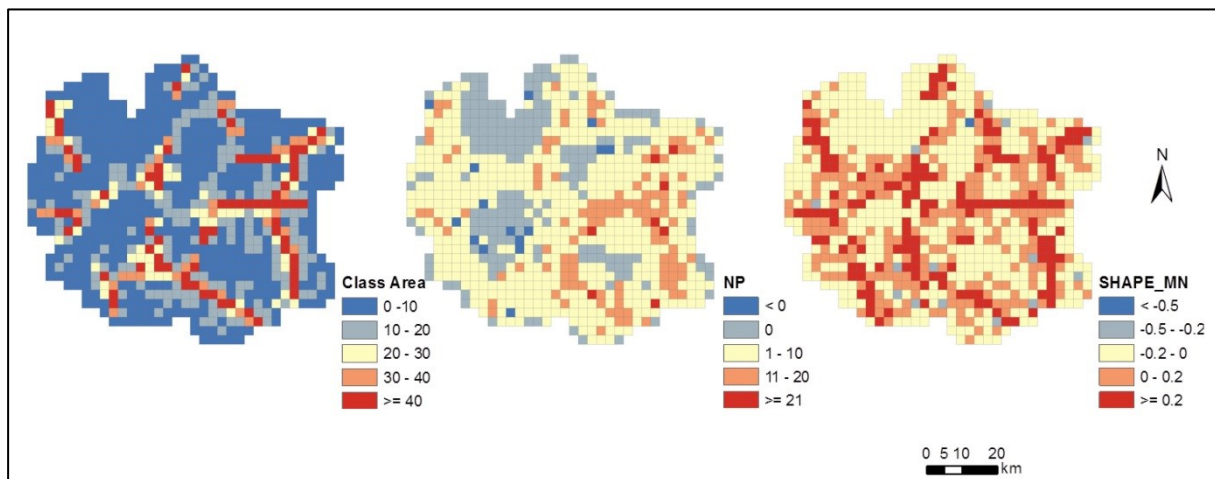


With regard to the CDS, the compact urban pattern is observed which can be attributed to the considerable edge growth of historical urban patches. In specific, the highest LPI value in CDS scenario indicates that urban growth under this scenario has a preference to occur around the city center that is more attractive for development. Hence, the urban patches around the city center grow together to form larger patches, which is described as “dense-onion” model by Herold et al (2003). The lowest value of SHAPE_AM suggests the urban areas are growing more compact. It can be seen from Figure 5-25 that almost all the vacant land suitable for development in the city core is used by 2020. The blocks in the city core have NP and SHAPE_MN values lower than 0. This indicates that the urban patches grow

together to former larger and more compact urban patches. However, most of distant fringe and rural areas still remain unchanged or grow at a slow rate under CDS.

The significant increases in NP and SHAPE_AM values indicate the increasing fragmentation and irregularity of the urban spatial pattern with continued urbanization under DDS scenario. In concert with the increase in NP, the corresponding decrease in ENN_AM suggests that distance between urban patches dramatically declines. The intensive urban sprawl speeds up during the 2010-2020. The development centers appear to be less attractive for development compared to other scenario, which is reflected by the slight increase in LPI since 2010. Figure 5-26 shows that the urban areas spread outward from the city core and along the major road. Many blocks have high NP and SHAPE_MN values, which indicate that the new development creates many smaller and more fragmented patches in 2020. While the central urban area changes slowly, there is a rapid increase in the new urban patches. The open spaces surrounded by developed urban land are created under this scenario.

