Evaluating Urban Expansion Using Integrated Remote Sensing and GIS technique: A Case Study in Greater Chengdu, China

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Sisi Zhang, 2016

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ABSTRACT

The overall goal of this thesis is to better understand changes in the spatial pattern of urban growth and its impact on landscape configuration by conducting a case study in Greater Chengdu, an inland megacity in China. The objectives are as follows: 1) Quantifying changes in the spatial pattern of the study area between 2003 and 2013; 2) Evaluating the degree of urban sprawl over that period; 3) Evaluating urban expansion dynamics; and 4) Examining and defining the types of urban growth. Satellite imagery was employed to distinguish and identify different land surface categories. Integrated remote sensing and GIS (Geographic Information System) technique was used to analyse both qualitative and quantitative perspectives regarding the objectives. The results indicate that the urban area of Greater Chengdu doubled from 525.5 km^2 to 1191.85 km^2 during 2003 to 2013. The geographic footprint demonstrates that the distribution of the built-up area was dispersed and continues to grow more dispersed. The dominant type of urban growth is outward expansion, by which the city grew within a 10 km to 25 km radius surrounding the city center. A substantial infill phenomenon exists between a 5 km and 10 km radius from the city center. The urban core boundary expanded outward by 5 km, while the fringe of suburban area expanded outward by 10 km during the time period, which both indicate a substantial outward expansion over the city. The significant contribution of this study could benefit to many aspects such as comparative studies between cities or continuous studies relevant to urban growth.

Key Words: *Urban expansion, remote sensing, GIS, Shannon's Entropy, Landscape metrics, ULAT*

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LIST OF ABBREVIATIONS

LDR	Less Developed Regions
MDR	More Developed Regions
GIS	Geographic Information System
Landsat ETM+	Landsat Enhanced Thematic Mapper Plus
Landsat OLI	Landsat Operational Land Imager
USGS	United States Geological Survey
NASA	National Aeronautics and Space Administration
LUCC	Land Use and Land Cover Change
BA	Built-up Area
WA	Waterbodies
VE	Vegetation
FO	Forest
BL	Bare Land
NP	Number of Patches
MPS	Mean Patch Size
PLAND	Percentage of Landscape
UGAT	Urban Growth Analysis Tool
UOS	Urbanized Open Space
POS	Peripheral Open Space

Chapter 1 : INTRODUCTION

1.1 Urban expansion: its causes and consequences

According to the World Urbanization Prospects reported by the United Nations (UN, 2012), from 1965 to 2010, the global population increased from 3.3 billion to 6.9 billion, and the total amount of population will exceed 9.3 billion by 2050. Along with the population growth, more and more people chose to live in urban areas. The percentage of the world's population residing in urban areas increased from 35.5% in 1965 to 51.6% in 2010, and, by 2050, this number will reach at 67.2% (UN, 2012), which means over half of the population on the earth will live in urban areas by 2050. The increasing urban population causes increasing demand on urban land use. This movement leads to tremendous rural-urban land conversion, which has become a significant research topic in recent decades (Angel et al., 2007; Bhatta et al., 2010b; Martinuzzi et al., 2007; Sudhira et al., 2004; Wu et al., 2015).

Unprecedented urbanization causes rapid urban expansion, which can be unhealthy without reasonable urban planning. Some researchers employ the term "urban sprawl" to describe unhealthy urban expansion (Angel et al., 2011; Jat et al., 2008; Yue et al., 2013). Unhealthy urban expansion, or in other words, urban sprawl, refers to an uncontrolled and dispersed process of urban growth characterized by automobile-dependency, low urban area density and low population density (Bhatta et al., 2010b; Jiang et al., 2007), which has gained widespread social focus. Urban sprawl increases congestion, decreases the urban employment rate, and decreases access to public services. It directly causes many environmental and social problems, such as traffic problems, loss of open space, uneven distribution of local resources, and increased crime (Bhatta et al., 2010b; Ji et al., 2006; Jiang et al., 2007; Lambin et al., 2001; Sudhira et al., 2004; Yu & Ng, 2007). In addition, urban sprawl is associated with problems such as air pollution, water contamination, arable land loss and climate change (Bhatta et al., 2010a; X. Xu & Min, 2013; Yu & Ng, 2007).

1.2 Urban expansion in developing countries

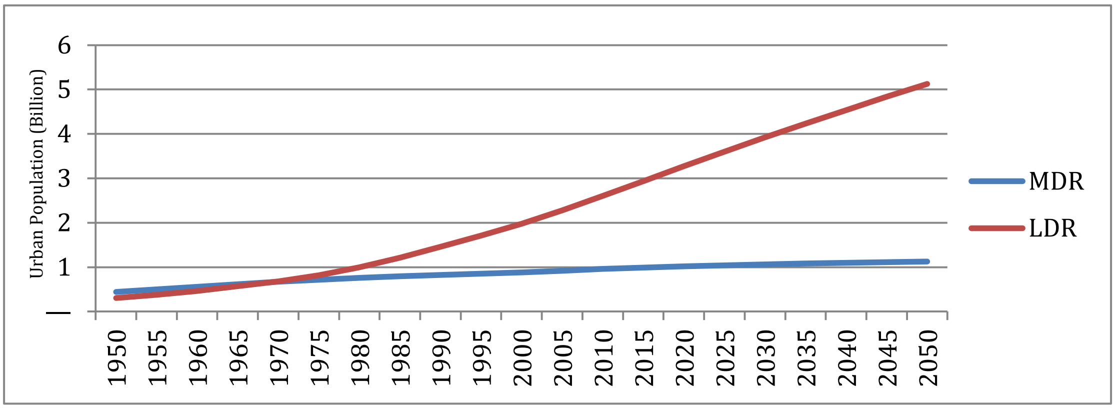


Figure 1-1. Urban Population Change in MDR and LDR from 1950 to 2050 (UN, 2012) From 1950 to 1975, the difference of urban population between MDR and LDR was non-significant; after 1975 urban population in LDR increased much faster than those in MDR According to the UN, by 2050, the urban population in LDR will be four times higher than the urban population in MDR (UN, 2012).

According to the World Urbanization Prospects (UN, 2012), in 1950 the urban population was 0.4 billion and 0.3 billion in more developed regions (MDR) and less developed regions (LDR) respectively. However, in 2010, there were 0.9 billion urban residents in MDR and were 2.6 billion in LDR. Moreover, by 2050, it is predicted that the number of urban residents in MDR and LDR will increase to 1.1 billion and 5.1 billion (Figure 1-1), respectively. Since 1975, the urban population in LDR has risen dramatically, which has significantly increased the rate of rural-urban conversion in those regions, especially in developing countries (Avelar et al., 2009; Bhatta et al., 2010a; Deng et al., 2009; Schneider et al., 2005; Seto & Fragkias, 2005; Sudhira et al., 2004). Dewan & Yamaguchi (2009) investigated the urban area change between 1975 and 2003 in Greater Dhaka, the capital city of Bangladesh, and found that the city doubled over that time period. Sharma & Joshi (2013) monitored the increase of built-up area in Delhi, India between 1998 and 2011, and posited that these areas increased 12%, by 7,000 hectares over this time. Researchers who focused on rural-urban conversion in China found that, in cities like Nanjing and

Hangzhou (Xu et al., 2007; Zhang et al., 2013) and regions such as Zhujiang Delta (Weng, 2002), the urban area continues to increase rapidly.

1.3 Urban expansion in China

Urban population rose from 17.9% in 1978 to 52.6% in 2012 in China (Bai et al., 2014), accompanied with a tremendous landscape urbanization. During the last decade, the urban built-up area increased by 78.5% (Bai et al., 2014). However, as shown in Figure 1-2, the urban population in China is not distributed evenly across the country because of geographical limitations such as mountainous topography and desert regions. Over 95% of the urban population resides in only 1/3 of the country's land surface (Bai et al., 2014), which causes considerable localized environmental issues such as air pollution, water contamination and urban heat island phenomenon, and poses significant challenges to public health, environment and ecological balance and urban sustainability (Chen et al., 2006; Weber & Puissant, 2003; J. Wu et al., 2011; Xu & Min, 2013).

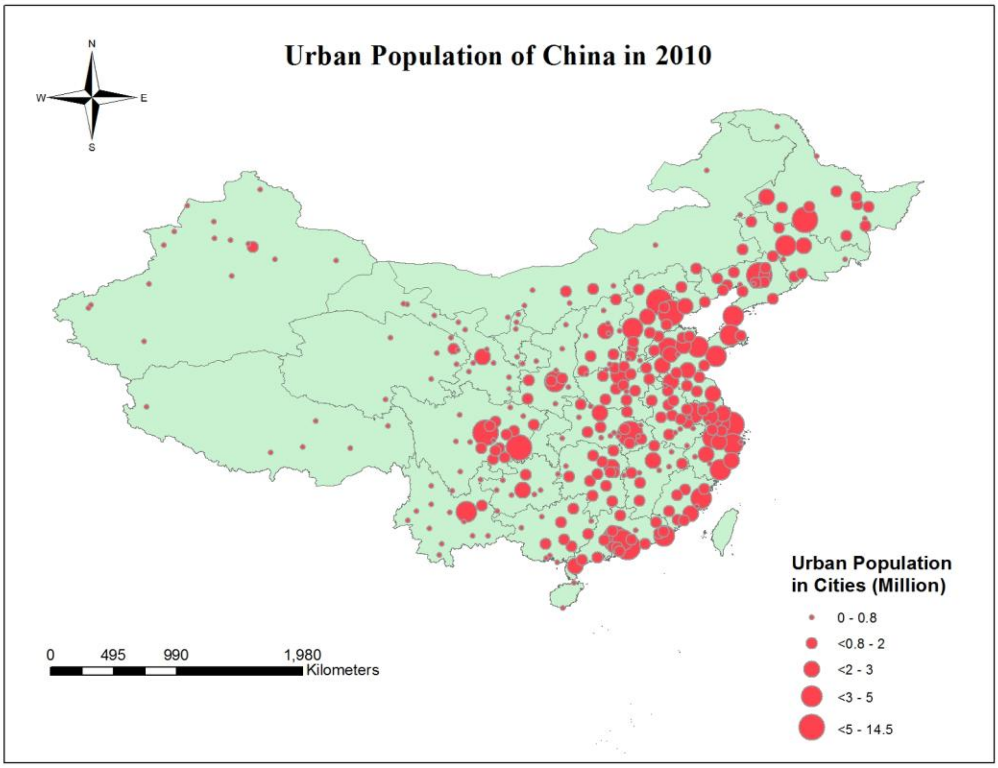


Figure 1-2. Urban Population of China in 2010.

Xu & Min (2013) grouped 18 mid-sized to large-sized Chinese cities into three categories (East, Middle and West) according to their locations, examined urban expansion under regional scale, and found strong evidence of rapid urban expansion throughout the cities. The result also indicated that from 1980 to 2008, the average expansion rate of cities in the Middle and West groups continued to increase. Shi et al. (2015) monitored urban expansion in coastal regions of China and found that the urban expansion in coastal region of China is driven by government policy. As a country that possesses around one fifth of the world's population (UN, 2015), high population, limited livable land and potential social environmental issues means that urban expansion in China must be carefully addressed.

1.4 Why Chengdu?

A megacity is defined as an urban agglomeration with at least 10 million inhabitants. These cities attract extensive attention from researchers not only because of their considerable population, but also because of the social and environmental problems that accompany large urban agglomerations (Mitchell, 1999; Taubenböck et al., 2012).

China is a developing country with around 1.34 billion inhabitants (National Bureau of Statistics, 2010). In 2010, the ratio of urban population to total population was 49.68%, which was a 13.46% increase from 2000 (National Bureau of Statistics, 2011). This increase indicates a tremendous amount of rural-urban movement in China during the time period. According to the 2010 National Census Data (National Bureau of Statistics, 2010), in 2010, there are six megacities, Beijing, Tianjin, Shanghai, Chongqing, Guangzhou and Shenzhen, of which one is the capital city (Beijing) and four are coastal cities (Tianjin, Shanghai, Guangzhou, Shenzhen). During last few decades, many researchers of urban expansion studies in China have focused on either the capital city or the coastal megacities (Gaubatz, 1999; Han et al., 2009; Jiang et al., 2007; Weng, 2002; Yu & Ng, 2007); few have studied the inland megacities. As the urban population increases, urban expansion becomes an increasingly critical topic that needs to be discussed carefully in not only coastal megacities, but also in those megacities that are located in inland China, such as Chengdu.