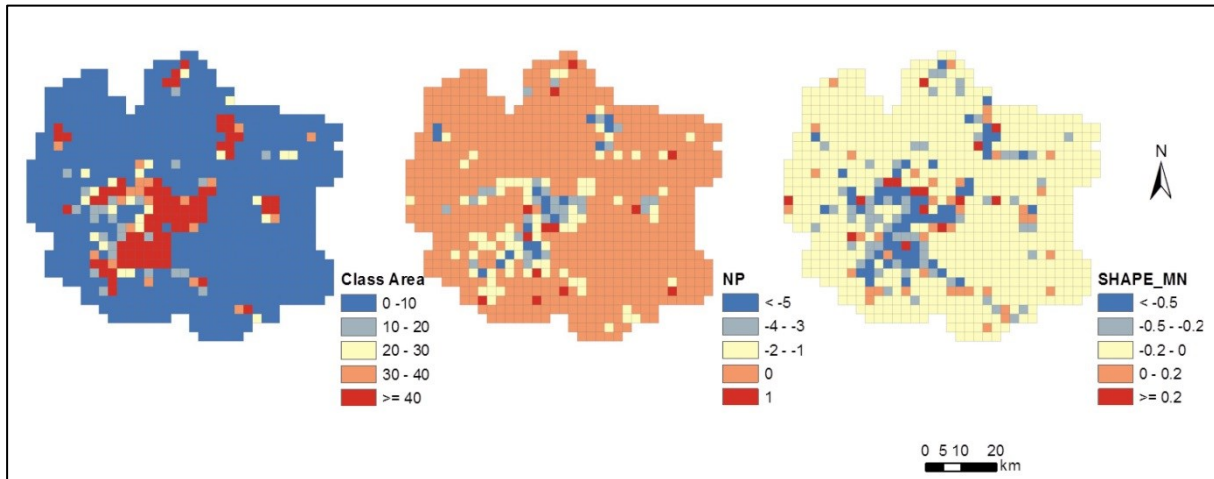
Figure 5-26: Binary comparison between DDS senario and observed urban spatial pattern 2010 in Class Area, NP, and SHAPE_MN values



Although the smallest number of urban patches is observed under MDS scenario, the LPI value is not the highest due to the development of several hotspots with relatively large size. Like the PSS scenario, the urban growth under MDS shows that the dominant trend of urban growth is the emergence of new development hotspots as shown in Figure 5-27. Most of land development is focused on the regions, where a large numbers of non-urban patches are encroached into urban land to form compact patches. Subsequently, the areas of diffuse sprawl are connected to the hotspots. Concomitant with the urbanization trend, however, spaces between the fragmented

patches are further urbanized and enveloped on each other, which is similar to the CDS scenario.

Figure 5-27: Binary comparison between MDS senario and observed urban spatial pattern 2010 in Class Area, NP, and SHAPE_MN values



Although various studies have been carried out to explore the methods of developing different scenarios, there is no consensus on which indicator is more appropriate in evaluating the urban growth scenarios. By using a set of spatial metrics, we were able to identify the differences of urban land use patterns among the five scenarios and get a valuable insight into the future urban growth pattern. One important problem that has been often ignored by previous studies is the effects of scale on scenario evaluation. Scale effect refers to the variation in the results of statistical analysis caused by the variation of scale (Buyantuyev et al., 2010). In this study, two different scales were adopted to evaluate and compare the scenarios. The spatial metrics were calculated based on the block which makes it possible to discover and locate the patterns in different urban areas. Moreover, the local scale with a multi-temporal perspective enables us to better evaluate small-scale urbanization process, which cannot be detected at the global scale. The study presented here allows the integration of global and local scales and is able to highlight the consequences of urbanization at different scales.

The scenarios represent alternative policy, and the ways in which each policy could potentially unfold into the future. The scenarios may be of use for planners to better understand the consequences of drivers on urbanization (Aguilera et al., 2011; Fuglsang et al., 2013; Song et al., 2006). BUS scenario suggests that urban development will continue through both expansion of existing urban areas and outward diffuse sprawl in the future. If it continues as indicated by the BUS scenario, the conflict between rapid urban growth demand and the limitation of scarce land

resources will intensify. The polycentric development was promoted as the development strategy since 2001. According to the historical growth trend, however, the polycentric development pattern is not significant by 2020. The development still focuses in the city core with rapid urban growth rate. A shift away from BUS might lead to significant alteration for Xuzhou city. There are still possibilities to enforce the polycentric development if the master plan is strictly implemented as shown in PSS scenario. The implementation of master plan leads to generation of new hotspots in fringe and rural areas for future development. Consequently the closer linkage between the former city core and new development hotspots is established, which is necessary for solving the imbalance of development among the city core, fringe and rural areas. However, the development is also scattered across the study area when other factors are not considered. In the compact development scenario, the development continues through infill in the existing city core and edge-expansion growth. The compact urban pattern is generally considered to be more efficient in the use of natural resources. Therefore it is regarded as a sustainable urban pattern (Li et al., 2008; Thinh et al., 2002b). However, the compact development within the city core makes it denser because the constraints within city core are not involved in the CA model. The densification of city core results in its limitless expansion and the loss of green open space, which influence the quality of urban life and urban environment. Concerning this shortcoming, DDS was simulated with the consideration of the demands of residents. As described in the storyline of dispersed scenario, the economy growth would result in increasing residents living in the fringe and rural areas and the development of new residential areas would be stimulated. DDS assumes the loss of agricultural and natural areas. The increasing residents would also encourage a large increase in road construction, and infrastructures. The economically oriented scenario presents more diffuse patterns (Reginster & Rounsevell, 2006). The study also confirms that the DSS scenario presents a more diffuse sprawl pattern which is recognized to have a negative impact on environment and sustainable development. Considering this fact and urban development policy, in addition to the implementation of compact development, the scientific urban planning policies should also be required in order to avoid the limitless expansion of city core and to balance the conflicts among the inter-administrative regions. The demand of people for better residential environment also needs to be satisfied. This development strategy in MDS scenario optimizes the growth allocation in an

environmentally and economically efficient way, which can support sustainable urban development in Xuzhou city.

6. Conclusion

In the previous chapters, the theoretical background with the concept and methods for monitoring and analyzing of urban growth are outlined (see chapter 2). Moreover, the study area of Xuzhou city and the related spatial data are described in chapter 3. Chapter 4 provides the methodological framework with integrating RS, GIS, and CA modeling for this study. By applying the methods in the study area, the results obtained in Xuzhou city are presented in chapter 5. In the following chapter, the answers to the research questions and the major findings are concluded. Based on the results the development recommendation and outlook are proposed.

6.1 The answers to the research questions

Firstly, it is important to generate the accurate classification results for the further analysis by using Landsat images. In chapter 2.2.1, the methods of remote sensing processing are outlined on the basis of existing literatures. It serves as background knowledge of the possible method that could be effective in extracting land cover information. Meanwhile, the detailed classification method used in this study is proposed in chapter 4.1.1, which provided an answer to the first research question raised in chapter 1.2.2.

- 1) How to improve the classification accuracy in order to provide the high quality land cover information for further analysis?

There are a number of methodical approaches used already for the remote sensing image classification. In chapter 2.2.1, the effort was made to generally describe and to evaluate major approaches on this realm. As the two sides of a coin, each of them has its particular advantages and disadvantages. In the author's opinion, however, the identification of a suitable method needs to be tested. The additional methods and data are also required. For instance, the combination of sub-pixel classifier and multiple NDVI is an effective way for classifying urban land cover from remote sensing images. The foundation of the methods is Vegetation-Impervious Surface-Soil (V-I-S) model, which provides a more realistic depiction of the spatial land cover arrangement in the study areas. It has proved to be useful in urban RS, since it is based on the physical compositions of the urban environment (Setiawan et al., 2006). Although the V-I-S model is not developed for the purpose of classifying land cover, rather for the identification and characterization of land cover in urban areas, it has proved to be useful in solving the mixed problems and identifying the classes with similar spectral values when integrating with hierarchical classification scheme, since it is based on the physical compositions of the urban environment (Setiawan et al.,