As of 2010, Chengdu was the most populated mid-size city in China, which then had an urban population of more than 9.23 million. This number increased to 10.04 million by the end of 2013 (Figure 2-1), which turned Chengdu from the most populated mid-size city into the seventh megacity in China (Chengdu Bureau of Statistics, 2014). The urban population in Chengdu has increased at a dramatic pace. According to the Statistic Yearbook of Chengdu in 2011, during the last ten years, the average annual population growth rate was 2.84% (Chengdu Bureau of Statistics, 2011), and the urban population is predicted to reach up to 14.05 million in 2025.

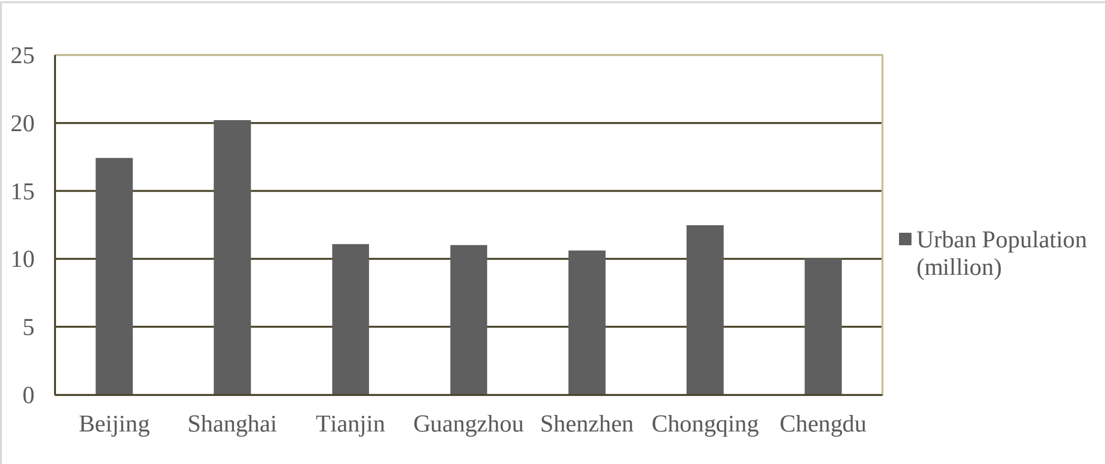


Figure 0-3. The urban population of Chinese mega cities and Chengdu in 2013. Among the seven megacities, four are municipalities directly under the central government's control (Beijing, Tianjin, Shanghai and Chongqing). Guangzhou and Shenzhen are two coastal cities in Pearl Delta Region. Chengdu is the only inland city with over 10 million residents that is not controlled directly by central government.

As a megacity and the most important administrative region in south-western China, Chengdu is experiencing a tremendous rural-urban conversion, which has been further stimulated by the Go-West Policy since 2000 (Schneider *et al.*, 2005). However, because of the rapidity of urbanization, the degree of urban sprawl in the city is unknown, and how this urban expansion will impact urban landscape configuration is still unclear.

1.5 Objectives

In order to promote better decision-making, it is important to understand the spatial pattern and magnitude of the city's urban growth. The overall goal of this study is to better understand the urban land use and land cover pattern changes in response to urban expansion and the dynamics of urban expansion. The expected results of this research may help urban planners and policy makers in building and adopting the planning and promoting better decision-making. Also, the results will provide an analyzing method for other cities and make it possible in comparing study with them. The objectives of research are as follows:

1) Quantifying the spatial land use pattern change of the study area during the year 2003 and 2013;

2) Evaluating the degree of urban sprawl according to urban land cover change;

3) Analyzing landscape configuration in order to evaluate urban expansion dynamics;

4) Examining and defining the types of urban growth among the newly developed built-up areas.

Chapter 2 : LITERATURE REVIEW

2.1 Applications of Remote sensing and GIS techniques

2.1.1 Why remote sensing?

Physical urban expansion research requires qualitative and quantitative information about land cover classes. There are several approaches available for obtainining this information: surveys, historical master plans, aerial photos and remotely sensed imagery (Jensen & Lulla, 1987). Accurate land information can be acquired through a survey; however surveying is usually time consuming, especially for a large area. Historical master plans offer informative data, but are less accurate with respect to change over time because of the nature of archival files. Aerial photos have a high accuracy in reflecting land cover situation, but the coverage of aerial photos is relative small: for the research of a large city, one single aerial photo is unable to cover the whole area, and thus requires more photos and a higher cost. Hence, considering the balance of time, accuracy and cost, remote sensing imagery is the most effective approach to obtain the land information needed to research urban expansion.

2.1.2 Remote sensing and geographic information system

Remote sensing technique and geographic information system (GIS) have been widely used in the study of urban expansion in the last few decades (Bagan & Yamagata, 2012; Banzhaf et al., 2009; Batisani & Yarnal, 2009; Dewan & Yamaguchi, 2009; Martinuzzi et al., 2007; Mundia & Aniya, 2005; Weng, 2002; Yuan et al., 2005). Because of the spatial-temporal characteristics, remote sensing techniques can effectively detect land cover pattern changes caused by rapid urban growth over a certain time period (Martinuzzi et al., 2007). Remotely sensed data provides an opportunity to detect historical land use and land cover changes in the same area by comparing satellite image acquired at different times. Due to the nature of satellite imagery, simply using remote sensing does not allow for further analysis after detecting different land use categories; hence GIS technique is integrated.

GIS technique offers the possibility of combining and analyzing geographic data by using computer technology (Mundia & Aniya, 2005). Integrating remote sensing and GIS techniques makes it possible to quantify urban expansion, do the post-classification comparison, and further identify the causes and consequences of urban expansion. Sudhira et al. (2004) noted that the convergence of GIS, remote sensing, and database management systems can be effective in quantifying, monitoring, and modeling urban spatial-temporal dimensions and urban spatial dynamics by integrating and calculating landscape properties with different attributes.

2.1.3 Landsat overview

Landsat is a program that provides a set of remote sensing platforms and products that is jointly managed by the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA). This program began in 1972. As one of the longest space-based record program (NASA, 2014), Landsat has continuously collected remote sensing imagery around the world for over 40 years and offers invaluable information for researchers in geosciences (USGS, 2014). On February 11^{th}, 2013, NASA launched an 8^{th} Landsat satellite, named Landsat-8. (The previous satellites were named Landsat-1, Landsat-2, Landsat-3, Landsat-4, Landsat-5, Landsat-6 (failed), Landsat-7.) The Landsat ETM+-7 and Landsat OLI-8 are two Landsat satellites still working (Table 2-1).

Table 2-1. General band information of Landsat 7 (ETM+) and Landsat 8 (OLI)

Landsat 7 (ETM+)				Landsat 8 (OLI)			
No.	Band	Wavelength (μm)	Resolution (m)	No.	Band	Wavelength (μm)	Resolution (m)
				1	Coastal	0.433 – 0.453	30
1	Blue	0.45 – 0.52	30	2	Blue	0.450 – 0.515	30
2	Green	0.52 – 0.60	30	3	Green	0.525 – 0.600	30
3	Red	0.63 – 0.69	30	4	Red	0.630 – 0.680	30
4	NIR	0.77 – 0.90	30	5	NIR	0.845 – 0.885	30
5	SWIR1	1.55 – 1.75	30	6	SWIR1	1.56 – 1.66	30
7	SWIR2	2.09 – 2.35	30	7	SWIR2	2.10 – 2.30	30
8	Pan	0.52 – 0.90	15	8	Pan	0.500 – 0.680	15
				9	Circus	1.36 – 1.39	30
6	TIR	10.40 – 12.50	30/60	10	TIRS1	10.6 – 11.2	100
				11	TIRS2	11.5 – 12.5	100

2.2 Previous research on urban expansion by using Remote Sensing and GIS

Urban expansion is a phenomenon highly associated with the human behaviour of migration. Population growth is considered one of the most significant causal factors of urban expansion; thus, many researchers have tried to evaluate urban expansion as a product of population growth rate or population density (Bagan & Yamagata, 2012; Kaya & Curran, 2006; Martinuzzi et al., 2007). It has been assumed that urban sprawl index can be defined as the ratio of the urban built-up area growth rate to the population growth rate (Sudhira et al., 2004). Thus, researchers refer to urban area as sprawling if the urban built-up area growth rate exceeds population growth rate. However, this model is not applicable in countries with different population densities at the same time. For example, in some developing countries, the population density in urban areas is relatively high; thus, an annual urban built-up area growth rate that surpasses annual population growth rate may not indicate urban sprawl. Hence, urban sprawl usually is discussed without an absolutely accurate definition (Bhatta *et al.*, 2010b; Wilson *et al.*, 2003).

Because urban expansion results in tremendous urban land cover type change, many researchers have made progress towards an accurate definition by evaluating land use and land cover change (LUCC) in urban areas (Bagan & Yamagata, 2012; Banzhaf et al., 2009; Serra et al., 2008; Weng, 2002; Yuan et al., 2005). The increase of urban built-up areas is significant to the study of urban expansion. With the application of remote sensing and GIS techniques, LUCC change can be detected quantitatively, which will help researchers identify clearly how and how much different urban land cover patterns have changed during a time period. However, during the process of urban growth, land cover pattern change is just one indicator of the changes that have occurred. Merely describing different urban land cover pattern change cannot identify urban expansion dynamics clearly.

Researchers have developed an urban expansion measuring model by combining geospatial indices with socio-economic indices (Huang et al., 2009; Jiang et al., 2007; Jiang et al., 2013). Jiang et al. (2007) indicate that the causes, the evolution, and the consequence of this landscape pattern change should be discussed with geospatial indices. In the study, Jiang et al. (2007) focused on three out of the thirteen total indices to measure urban expansion in Beijing, China: shape index, area index and leapfrog development index. Their study showed that using those indices can effectively reduce the interpretation difficulty in urban expansion. However, it also relies extensively on ancillary data such as statistical data, which is lacking or difficult to obtain in some developing or less developed countries. Thus, the extensive demands for data from different sources makes it impossible to apply this method in such countries.

Many studies have used landscape metrics to modeling urban expansion phenomenon and evaluate expansion dynamic (Batisani & Yarnal, 2009; Feng & Li, 2012; Jat et al., 2008; Xu & Min, 2013). Landscape metrics are primarily used for urban ecology investigation because they can show the urbanization process through the changing landscape form, and can be adopted to monitor the urban landscape pattern change in a certain time period. Schneider and Woodcock (2008) note that landscape metrics are an effective approach to better understand urban configuration, especially now that the trend of urban landscape change usually begins with the extension of a plot. Numerous landscape metrics can be used for the study of landscape distribution. However, many of them are highly correlated to each other and thus provide redundant information, which will impact the result of research (Bhatta et al., 2010a; Schneider & Woodcock, 2008). Thus, in order to reduce information redundancy, carefully choosing landscape metrics is indispensable. Some researchers also prefer to use a moving window within a transect (a particular rectangular area) to analyze landscape metrics. However in some cities (e.g. Greater Chengdu) the urban growth is not strictly within a transect, so deciding on a systematic division within the study area is necessary.

Rapid urban land cover pattern change has become an important topic because the trend of urban expansion has spread all over the world, especially in developing countries, in recent years (Bhatta et al., 2010a). In some developing countries with heavy population density such as Bangladesh, India, and China, urban expansion has increased much faster than in developed countries in recent years, and rapid urban expansion is not always balanced with urban sustainability (Dewan & Yamaguchi, 2009; Jat et al., 2008; Yu & Ng, 2007; Shahraki et al., 2011; Zhang et al., 2013). In China, the study of urban expansion in last few decades has mainly focused on the capital city, coastal cities and the cities that benefit from policy changes in 1990s, such as Beijing, Shanghai, Guangzhou and Shenzhen (Jiang et al., 2007; Sun et al., 2013; Yu & Ng, 2007), However in Chengdu, an inland megacity and one of the most significant provincial capital cities in the less developed region in China (western China), urban expansion has been rarely mentioned, even though the city is experiencing rapid urbanization.

Chapter 3 : DATA AND METHODS

3.1 Study area

Greater Chengdu (GC) is composed of nine districts and two counties, which are 1. Wuhou District; 2. Jinjiang District; 3. Qingyang District; 4. Chenghua District; 5. Jinniu District; 6. Shuangliu County, 7. Longquanyi District; 8. Wenjiang District 9. Qingbaijiang District; 10. Pi County; and 11. Xindu District (Figure 3-1). The inner city consists of districts 1,2,3,4 and 5. Excludes the inner city, districts 7, 9 and 11 composes eastern Greater Chengdu, while county 6, districts 8 and county 10 composes western Greater Chengdu. The total area of GC is 3677 km2. According to the 2012 Chengdu Statistics Yearbook (Chengdu Bureau of Statistics, 2014), the total population of GC was 7 million at the end of 2013.

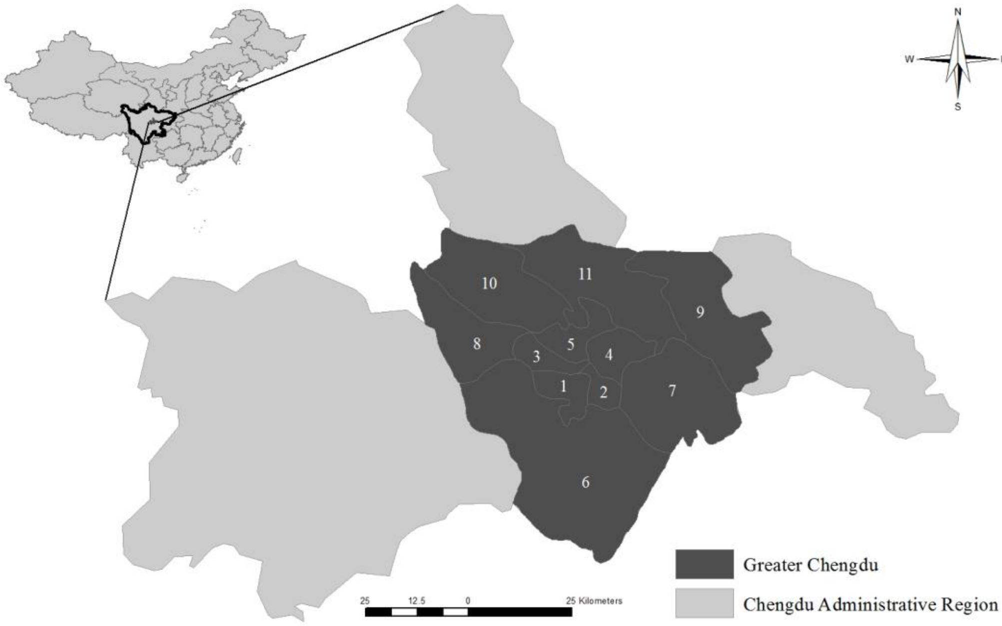


Figure 3-1. Greater Chengdu (GC).

Been known as an ancient city with over 2500 years history (Schneider *et al.,* 2005), Chengdu is the capital city of Sichuan province in south-western China (Figure 3-1). It is also a cultural center in the Sichuan province. The annual average temperature is 15 degrees centigrade. Since China Western Development Plan (also called the “Go-West” policy) was proposed at the beginning of 21th century, Chengdu has experienced and is experiencing a remarkable population increase and rapid urbanization. According to the report of sixth provincial census investigation in 2010 (Sichuan Bureau of Statistics, 2010), the total population in the Chengdu administrative region grew by 24.93% over the past ten years, reaching 1.4 billion in 2010. Increasing along with population growth, the Gross Domestic Product (GDP) per capita in Chengdu was 16,239 (yuan) in 2002, but rocketed to 69,365 (yuan) in 2012, with an average annual growth rate of 15.63% (Chengdu Bureau of Statistics, 2014).

3.2 Remotely sensed data and data processing

Remotely sensed data has been used in a multitude of studies of urban growth during the last few decades (Batisani & Yarnal, 2009; Bhatta et al., 2010a; Deng et al., 2009; Dewan & Yamaguchi, 2009; Serra et al., 2008; Sudhira et al., 2004; Weber & Puissant, 2003; Yeh & Xia, 2001; Yu & Ng, 2007) because it is able to provide consistent and continuous imagery that covers either a regional or global area (Bagan & Yamagata, 2012). For example, Weng (2002) and Yuan *et al.* (2005) demonstrated that this technique has the potential to provide accurate and timely information to detect urban landscape pattern change on a certain scale, like a metropolitan area or a coastal region. In addition, previous research (Bagan & Yamagata, 2012; Carlson et al., 2000; Herold et al., 2005) has shown that remote sensing is effective in studying urban growth pattern change. In Jat et al.'s (2008), Sudhira et al.'s (2004) and Yu & Ng's (2007) studies, remote sensing was used to provide classified land use categories for further urban expansion studies. Integrated with GIS technique, it is possible to classify remotely sensed data, convert multiple-sources data into a similar format, and put them in different layers to do the further spatial analysis. The workflow of my research is shown in Figure 3-2.

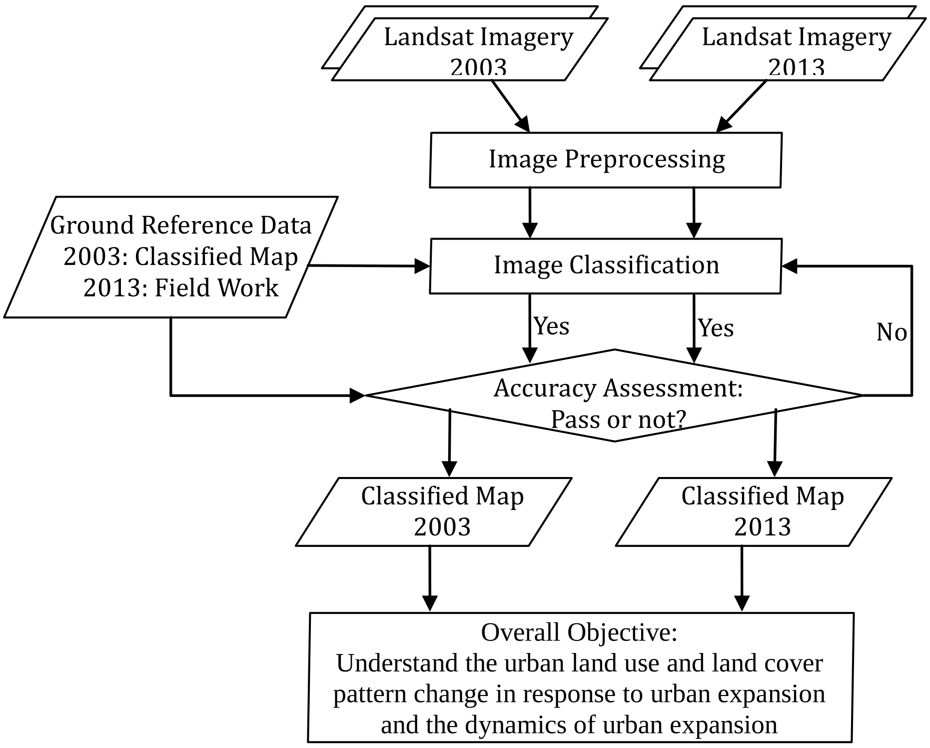


Figure 3-2. The Workflow.

Two pairs of Landsat images obtained from the U.S. Geological Survey (USGS) in different years (2003 and 2013) are used to monitor land cover pattern change during the time period (Table 3-1). An imagery mosaic was conducted for the imagery of 2013 in order to cover the whole study area. All bands are used excluding the thermal band due to its coarse resolution. Every pair of images is classified and compared with each other in order to reduce the misclassification caused by seasonal differential (for example, the reflectance of cropland before the crops are seeded and after crops are harvested is similar with those of bare land). Because the study area is a cloud-rich area, most of the chosen images were not obtained in the summer (July and August).

Table 3-1. Remote sensing data set

1. Landsat ETM+ image	Path129/Row39	2002-Oct-07
2. Landsat ETM+ image	Path129/Row39	2003-Jan-27
3. Landsat OLI image	Path129/Row39	2013-Apr-20
4. Landsat OLI image	Path129/Row39	2013-Nov-30
5. Landsat OLI image	Path130/Row39	2013-Aug-17
6. Landsat OLI image	Path130/Row39	2013-Dec-07

PCI Geomatica 2013 (PCI Geomatics Enterprises Inc.) was employed to do the image pre-processing, classification and accuracy assessment. During the process of image classification, a maximum likelihood classifier was used to do the supervised classification, and the modification of Anderson Level-I Scheme was conducted to determine the classes (Anderson *et al.*, 1976). This method has been used for image classification in numerous studies (Deng *et al*., 2009; Mundia & Aniya, 2005; Weng, 2002; Yuan *et al.*, 2005). In this study, five categories were used: Built-up Area (BA), Waterbodies (WA), Vegetation (VE), Forest (FO) and Bare Land (BL), respectively. Table 3-2 lists the five different land use and land cover categories and the definitions for each category. A classified map was used for sample training and for assessing classification accuracy for the 2003 classified map, while the ground truth information acquired in the field was used for the same process for the 2013 classified map.

Post-classification technique was adopted to reduce classification errors caused by similarities in the spectral signature. Accuracy assessment was conducted by using a stratified random sample method. Three hundred randomly selected points were generated; 200 of them were used to do the supervised classification and the rest of them were for accuracy assessment. The reference data for the 2013 OLI image was acquired from two sources: fieldwork and expert knowledge. Ground reference information was acquired from fieldwork. During this fieldwork, 300 samples were collected: 200 samples were used for the classification training and the rest of them for the accuracy assessment.

Table 3-2. The definition of land use classes

Categories	Abbr.	Definition
Built-up Area	BA	Rural & urban impervious area; industrial area; road
Waterbodies	WA	River; lake; reservoir; bottomland
Vegetation	VE	Paddy field; dry cropland; grass
Forest	FO	Forestland; open forest land; shrub
Bare Land	BL	Flood plain; construction area

3.3 Shannon's entropy

For urban planners, urban landscape pattern changes in terms of shape, size or configuration should be considered before making a decision. Many researchers have studied ways to quantify urban land use change (Martinuzzi et al., 2007; Serra et al., 2008). However, for change detection of urban sprawl, measuring the relationship between urban landscape pattern change and its process should also be considered (Yeh & Xia, 2001). In the literature, several methods have been used to measure urban sprawl such as mathematical methods, statistical parameters and metrics (Batisani & Yarnal, 2009; Bhatta et al., 2010a; Jat et al., 2008; Ji et al., 2006; Jiang et al., 2007; Martinuzzi et al., 2007; Sudhira et al., 2004; Sun et al., 2007). Yeh & Xia (2001) measured urban sprawl by using an entropy method. Shannon's entropy is a concept of information communication. It measures uncertainty in a random variable. Entropy methods have frequently been used in the study of urban sprawl in many developed countries over the last few decades (Bhatta et al., 2010a; Sudhira et al., 2004; Sun et al., 2007). However in developing countries, little research of urban sprawl has been conducted by using entropy. In the study of urban sprawl, Shannon's entropy can be used to measure degrees of spatial concentration or the dispersion of a geographic variable in a certain study area, and to identify the distribution of built-up areas in a newly developed zone to evaluate if the growth is compact or dispersed (Jat et al., 2008; Yeh & Xia, 2001). Shannon's entropy can be calculated as follows:

$$H_n = -\sum_{i}^{n} P_i \ln(P_i) \qquad \text{(Eq. 3.1)}$$

Where

P_i refers to the proportion of observed change (x_i) happened in i^{th} zone and can be calculated as $P_i = x_i / A_i$;

A_i refers to the total area of i^{th} zone.

n refers to the total number of individual zones in study area;

H_n refers to the Shannon's entropy value, ranging from 0 to ln*n*.

Ln*n* is the upper limit of the Shannon's entropy value. A value closer to ln*n* indicates the substantial occurrence of urban sprawl, which means the dispersed distribution of urban growth; conversely, the value closer to 0 indicates the compact distribution of urban built-up area growth. Within the study area, because of the round-like boundary of study area (Figure 2-1), the individual zones are developed by generating buffer rings surrounding the city center with the distance of 5 km. Despite not having a current threshold to sharply classify sprawl or non-sprawl, Shannon's entropy is effective in measuring urban sprawl by providing a range to quantify which configuration urban growth is closer to (Bhatta et al., 2010b; Jat et al., 2008; Yeh & Xia,
2001).