2006). In this study, the implementation of the V-I-S based hierarchy classification scheme consisted of two steps: (1) sub-pixel classification; and (2) multiple NDVI values comparison. Sub-pixel classifier represents the value of each cell in terms of degree of specific land-use type, which allows for robust and potentially more accurate spatio-temporal modeling. It was applied to solve the mixed pixel problem between vegetation and built-up or soil. However, soil and built-up types were difficult to be clearly separated due to the similar spectral values. Comparison of multiple NDVI values derived from multitemporal remote sensing images is a useful method to separate these two classes. The comparison of the performance of two classification methods (traditional and hierarchy classification methods) presented in chapter 5.1.1 reveals that the hierarchy classification methods can achieve higher accuracy results in both Xuzhou city and Dortmund city region. It turns out to be a suitable method for obtaining accuracy land cover information from Landsat images especially in urban areas.

After generating the accurate land cover maps, it is necessary to conduct a comprehensive analysis of urban growth patterns for better understanding the urbanization process and assessing its impacts on environment. Hence, the next research question is raised:

2) Which indicators can be used to reflect and quantify the urban growth patterns? In this article, not only changes in the area of each land cover type, but also, importantly, the land cover change pattern was detected through spatial analysis. "Everything is related to everything else, but near things are more related than distant things." The first law of geography by Tobler (1970) is of central significance for understanding urban dynamics. Buffer analysis identified the regularity of the land cover change patterns with the distance to existing built-up areas. Near-existing built-up land has a stronger impact on the development of built-up land than distant one. The analysis also highlighted the capability of jaggedness degree for better understanding the urban growth pattern. The jaggedness degree is sensitive to the compactness of urban forms (Thin, 2003). If the urban area grows spatially more compact, then the degree decreases accordingly. It is important to notice that the variation of jaggedness degree is related to the buffer analysis results over the study period. During the period of 2001 to 2005 in Xuzhou city, the marked increase in the share and intensity of new developed urban areas in outer buffer zone was reflected by the jump of jaggedness degree. Moreover, the continuous decline of the

jaggedness degree was a quantitative proof for the high share and intensity in the first buffer zone for Dortmund city region.

In addition to the comparison between Xuzhou city and Dortmund city region by using spatial indicators, spatial metrics were applied as a useful tool in description, analysis, and tracking of changes in land use shapes and patterns for Xuzhou city. Urbanization alters the spatial structures and patterns of land cover within a region (Jenerette & Wu, 2001). The literature review emphasized the usefulness of spatial metrics, which can be applied to provide an improved description and representation of the urban areas. In this study, the integration of remote sensing and spatial metrics can offer and reveal the characteristics about urban patterns and changes, allowing for quantitative representations and a better understanding of urban growth process and impact of urbanization. The variations of different spatial metrics represent specific spatial and temporal dynamics of urban growth. Class Area, NP, LPI, SHAPE, and ENN were used in this study with focusing on three aspects of spatial pattern: the shape of urban patches, fragmentation, and aggregation. At the global scale, the quantitation of spatial patterns was a simple way to enrich traditional analysis of land cover change. One important problem that has been often ignored by previous studies is the effects of scale on scenario evaluation. In order to obtain more detailed information of how the urban grows, further examination of urban spatial patterns at a local scale was conducted. The spatial metrics were calculated based on the block which makes it possible to discover and locate patterns in different urban areas. Moreover, the local scale with a multi-temporal perspective allowed us to better evaluate small-scale urbanization process, which cannot be detected at the global scale.

Besides the scale related to the use of spatial metrics, the application field of spatial metrics is also varied. The temporal change of spatial metrics can provide a better understanding of the relationship between urban spatial pattern and urbanization process. Furthermore, the spatial metrics were also involved to conduct the calibration and validation of CA models, as well as the evaluation of different scenarios in chapter 4.3. The results shown in chapter 5.3 demonstrate their effectiveness in interpretation, assessment and verification of spatial models.

In the next step, chapter 4.2.2 provides the answers to the third question and chapter 5.2.2 gives the results for the application of the proposed methods.

3) How to explore the underlying cause-effect relationships in the urban growth process?