3.4 Landscape metrics: number of patches, mean patch size and percentage change of landscape

Urban land use change refers to the way different landscapes expand or shrink under the impact of human activity during the process of urban growth (Niemela et al., 2011). Among landscape pattern changes, one of the most significant phenomena is built-up area expansion caused by construction. Thus, many landscape metrics have been developed to analysis landscape pattern change (Schneider & Woodcock, 2008; Sudhira et al., 2004; Yu & Ng, 2007). Landscape metrics can be used to analyze the heterogeneity of land cover pattern or the landscape diversity in ecological investigation. The calculation of landscape metrics can help to explain landscape configuration during the process of urbanization.

In the study of urban growth pattern, patch indices and density indices can evaluate the distribution of landscape patterns and the density of a particular landscape (i.e. built-up area) in a regional or global scale (Bagan & Yamagata, 2012; Jat et al., 2008; Ji et al., 2006; Jiang et al., 2007; Serra et al., 2008). To avoid metrics redundancy, three metrics were chosen: number of patches (NP), mean patch size (MPS) and percentage of landscape (PLAND). All three landscape metrics (NP, MPS, PLAND) are class-level metrics. Fragstats v4.2 (McGarigal & Marks, 1995) and ArcGIS (ESRI, 2011) were employed as the landscape configuration analysis software.

Patch refers to an independent landscape that is different from its surroundings (Bhatta *et al.*, 2010b). The NP is an index to evaluate the homogeneity of landscape. As a landscape metric, researchers usually employed NP to evaluate landscape distribution evenness and landscape diversity (Harrison, 1999). In the study of the urban expansion dynamic, NP has been effective in analyzing urban configuration, since those metrics treated the impact of human activities on urban configuration as the patch expansion (Schneider & Woodcock, 2008). Spatially, high NP indicates a dispersed distribution of a specific patch (i.e. urban built-up area), while low NP refers to a compact distribution of patches.

MPS is an index for evaluating patch size by calculating the mean size of all patches in one class. Increasing MPS shows contiguous patch growth. If the patch in the metric MPS represents a built-up area, specifically, the increase of MPS value can indicate that urban growth has expanded from the existing urban built-up area outward towards the suburban area continuously, rather than become dispersed throughout the urban area. Increasing MPS value also shows the growth within the city center. Regarding the distance (i.e. buffer rings surround the city center), the occurrence of infilling phenomenon in certain areas can be detected if the MPS increases while NP decreases at the same time (Schneider et al., 2005).

PLAND identifies only the density of the BA in an individual zone, and ignores other patches. By comparing the PLANDs at different times in the study area, the dynamics of urban expansion can be detected. Different from Shannon's entropy, the index that identifies the degree of urban sprawl, PLAND is an index that provides an approach for further classifying the study area based on different built-up density level. In this study, after acquiring PLAND value, the reclassification of the classified map was done based on the different magnitudes of PLAND change in each unit area (i.e. no change level, change =<50% level, and change >50% level). Significant increases of the BA indicate relative high dynamics of urban expansion, while low or no change indicates the slow pace of urban expansion.

3.5 Typology of urban growth

The type of urban growth can be divided into three categories: infill, expansion and leapfrog (Angel et al., 2007; Corner et al., 1995; Wu et al., 2015; C. Xu et al., 2007; Yue et al., 2013). These three categories can be detected by using the Urban Growth Analysis Tool (UGAT) developed by Angel et al. (2007). With this analysis tool, the calculation is done based on a moving circle with the area of 1km^2. Each circle is considered as a "neighbourhood". Urbanized Open Space (UOS) refers to non-built-up area within a neighbourhood where "more than 50% of the area is built-up area"; Peripheral Open Space (POS) is "non-built-up area that is within 100m of built-up area" (Angel et al., 2007). The area that belongs to either one of those three different types (Urban Built-up Area, UOS and POS) is counted as Urban Footprint. The definitions of the three urban growth types can be described as follows: 1) the infill growth refers to "new development built-up area occurring within the existing Urbanized Open Space"; 2) the expansion type of growth is "non-infill new development built-up area which is overlapped with existing Urban Footprint"; 3) the leapfrog development represents "new development built-up area which is not overlapped with existing Urban Footprint." (Angel et al., 2007, 2011; Corner et al., 2014). The definitions are shown in Figure 3-3.

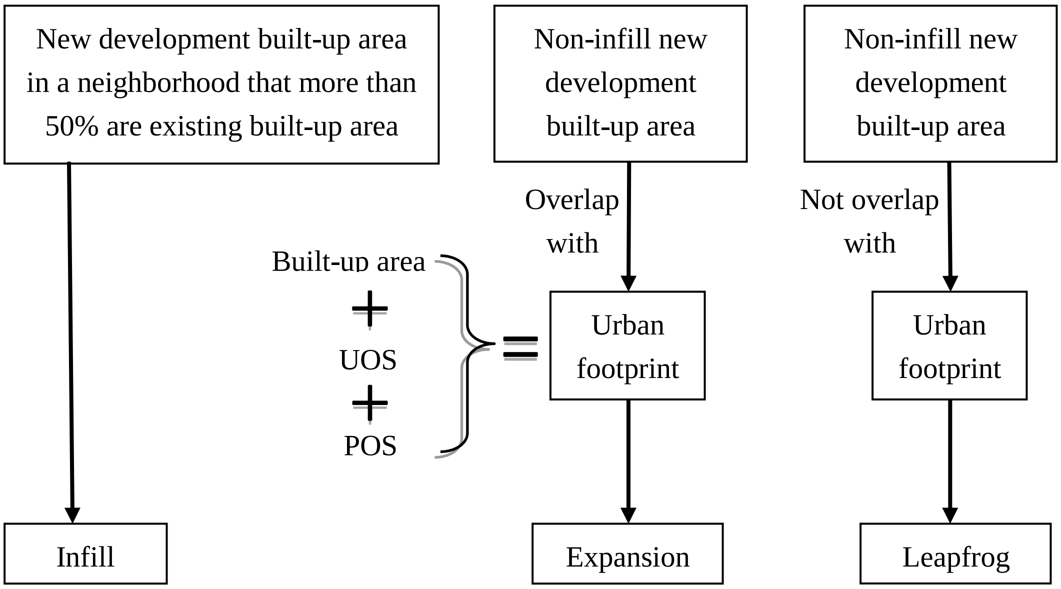


Figure 3-3. The definitions of three types of urban growth.

Chapter 4 : RESULTS AND DISCUSSION

4.1 Spatial-temporal land use and land cover changes between 2003 and 2013

Table 4-1 shows the confusion matrix for the classification. It indicates that the overall classification accuracy of land use maps is 85.33% for 2003 and 86.67% for 2013. The Kappa coefficient for the maps of 2003 and of 2013 are 0.81 and 0.83, respectively. The producer's accuracy ranges from 70.97% to 95.54% (70.97%; 93.75%; 95.54%; 79.55% and 83.33% for the categories of BA (built-up area), WA (waterbodies), VE (vegetation), FO (forest) and BL (bare land), respectively) for the map of 2003. For the map of 2013, it ranges from 83.33% to 100% (84.71%; 100%; 83.74%; 91.49% and 83.33% for BA, WA, VE, FO and BL, respectively). The user's accuracy of each class ranges from 31.25% to 92.11% in 2003 (88%; 85.71%; 86.99%; 92.11% and 31.25% for BA, WA, VE, FO and BL, respectively). In 2013, it ranges from 48.39% to 96.26% (92.31%; 87.1%; 96.26%; 81.13% and 48.39% for BA, WA, VE, FO and BL, respectively). The user's accuracy of Bare Land (BL) is the lowest among those of the five classes in either the 2003 or the 2013 maps, with the value of 31.25% and 48.39%. This is probably due to the similar spectral reflectance between BL and some industrial area that belongs to BA.

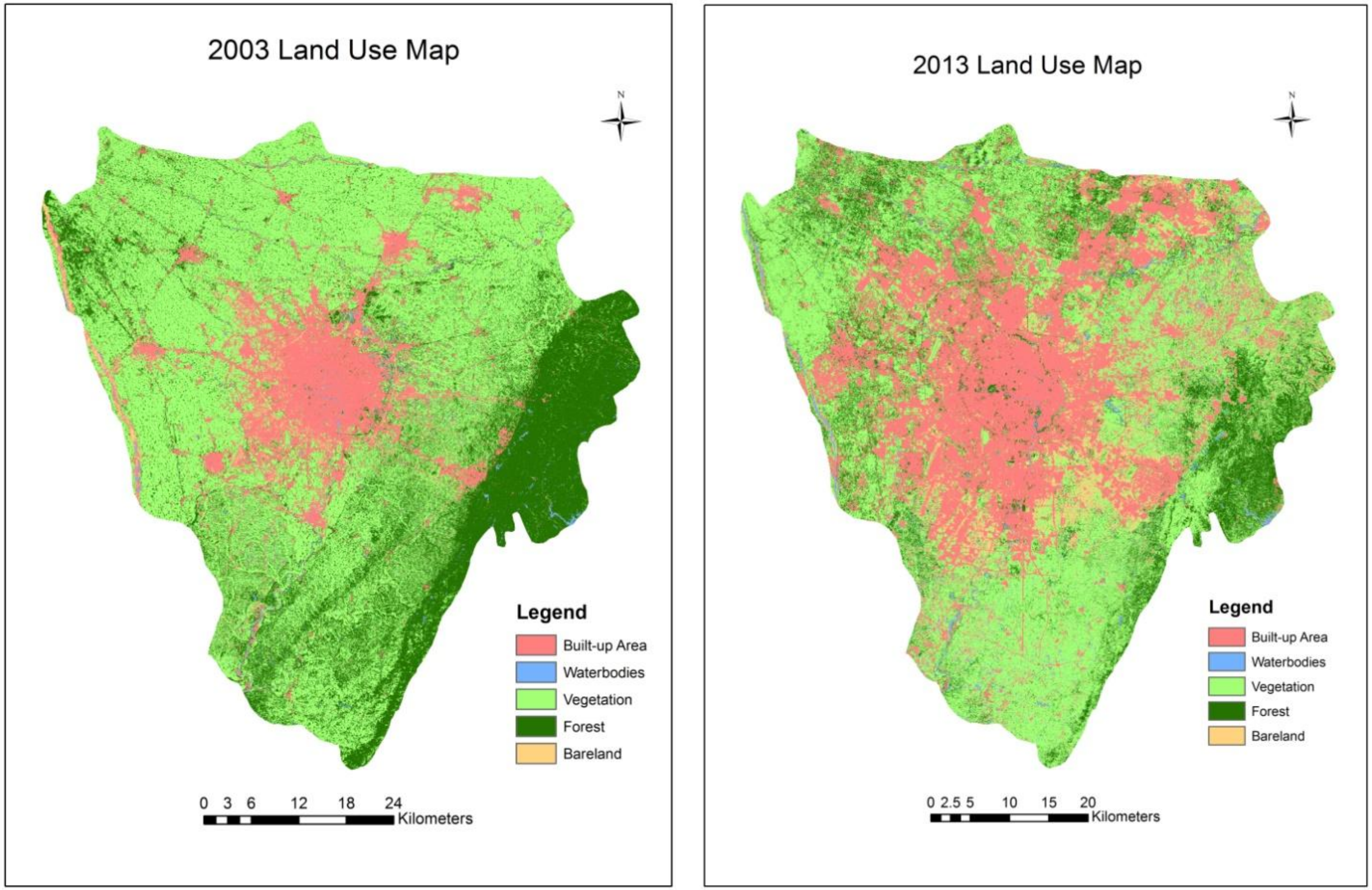
Table 4-1. Confusion matrix of land use map in 2003 (a) and in 2013 (b)

2003	Reference Data							User's Accuracy
Classified Data		BA	WA	VE	FO	BL	Total	
	BA	44	0	2	3	1	50	88%
	WA	1	30	1	3	0	35	85.7%
	VE	4	0	107	12	0	123	87%
	FO	2	2	2	70	0	76	92.1%
	BL	11	0	0	0	5	16	31.3%
	Total	62	32	112	88	6	300	
Producer's Accuracy		71%	93.8%	95.5%	79.6%	83.3%		**85.3%**

(a)

2013	Reference Data							User's Accuracy
Classified Data		BA	WA	VE	FO	BL	Total	
	BA	72	0	2	1	3	78	92.3%
	WA	0	27	3	1	0	31	87.1%
	VE	2	0	103	2	0	107	96.3%
	FO	0	0	10	43	0	53	81.1%
	BL	11	0	5	0	15	31	48.4%
	Total	85	27	123	47	18	300	
Producer's Accuracy		84.7%	100%	83.7%	91.5%	83.3%		**86.7%**

(b)



(a) (b)

Figure 4-1. Land use map in 2003 (a) and in 2013 (b).