The study divides the question into two parts: the first one is to explore the relationships between urban spatial patterns and urban growth: the second one is to investigate the effects of driving factors on the urban growth.

As concluded in chapter 2.2.2, the efforts to understand the relationships between spatial patterns and urbanization have been made. In order to bridge these gaps in the previous studies and to effectively capture and analyze the urbanization process, it is necessary to explore the quantitative relationships between urban growth patterns and urbanization with taking into account its spatial dynamics effects. The GWR model used in this study includes a spatial component in its specifications. This indicates that the coefficients estimated for this regression vary according to geographical location. The results in chapter 5.2.1 show that GWR model can provide detailed site information on the different roles of urbanization in different parts of the study area, rather than generating an average coefficient for the entire area, which improves the model ability to explain the local situation of spatial patterns. The comparison of GWR and OLS models suggests that GWR models perform better than OLS in explaining variances in the relationships. Furthermore, GWR models improve the reliability of relationships by effectively reducing spatial autocorrelations in residuals. Therefore GWR model is useful for establishing more effective plans to mitigate the negative effects of urban growth on spatial patterns. The next step is to analyze the effects of a set of driving factors on urbanization by adopting the logistic regression. The urban growth probability was defined as the dependent variable, and a set of factors were set as independent variables. In order to obtain the optimal set of variable combinations with the highest ROC value, the logistic regression was estimated for different sets of variable combinations. The optimal factors and the relative importance of the driving factors varied over time along with the urbanization process, thus, providing an insight into the urbanization process.

Based on the analysis of historical urban growth trend, the CA models were developed to simulate the future urban development. The fourth research question is related to the calibration of CA models. Chapter 4.3.2 provides the answer to this question.

4) How to determine the parameter values of CA models in order to accurately reproduce historical urban growth?

The model can simulate the past urban growth and a wide variety of future scenarios based on the parameter values. Consequently, the method of parameter estimation is an important task. Furthermore, the calibration of CA models is difficult, particularly when there are many parameters to be considered in understanding spatial and temporal processes of urban growth (Cheng & Masser, 2004). Therefore selecting an appropriate method for the study is a challenge. An advantage of the logistic regression is its ability to estimate the weights of various spatial factors by developing statistical relationships between historical urban growth and spatial factors (Arsanjani et al., 2013; Ward et al., 2000). The shortage, however, is that it does not include all the relevant variables and cannot explain their temporal dynamics of relationships (Hu & Lo, 2007). For instance, the neighborhood configuration and random variable cannot be estimated using the logistic regression. The trial and error method is a more rigorous calibration method but with intensive computation. Different from other calibration method used in previous studies, a hybrid calibration method consisting of the logistic regression and the trial and error has proved an effective and quick approach for calibrating the CA model in this study. The presented approach potentially captures the complex interaction of various environmental and socio-economic variables and promotes the computational efficiency of calibration. Moreover, it allows for sensitive analysis which demonstrates that the results of the CA model are sensitive to the parameter values, for example the neighborhood configurations and random variable. This is an important issue in CA models for understanding the urbanization process and its uncertainty.

Our study agrees well with the previously reported the usefulness of figure of merit and spatial metrics in the validation of CA model (García et al., 2012; Wang et al., 2013). While the study differed in that is the study focused on the effectiveness of combination of the two indicators in quantifying the agreement between simulated and observed urban land use maps. Firstly, figure of merit value was used to quantify the agreement using pixel by pixel comparison. It is a simple but promising way to measure location errors (Pontius et al., 2007). Secondly, the relative difference of spatial metric was utilized to objectively assess the goodness-of-fit of the outcomes with the actual urban patterns. For analyzing urbanization process, the urban spatial patterns are likely to be more important than the absolute locations of new urban pixels (Jenerette & Wu, 2001). That is why spatial metrics were used to analyze the spatial patterns of model results. The rapid urbanization process may lead to the variation in the urban spatial patterns, which can be captured by a set of spatial

metrics. Furthermore, each simulation will generate different results due to the involvement of random variables, but the stochastic CA can maintain stability in spatial pattern (Yeh & Li, 2006). Consequently, the integration of figure of merit with spatial metrics can provide an effective way to identify the suitable random variables. In summary, the mixed measurement is capable of accurately capturing the effects of variables on urban spatial allocation and patterns, with that the model can produce more accurate result. The developed model has proved to be capable of accurately modeling the historical urban growth of Xuzhou city.

The last research question deals with the contribution of CA models to decision making processes. Chapter 4.3.3 provides the answer to this question and chapter 5.3.2 provides the results for the application of proposed methods. These chapters are the one of the main innovative parts in this study.

5) How to connect the CA models with the urban decision making process?

The establishment of connection between CA models and the urban decision making process needs to be considered as an important aspect of urban spatial models when such models are applied in the context of realistic cities. As concluded in chapter 2.3, as a means of spatial optimization and predictions for the future, urban growth scenario has been in the planner's toolkit for several decades. In this study, the efforts were made to illustrate a way in which CA models can be better linked with the decision making process.

The CA model is flexible and has the potential to incorporate the variations of parameters, which is regarded as a precondition for generating different urban growth trend. In order to provide a comprehensive and alternative context for the decision makers, the calibrated CA models were applied to simulate five development scenarios in 2020 for Xuzhou city under different spatial plans and policies, which are strongly linked to the current existing concerns of the policy makers of Xuzhou city addressing the key question. The five scenarios are: business as usual scenario, planning strengthened scenario, compact development scenario, disperse development scenario, and moderate development scenario. Each scenario has its own probabilities of urban growth associated with the different growth tendencies. Under each scenario the parameters are modified according to the specific definitions.

The challenge for a scenario simulation is to correctly define the relative importance of the global factors in qualitative terms, and then to translate the qualitative process

description into quantitative scenarios of urban land use. This study proposed a combined methodology of translating the alternative futures into quantitative scenarios by integrating AHP, MCE and CA models. The pairwise function of different options quantified by AHP enables the decision makers to express their insights into the growth of Xuzhou city. The main advantage of this method is related to the structural conceptualization of decision making, in which several parameters may be compared, thus, bridging the gap between qualitative analysis and quantitative outputs.

The combination of scenario simulation and the spatial metrics has proved to be capable of making the processes and patterns of urban growth more prominent than using simulation on its own, and the spatial metrics also serves as a comparative platform to other cities. The examination and evaluation of future urban growth scenarios under different “what-if” conditions can assist decision makers in analyzing the impacts of different development strategies, and can form a basis for urban planning policy recommendations towards sustainable urban development.

In brief, the connection between CA models and the decision making process could be concluded mainly from three steps: design of development scenarios, identification of parameters, and evaluation of scenarios.

6.2 Development implications

The study presented wide comparisons between Xuzhou city and Dortmund city region in both the amount of land cover classes and urban growth characteristics in order to provide a better understanding of different underlying processes. Although there are some common features, different areas adopt different paths due to their different cultural backgrounds and developmental stages, resulting in different land-use patterns.

The results of our analysis confirmed a general trend of relatively slow urban growth process in developed countries compared with that in developing countries. The development in Dortmund city region was characterized by the smooth growth with continuous urban patches, which resulted in compact development during the study period. This corresponds with the findings from other cities in the developed countries (Luck & Wu, 2002; Schneider & Woodcock, 2008). In contrast to Dortmund city region, Xuzhou city was characterized by the rapid urbanization. The similar trends of urbanization are revealed by the case studies on other areas in developing countries (Dewan & Yamaguchi, 2009a; Estoque & Murayama, 2013; Wu & Zhang,

2012). By combining urban growth pattern analysis with land-use change detection, this study identified spatial characteristics of the urban development of Xuzhou city, which can be divided into the following three phases:

Initial rapid development phase (1990-2001):

During this period, the expansion of the new built-up land tended to cluster around the city core, while new developments in the open area were rather scarce.