Figure 4-1 is a spatial land use and land cover change map between 2003 and 2013, In Figure 4-1, a significant expansion of BA (the pink area) can be detected during the time period, which is supported by Figure 4-2, a comparative chart of the area of each land use type in 2003 and in 2013. Figure 4-2 demonstrates a significant increase of built-up area occurred. In 2003, the area of BA was 525.5 km^2, in 2013 it increased up to 1192 km^2, almost doubled. However, on the opposite, the area of VE and of FO decreased. The area of VE in 2003 was around 2050 km^2; over the time period it dropped by 340 km^2, down to 1710 km^2. Similar trend for the area of FO: in 2003 it was 1015 km^2, then half of the forest has turned to other land cover types. In 2013 it was only 579 km^2. From 2003 to 2013, the area of WA remains no change, while that of BL has a slight increase. The decrease of VE and of FO might result from the increase of BA.

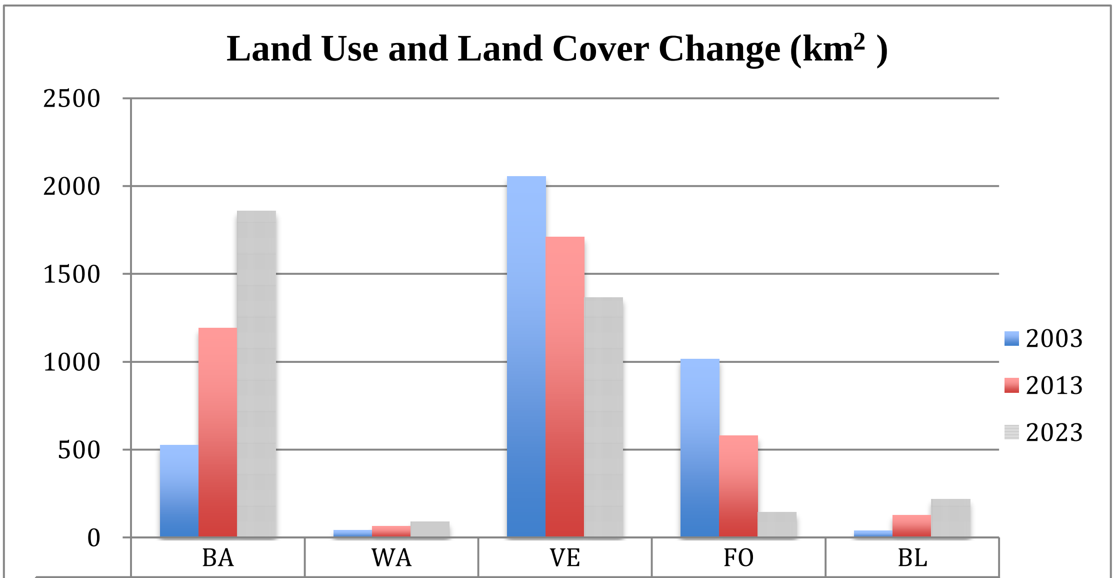
Figure 4-1 and Figure 4-2 demonstrates that the Greater Chengdu has experienced dramatic urban expansion over the time period. The BA in 2013 is 2 times than that in 2003. A significant expansion occurred in such a short time (11 years) might relate to population increasing. In 2003, the overall population in Greater Chengdu was 5.89 million (Chengdu Bureau of Statistics, 2004), while the urban population was 3.09 million. In 2013, these two numbers increased up to 7.15 million and 5.57 million, respectively. In 2003, Qingyang District had a highest urban population rate with 90%; In 2013, All five districts (Jinjiang District, Qingyang District, Wuhou District, Jinniu District and Chenghu District) in inner city had the 100% urban population out of the overall population (Chengdu Bureau of Statistics, 2014).

The population increase could be an indispensable factor that causes urban expansion (Herold et al., 2003; Lambin et al., 2003; Yue et al., 2013). The population migration can be influenced by several factors. First is the policy influence. As one of the most important capital city in western China, Chengdu serves as an commercial, industrial, logistic and technological center of southwestern China (Ye et al., 2013) Its growth is stimulated by several policies, and amongst those policies "Go-West" and "Coordinated urban-rural development" are two policies that launched by Central Government. In order to achieve the goal of developing inland cities in western China and to reallocating surplus rural workforce, "Go-West" policy and "Coordinated Urban-Rural Development" policy have been launched in 2000 and in 2003, respectively. Chengdu was designated as a pilot region to implement those policies. In supporting the pilot project, the government provided ample funding to create many jobs as initial incentives for more people migrate to Chengdu. The second is the physical factor. The Greater Chengdu is located on a flat plain and in an extremely fertile rich delta (Ye et al., 2013) where various types of infrastructure systems, such as transportation and water pipes are easier to develop than in mountainous areas. This combined with the fact that people have more conveniences that are relatively easy to access, make Chengdu a more suitable and desirable place for people to live.

As shown in Figure 4-1, Along with urban area expanded outward, the boundaries of the BA of the inner city and of its peripheral towns (small pink areas around the central one) shifted. The boundaries in 2003 are much clearer to distinguish than in 2013. The inner city and its peripheral towns in 2003 are isolated with each other, only connected by roads. However, in 2013, the BA of the inner city expanded outward and, within the study area, is merged with the BA of the peripheral town, so much so that no significant boundary of BA distinguishes the inner city from the peripheral towns, the overall boundary of BA in 2013 is harder to label due to much dispersed distribution of BA.

In addition, the Figure 4-1 clearly shows that the distribution of BA changes from multinuclear in 2003 to mononuclear in 2013. The new development area of BA went outward almost in all directions. In 2003, several peripheral satellite towns were connected with the inner city; however by 2013 they were joined more closely with the inner city during the process of urban growth. Among the peripheral towns, those located in western Greater Chengdu merged into inner city entirely, while those in eastern Greater Chengdu are only partially merged and still can be distinguished. Hence, even though the urban area expanded in all direction, it is quite evident that western Greater Chengdu has been growing faster than eastern Greater Chengdu. This is also evident by looking through the urban population change in two different areas: The urban population in eastern Greater Chengdu was 0.43 million in 2003 and 0.88 million in 2013, for a twofold increase over that decade (Chengdu Bureau of

Statistics, 2004); while that in western Greater Chengdu, it was 0.37 million in 2003 and 1.17 million in 2013, for almost a fourfold increase over that decade (Chengdu Bureau of Statistics, 2014).



	BA	WA	VE	FO	BL
2003	525.50	42.56	2054.50	1015.10	38.94
2013	1191.85	66.13	1710.65	579.15	128.83
2023	1858.2	89.7	1366.8	143.2	218.72

Figure 4-2. Land Use and Land Cover Change.

The speculated future land use change is also shown in Figure 4-2. The BA will increase up to 1858 km^2 in 2023, according to the current rate. Accompanying the significant increase of BA, VE and FO decreased during the time period. The area of VE was 2054.5 km^2 in 2003 and 1710.65 km^2 in 2013, which was a decline of 343.85 km^{2,} while the FO was 1015.1 km^2 in 2003 and 579.15 km2 in 2013, a decrease of 435.95 km^2.   If the continuous decrease occurs, the area of VE and of FO will drop down to 1366 km^2 and 143 km^2, respectively. The intensive FO area of 2003 in eastern Greater Chengdu (dark green area) converted to VE in 2013 (Figure 4-1). In 2013, the WA remained unchanged, while the BL nearly tripled, from 38.94 km^2 in 2003 to 128.83 km^2 in 2013. The newly development BL in 2013 falls almost all around the inner city, especially in the southern part of the suburban area, mainly due to the infrastructure construction during the process of urbanization.

The LUCC map between 2003 and 2013 is shown in Figure 4-3. In the legend, the first column (“BA”, “WA”, etc.) represents the area with no change; the other columns represents that the areas that were converted from one class to another (i.e. “From BA to WA” represents the area that converted from BA to WA). A dispersed but obvious land cover type conversion from VE or FO to BA (highlighted red area) occurred surrounding the inner city, which falls into the suburban area. The cross-tabulation analysis (Table 4-2) also demonstrates that mainly from VE and FO were converted to BA. Compared to the southwest part of suburban area, the new development BA in northeast part is more dispersed.

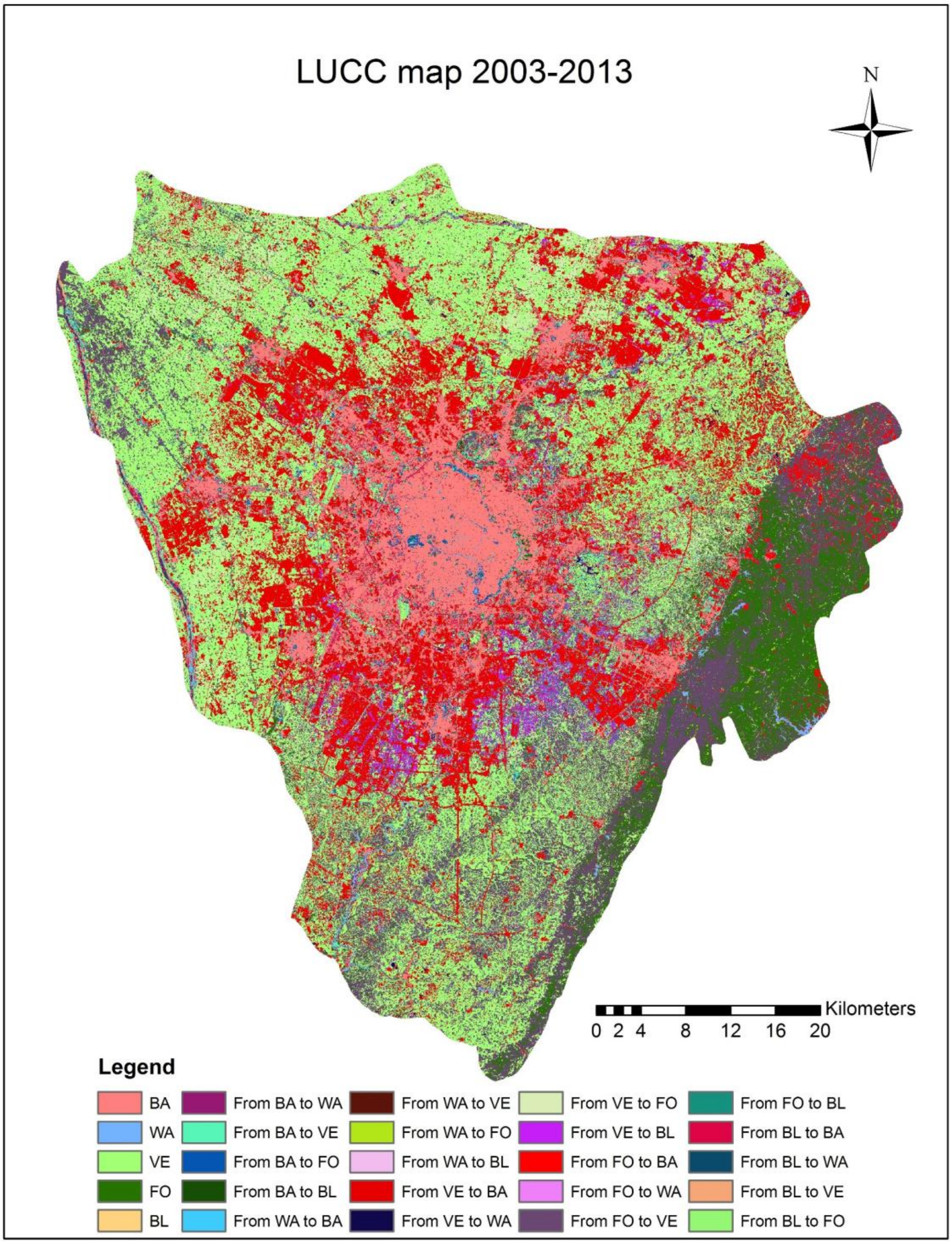


Figure 4-3. LUCC map during 2003 and 2013.