Transition phase (2001-2005):

Compared with the previous phase, a larger proportion of urban expansion in Xuzhou was focused on the development of new urban patches, rather than expansion of the existing urban patches. In order to promote regional economic integration as well as to avoid the “big-pancake” form, the polycentric development has been proposed as a new planning policy to guide the future development in Xuzhou since 2001. However, with the implementation of new planning policy, new developed area was found in the fringe area to improve the infrastructures and facilities conditions for further development.

Extensive phase (2005-2010):

After the improvement of living and working condition, the active area for development was not constrained to be in the city core, hence more and more new built-up land occurred in fringe area. The existing individual urban patches grew together to decrease the distance between patches, becoming more connected with central urban patches. Furthermore, diffuse sprawl urban development pattern was observed which indicates that historical urban patches grew together to form larger but more complicated patches.

Next, the significant cause-effect relationships in urban growth process were observed in this study. This corresponds with the findings in literature related to other cities in the world (Braumoh & Onishi, 2007, Clarke et al., 1997, Weng, 2007). The study extends these previous studies by investigating spatio-temporally varying effects of urbanization instead of global effects. Both negative and positive effects of urbanization on variation of spatial metrics values were explored. The significant correlations were found around the city core and fringe area in 1990-2001. This can be due to the locations closer to the city center offering more opportunities to access socioeconomic resources. After the rapid urbanization, however, the most significant effects of urbanization were located in the fringe area rather than in the city core,

especially in 2005-2010. Furthermore, the temporal changes of effects of urbanization on urban growth patterns were also assessed in this study. The effects of urbanization on the variations of spatial patterns varied over the study period, which can be explained by the socioeconomic processes and the consequence of urban development policy. The results generated from the logistic regression model indicate that the historical urban growth patterns in Xuzhou city can, in considerable part, be affected by distance to CBD, distance to district centers, distance to roads, slope, neighborhood effect, population density, and environmental factors with relatively high levels of explanation of the spatial variability. Among these factors, the socioeconomic and neighborhood factors significantly affected the urban growth. The optimal factors and the relative importance of the driving factors varied over time, which provides an insight into the urbanization process.

Finally, the study demonstrates that the CA modeling can offer an enhanced understanding of the urbanization process and the trend of the future urban development. In order to predict the alternative urban growth patterns for Xuzhou city, five scenarios were designed and evaluated (business as usual, planning strengthened, compact development, dispersed development, and moderate development). Although the scenarios are simple, they are rooted in some facts of Xuzhou urban growth patterns and spatial policies. The evaluation of scenarios suggests that the urban growth pattern is varied by the scenarios in Xuzhou city. To conclude, the future urban development is mainly governed by two categories: sustainable and non-sustainable development. The current urban development process is in a critical stage. If it continues as indicated by the business as usual scenario in the future, new urban areas are sparsely developed in fringe and rural areas. The conflict between rapid urban growth and limited land resource becomes more apparent. Comparing with other scenarios, the moderate development scenario could be considered as the best one in achieving the objectives of compact urban form, good residential environment, as well as environmentally and economically efficient development.

6.3 Recommendations

The development characteristics and land cover change in Xuzhou city provide good representatives of the medium sized Chinese cities, since most of them have experienced the same political and socioeconomic development. The sustainable

developments of these cities play a key role in the sustainable development of China. Based on the major findings in this study, the following recommendations are given:

As concluded in chapter 2.1.3, there are evidences indicating a significant correlation between urban form and sustainability. It can be seen that the urban development in Dortmund city region was more compact and generally extending around the existing built-up area, whereas the development in Xuzhou city was more dispersed. This urban form may cause much more ecological and environmental problems than a more compact pattern (Li et al., 2008). As presented in Dortmund city region, compact development has been considered as a sustainable development trend in reducing the negative effects of dispersed development and in guiding urban development to sustainability. Thus, the urban growth pattern of Dortmund city region could be valuable for Xuzhou city to solve a series of environmental and socioeconomic problems caused by sprawl and “leapfrog-style” urban development such as the gap of urban development between the city core and fringe and rural areas, the conflict between limited land resources and high pressure of urbanization, and so on.

However, there are some problems related to the concentric compact city, such as congestion, shortage of open space near to residential areas. The comparison analysis of different urban development scenarios suggests that the polycentric compact urban form can be considered as the best one in this study. Therefore, efforts should be made to generate compact form, for example, in-fill development or qualified brownfield development. The loss of farmland can be also attributed to scattered rural settlements and their construction on land of the rural areas. Therefore, the master plan of Xuzhou city needs to be strictly implemented for identifying the suitable location of each development hotspots in fringe and rural areas. The attraction of hotspot for urban growth needs to be emphasized in order to form polycentric development.

Through the analysis of the relationships between urbanization and the urban growth patterns in Xuzhou city over the study period, we can find the urban area not only increased dramatically but it became also more fragmented and irregular along with that urbanization process, especially in the rapid development areas. It is widely acknowledged that fragmented and irregular development patterns are associated with ecological and environmental problems, which threaten the sustainable development (Jenks et al., 1996). Therefore, for the future development, some

related plans and measures should be implemented to facilitate connectivity between built-up fragments around the new development hotspots.

Besides the urban spatial pattern, other important aspect related to the sustainable development is the environment. A decreasing effect of slope on urban growth during 2005-2010 in Xuzhou city was found, suggesting an increasing pressure for development in the mountainous areas where are regarded as ecologically valuable zones. Moreover, the policy factors (Subsidence and Environment) had slight effects on urban growth during the study period, indicating the lack of consideration of environment protection and scientific land use management during the rapid urbanization process. In recent years, with the depletion of coal deposit, the era of post-mining will begin. While the environment in Xuzhou city was significantly affected during the coal exploitation. Therefore the strict implementation of policies for protecting more ecologically valuable zones and environmentally sensitive areas is required.

6.4 Outlook

The methodology framework proposed for this study has demonstrated to be useful in monitoring and analyzing urban growth in Xuzhou city and in providing a support for decision making processes towards a sustainable development. Some valuable results provide a better understanding of historical and future urbanization process. However, in order to get more information to support the sustainable development, some other materials and methods may also be considered in the further study.

Scale is an important aspect in investigating and explaining the complex hierarchical organization of the geographic world (Marceau, 1999). It has been widely acknowledged that the spatial pattern is scale dependent since it changes with the scale of observation or analysis. In order to conduct the spatial pattern analysis at local scale, block was used as a sample unit. The different block size can result in different explanatory ability of models due to the scale effect. The preliminary test was conducted, nevertheless, further studies need to be carried out to consider the different block shapes and sizes in order to obtain an insight into their effects on spatial pattern analysis.

Besides the factors involved in this study, urban growth is also strongly affected by political, cultural and other factors, which are difficult to incorporate into spatial model due to their aspatial characteristics and the lack of data. Although the good agreement between model results and actual maps were observed, it is

recommended that more potential variables should be included in the future studies to improve the performance of spatial models and to evaluate the effects of the factors on urban growth.

The study only focused on the simulation of urban development without consideration of the detailed land use categories (commercial, industrial, and settlement land) due to the lack of detailed land use data. With taking into account the interactions among them, it would be interesting and valuable to simulate the change of several detailed land use categories within urban areas to provide a better understanding of the urban land use development.

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EIDESSTATTLICHE VERSICHERUNG

Hiermit versichere ich an Eides statt, dass ich die vorliegende Dissertationsschrift zum Thema

“Monitoring and analysis of urban growth process using Remote Sensing, GIS and Cellular Automata modeling: A case study of Xuzhou city, China”

selbstständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus Quellen entnommen wurden, habe ich als solche gekennzeichnet.

Des Weiteren erkläre ich an Eides statt, dass diese Arbeit weder in gleicher noch in ähnlicher Fassung einer akademischen Prüfung vorgelegt wurde.

Dortmund, 05.09.2014

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