In the southern suburban area, the conversion from VE to BL (purple area) indicates that substantial construction (an ongoing land conversion from VE to BA) occurs in this area. Table 4-2 also shows that, among five categories, VE is the land cover type that was converted the most into BL, with 82.9 km^2 of area converted. Because the bare land might be the in-progress construction area, the south Greater Chengdu might be where the urban built-up area grows in the following years.

Table 4-2 indicates the conversion of land cover types during the time period. Over half of the BA in 2013 had been converted from other types, to which the VE contribute the most with 576 km^2. In other words, one quarter of the VE in 2003 had been lost and converted to BA. The intensive conversion also occurred on the land cover type, FO. Over half of FO in 2003 was turned into VE in 2013, and over 160 km^2 of FO was converted to BA in 2013. Only one fourth of FO remained through 2003 to 2013.

The loss of vegetation and forest will negatively affect urban environment (Shi et al., 2015). Urban heat island effect is one issue been proved causes by the loss of greens such as vegetation and forest (Catalán et al., 2008; Chen et al., 2006; Shi et al., 2015). In Chen et al. (2015)'s work, they demonstrated that urban heat island intensity is correlated with the degradation of cropland in Shenzhen. In Greater Chengdu, due to the dramatic decrease of greens over the time period, the urban heat island effect can be a concern that cannot be neglected. In addition, some other factors such as animal and vegetation specifies, air quality and urban carbon cycle can also be impact due to the degradation of vegetation and forest.

Table 4-2. From-To change during 2003 and 2013

LUCC From-To Analysis						
		Area in 2013 (km^2)				
	Class	BA	WA	VE	FO	BL
Area in 2003 (km^2)	BA	409.1004	9.99	53.1513	34.3521	18.9027
	WA	13.5018	18.4977	4.7691	4.4217	1.3671
	VE	576.8307	19.926	1107.589	267.255	82.9026
	FO	163.1601	15.0777	541.0683	271.2285	24.5664
	BL	29.2563	2.6352	4.068	1.8918	1.0899

4.2 The degree of urban sprawl

Shannon's entropy analysis has been demonstrated effectively in the study of urban sprawl(Bhatta, 2009; Jat et al., 2008; Yeh & Xia, 2001). It is developed based on the division of different areas, as Figure 4-4 shows. The study area has been split to 10 individual zones according to 10 buffer rings surrounding the city center, with the equal interval distance of 5 km. The reason for dividing the study area by buffer ring is because of the round-like shape of the urban area. In addition, based on the distance differential, the division of buffer rings can be applied to the following landscape metric analysis. The city center has been defined by the city government as the coordinates 30.657512N, 104.065853E. The upper limit of the entropy value in this case is 2.3026, which means the entropy value ranges from 0 to 2.3026. A value closer to 0 (lower limit) indicates a relatively compact growth of BA or in other words, lower degree of urban sprawl, while one closer to 2.3026 (upper limit) demonstrates that the BA has become dispersed or higher degree of sprawl. In this study, the entropy value in 2003 was 1.5187 and in 2013 the value increased to 1.9435. Both two values are closer to upper limit (2.3026), which means the degree of urban sprawl in these two different years is high. Besides, the value in 2013 is higher than that in 2003, which means the degree of sprawl became higher over the time period. This indicates the built-up area grows much dispersed in 2013 than in 2003. The result of entropy analysis is also consistent with the result of the 2013 land use map and the LUCC from-to map. The red area (The vegetation and forest that converted to built-up area in 2013) in Figure 4.3 clearly shows the dispersed urban built-up area grows all around the existing built-up area. The dispersed distribution of built-up area might result from the growth of impervious area for new buildings. In addition, the growth of public transportation network might be another factor contributing to the dispersed growth of built-up area.

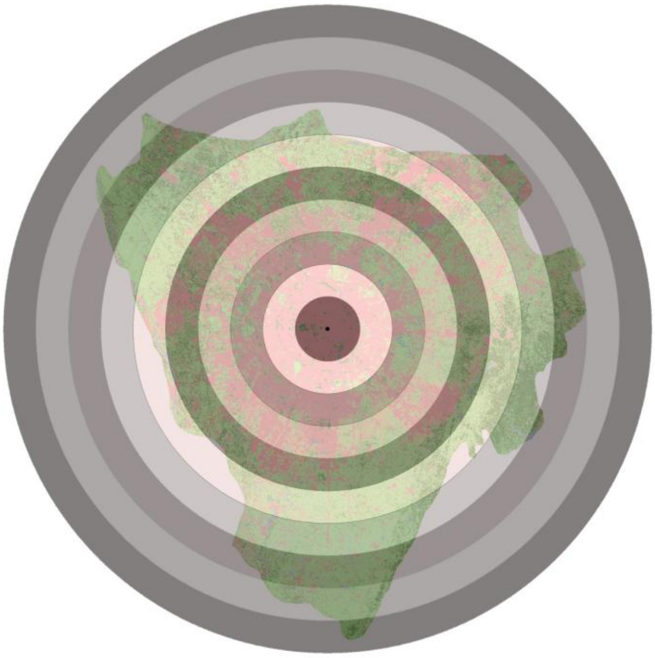


Figure 4-4. The division for entropy analysis. Around the city center (black point), ten buffer rings with the equal interval distance of 5 km were created in order to divide the study area into ten different areas.

4.3 Landscape metrics analysis

The NP analysis result is shown in Figure 4-5. Within 5 km, the NP of BA had a slightly increase, from 5 in 2003 to 48 in 2013. Due to the extremely high percentage of built-up area exists within this extent, the number of patches of built-up area increased indicates a potential urban redevelopment occurs, which lead to the dispersed distribution of built-up area, or in other words, the built-up area became much heterogonous within 5 km. In the ring area between 5 km to 20 km, the NP of BA decreased. However Figure 4-3 clearly shows an intensive growth of built-up area around the suburban area, thus, the decrease of patch numbers might response to the merge of existing built-up area. In this case, a potential infill phenomenon occurred. With the distance greater than 20 km, a significant increase of NP is identified. Given the low percentage of built-up area within this area, the increase of patch numbers indicates the dispersed newly development built-up area grows in this area. In addition, those new built-up area might partially explain the increase of the degree of urban sprawl over the time period.

Within 5 km to 20 km, the NP of BA (Figure 4-5a), WA (Figure 4-5b) and FO (Figure 4-5d) in 2013 is lower than that in 2003, which demonstrates that, within 20 km, those three types of land were either converted to other landscape, or merged with smaller patches. If they merged with small patches, they become more compact. Meanwhile, within 20 km, the results of VE and of BL are similar. For both land cover types, the value of NP remains constant within 10km, and increases between 10 km to 20 km, which means that, within this ring area, a significant land use type conversion related to those two types occurs.

Between 20 km and 50 km, the NP of BA, WA and FO is much higher in 2013 than in 2003. Since we know that the BA increases dramatically in suburban areas (Figure 4-5), the increased NP of BA indicates that a substantial but dispersed land use conversion occurs in suburban area. The increased NP of WA might result from seasonal differential or the increase of reservoirs. Figure 4-5c shows that the NP of VE increases between 10 km to 40 km. Because the area of VE decreased, the increase of NP may be the result of land use conversion and may indicate those large patches have been split into smaller patches. The NP of BL increases within the whole study area, but the most significant increase occurs within the area between 15 km and 30km, which indicates that most of the in-progress construction works fall into this area.

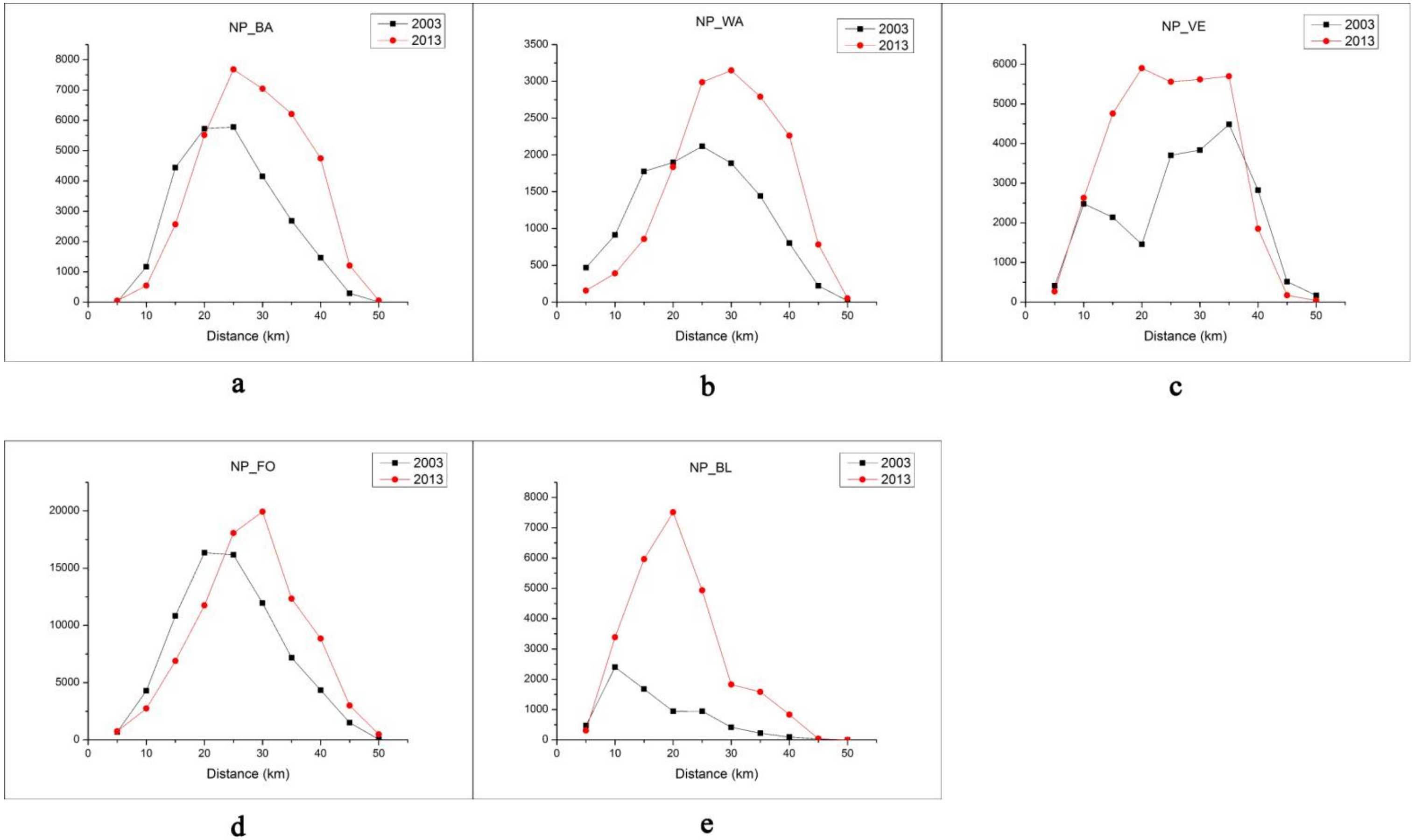


Figure 4-5. The number of patches (NP) of five categories: BA (a), WA (b), VE (c), FO (d) and BL (e).

MPS is metric to assess the degree of homogeneity (Seto & Fragkias, 2005). Within the distance of 5 km, the MPS of BA in 2013 (149.50 km^2) is much lower than in 2003 (1483.34 km^2) (Figure 4-6a_2); however, the NP of BA within this area increased from 5 in 2003 to 48 in 2013, which indicates a significantly dispersed growth of BA in the inner city. This may be caused by urban redevelopment. Meanwhile, within the distance greater than 5km, especially between 5km and 10km, the MPS of BA is higher in 2013 than in 2003, which may indicate an infill phenomenon occurs during the process of urban expansion. Between 35km and 50km, MPS of VE increases while that of FO decreases, mainly due to the land cover type conversion from FO to VE in the eastern GC (Figure 4-1).

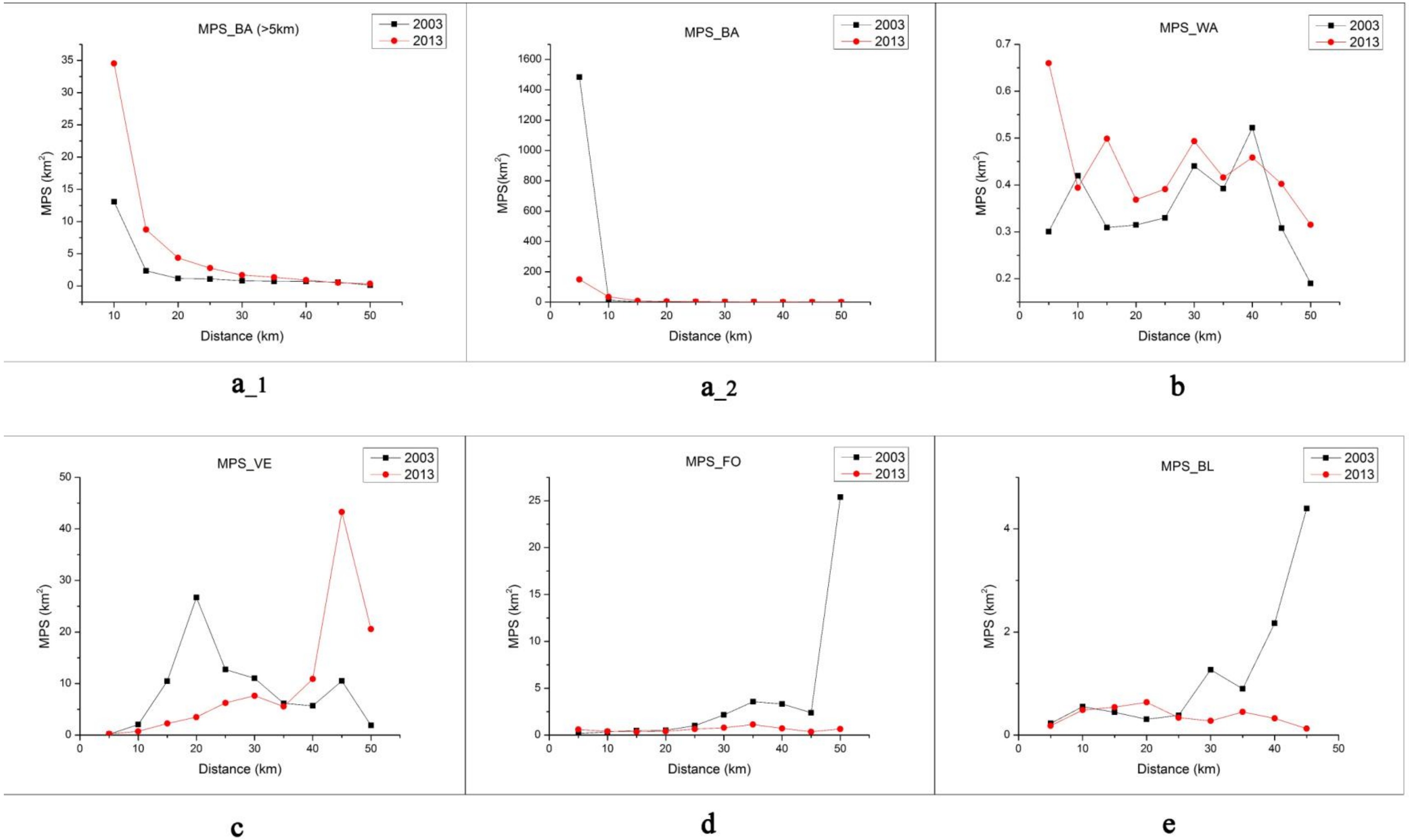


Figure 4-6. The Mean Patch Size (MPS) of five categories: From 5 km to 50 km: BA (a_1), from 0 km to 50 km: BA (a_2), WA (b), VE (c), FO (d) and BL (e).

Figure 4-7 shows the percentages of BA within different distances. Within 5 km, the PLAND of BA decreased slightly from 94% to 91%. Accompanying the decrease of PLAND, NP increases and MPS decreases, which demonstrates that the inner city experienced a substantial redevelopment, slightly and dispersed. More than 5 km from the city center, the percentage of built-up area increases, which indicates the occurrence of urban growth of GC. According to the division of urban area types defined by Angel et al. (2007), the "urban core" area refers to the area where the PLAND of built-up area is greater than 0.5; while "suburban" area is the area that the PLAND of built-up area is between 0.3 and 0.5. Thus, in 2003, the urban core area of GC is the round area with a radius of 10 km. In 2013, its boundary expands outward to 15 km (Figure 4-7). Meanwhile the boundary of the suburban area of GC in 2003 is no larger than 15 km; however, in 2013, the suburban area expands outward to 25 km and falls into the ring area between 15 km to 25 km. The magnitude of the outward shift of boundaries of the urban core area and the suburban area demonstrates that GC underwent a rapid urban expansion during this time period.

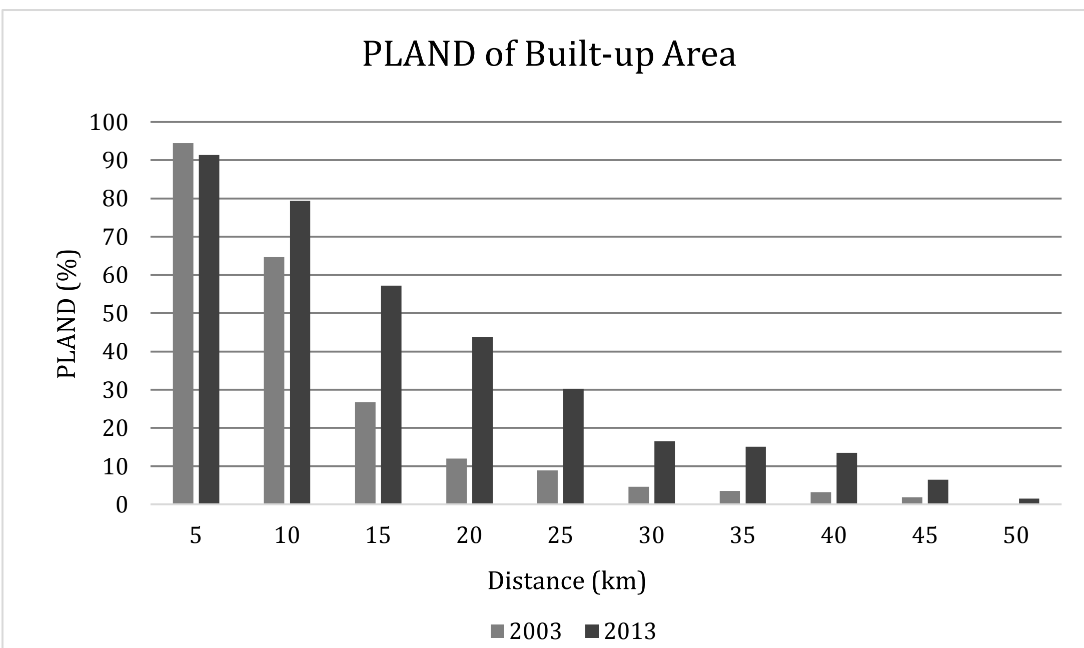


Figure 4-7. PLAND of Built-up Area (BA) in 2003 and in 2013.

After the LUCC map was produced, the pixels that represent the conversion from any other categories to BA were labeled. In order to display the density of percentage change, the original pixels were counted within each grid cell with the unit of 1km*1km. The percentage change of built-up area is computed within the grid. The pixels that span more than 1 grid are counted into the grid which contains the central point of the pixel. Thus, the percentage change in each grid can be calculated as: $P = n*900/10^6*100\%$, where P refers to the percentage change of BA within each grid cell and n refers to the number of pixels that were not BA in 2003 but converted to BA in 2013.

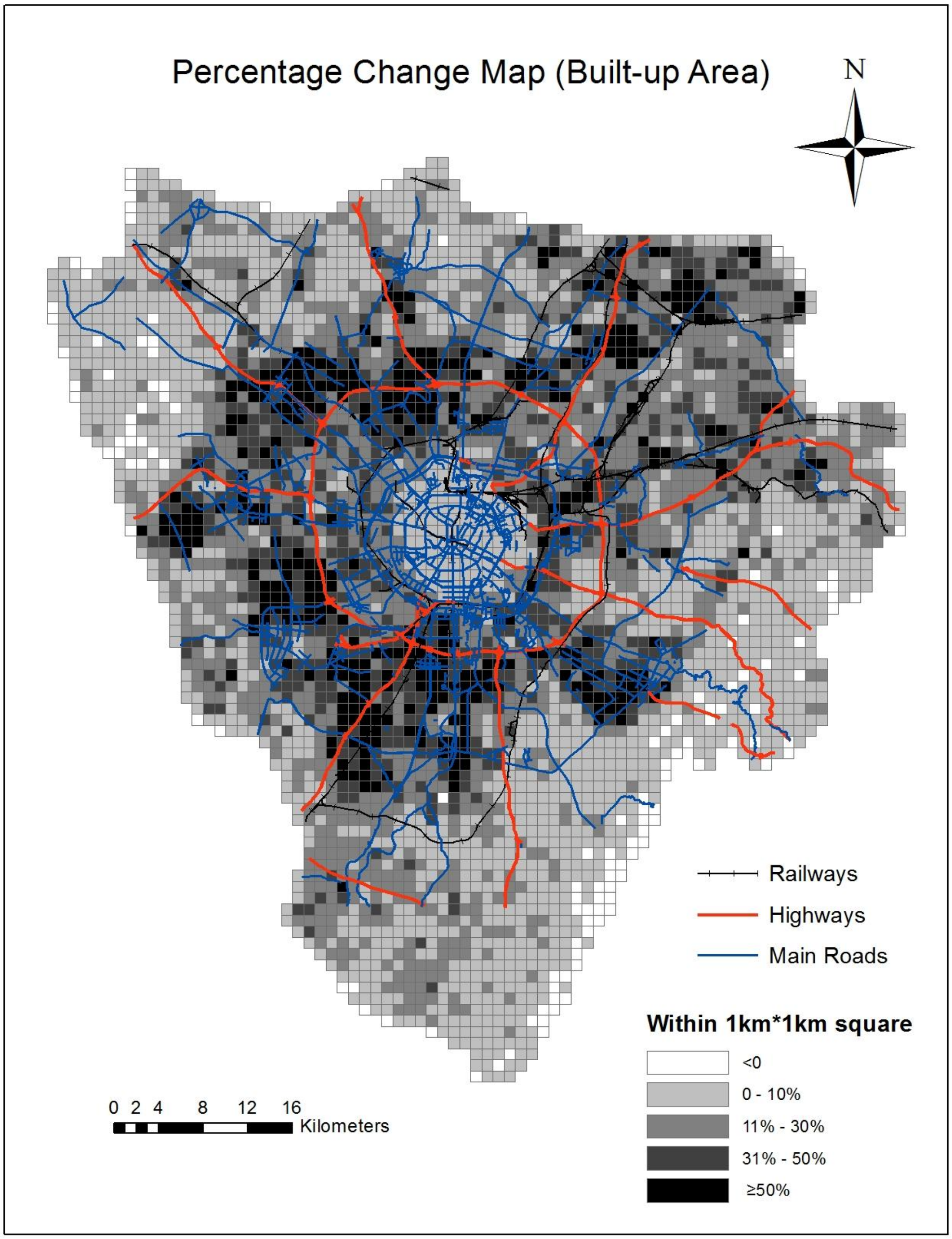


Figure 4-8. The percentage change of built-up area map in 1 square kilometer sections between 2003 and 2013.

Quantile classification was employed to divide the map into 5 different change levels: <0; 0~10%; 11%~30%; 31%~50%; and ≥51%, respectively. Higher values indicate higher proportions of area that were converted to built-up area, while lower values indicate the slight change from other land cover type to built-up area. Figure 4-8 displays the percentage change of built-up area. Within 5 km, the inner city had a change of less than 10%. The most intensive change (>31%) occurs between the radius of 10km and of 25km (Figure 4-9). This ring area is also the new development suburban area in 2013, defined by Angel et al. (2007). It developed along main roads, outward in all direction of suburban area except east sector. Highways only marginally contributed to the distribution of new development built-up area.

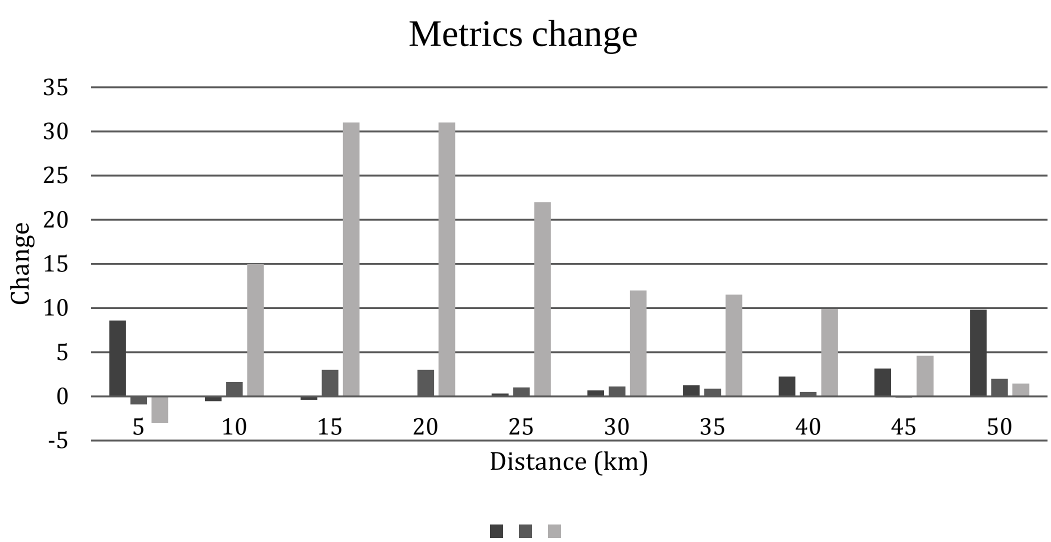


Figure 4-9. Metrics change of Built-up Area.

In this study, a within-city level landscape metrics analysis is conducted to examine the landscape variability of GC. Landscape fragmentation is observed within the study area, especially in the ring area that between 20km to 50km. The combination of small patches presents strong evidence that the urban pattern of Greater Chengdu became mononuclear. This pattern will be further enhanced if there is no change on current growth form. In addition, the significant expansion of urban core and suburban area indicates Greater Chengdu is undergoing a rapid urban growth. As the pilot region that implement “the coordinated urban-rural development” policy, rural development and urban development are considered integrated instead of isolated with each other, thus makes those satellite towns in 2003 grows and finally became part of the urban or suburban area.

4.4 The type of urban growth

The type of new development built-up area is shown in Figure 4-10. Three different types of urban growth are displayed by different colors. The green area refers to where infill growth occurs, pink to expansion, and blue to leapfrog growth. The total newly development built-up area is 780.5 km^2, in which infill type, expansion type and leapfrog type of growth is 87.1 km^2, 593.9 km^2 and 99.5 km^2, respectively. Among the total newly development built-up area that was converted from other land cover types, the dominant growth type is expansion, with 76.09% out of total area. The infill and leapfrog types of growth have similar proportions, with 11.16% and 12.75%, respectively. The most concentrated infill type of urban growth falls into the 5 km to 10 km ring, which means in this ring area the most prevailing growth is infill. The result is consistent with the result of MPS analysis of BA. In addition, the result further indicates that the urban core area experienced a redevelopment growth because this ring area was already urban core area in 2003. In the 10 km to 25 km rings, the dominant urban growth type is expansion. This is the ring area where the PLAND of BA increases by over 20% (Figure 4-9), which further demonstrates that the substantial outward expansion occurs in the suburban area. The leapfrog growth area was dispersed throughout the rings outside of 25 km, with no specific direction.

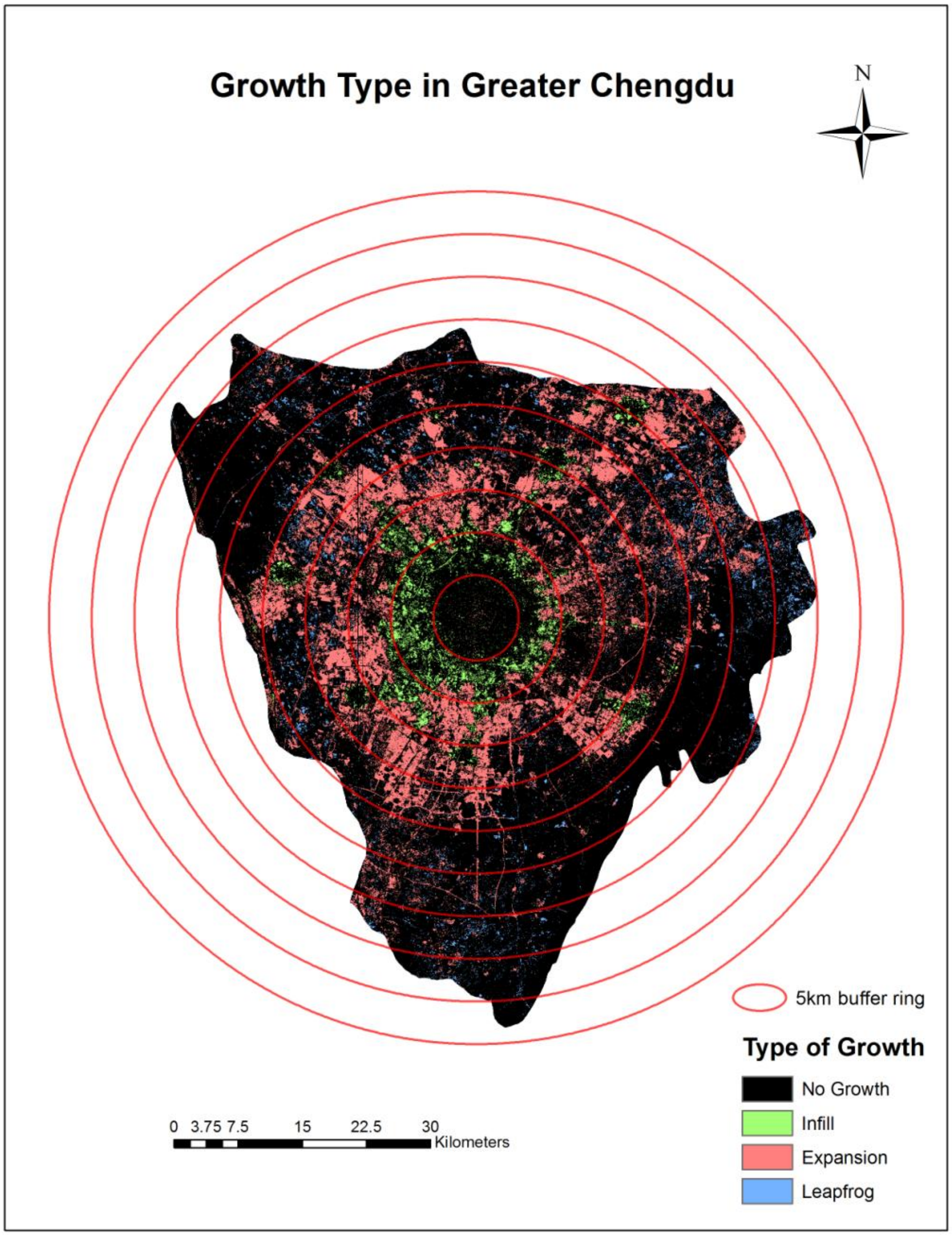


Figure 4-10. The different types of urban growth.

The round-like expansion is also been detected by ULAT analysis. Compare to other area, the eastern Greater Chengdu changes less no matter for the infill type growth or the expansion type growth. This is might due to the nature of the area – the eastern Greater Chengdu serves as logistic area for several years. On the contrary, in south Greater Chengdu, intensive expansion type built-up area locates in this area. In addition, the new road network is detected on the south of south Greater Chengdu. This might indicates new urban area will grow along this direction in the future. According to Tannier et al. (2012)'s conclusion, the closer the landscape to existing road, the higher the landscape connectivity is. In the future, the connection between landscapes of built-up area might be enhanced due to more roads are built.

The infill type of growth is generally referred to the remedy of urban sprawl. It's also associated with compact urban form (Wu et al., 2015). In this study, even though the result is unable to detect if the growth type shifted over the time period, it still demonstrates that in the future the area of infill type of growth will shift outward due to the intensive expansion occurs outward of the existing infill built-up area, and the significant outward expansion of urban core and suburban area.

The government of China has set a comprehensive and ambitious plan to increase the urban population up to 60% out of the total population by 2020 (Bai et al., 2014). The plan covers almost every feasible aspect of urbanization from urban scale to regional scale, from spatial distribution to sustainable development. However, at urban scale, the gap between the goal of the central government goal and the implementation of local government, as well as the balance between urban expansion and urban ecological environment should be monitored and addressed carefully during the process of urbanization.

Chapter 5 : CONCLUSIONS

5.1 Summary of research findings and analysis

Between 2003 and 2013, the built-up area of GC increased 126.8%, from 525.50km^2 in 2003 to 1191.85 km^2, which indicates a substantial rapid urban growth in GC. The result of LUCC and the dramatic increase of built-up area are at expense of the decrease of vegetation and forest. The vegetation and forest areas shrunk during this period, decreasing by 343.85 km^2 and 435.95 km^2, respectively. The bare land increased from 38.94 km^2 to 128.83 km^2, partly because of the increase of construction areas. The new development built-up area went outward in all directions, especially in northwest and southwest areas of GC. During the process of the outward increase of built-up area of the inner city, several satellite towns that can be clearly identified in 2003 were absorbed into part of the inner city by 2013. This indicates that the multinuclear built-up area of GC converted to mononuclear. Most of the urban growth occurred in suburban areas. The northeast suburban area is more dispersed than the southwest. The new development bare land falls into the southern part of the suburban area, which, along with new development built-up area in this area, indicates substantial urban growth in this direction. Among the five land cover categories, vegetation is the dominant one that was converted into bare land with the area of 82.9 km^2.

The entropy value in 2003 was 1.52, and increased to 1.94 in 2013. The upper limit of Shannon's entropy in this study is 2.3026. The values of those are both closer to upper limit but the value in 2013 exceeds that in 2003, these values indicate that the built-up area was dispersed in both 2003 and 2013, and even more dispersed in 2013 than in 2003. The result of entropy analysis is also consistent with the result of the land use maps and the LUCC from-to map.

The metric analysis results further indicate the intensive urban growth in the suburban area. Within the distance of 20 km, small patches of built-up area were merged together, which makes it become homogenous in this area; meanwhile beyond a distance of 20 km, the new development built-up area distribution was dispersed. Within the distance of 5 km, a slight growth of built-up area resulted from the occurrence of urban redevelopment in the inner city. An infill phenomenon may occur during the process of urban expansion in the ring area in between the 5 km to 10 km rings. In 2003, the urban core boundary is on the edge of the 10 km ring; however by 2013, it has expanded outward to 15 km. The suburban area in 2003 was between the 10 km to 15 km rings; in 2013 its boundary shifts outward to 25 km, which makes the suburban area in 2013 fall between the 15 km to 25 km rings. The most intensive change of built-up area occurs outside the inner city, within the 10 km to 25 km rings, where a new development urban core and suburban area emerged by 2013. Most of the built-up area development occurs along the main roads leading from the core and grows outward in all directions of the suburban area except the east sector. Highways have little effect on the distribution of new development urban area. Between the 10 km to 40 km rings, vegetation shrinks considerably, and the continuous vegetation landscape splits into smaller individual patches. The most ongoing construction work falls into the area between 15 km and 20 km from the city's center.

The dominant type of urban growth in GC between 2003 and 2013 is outward expansion, which mainly exists in the ring area between the distances of 10 km and 25 km. The prevailing type of growth in the 5 km to 10 km ring is infill. This area was already within the urban core in 2003, therefore urban redevelopment took place as infill. This result is also consistent with the result of MPS landscape metrics analysis. The leapfrog growth area is dispersed around the study area and is greater than 25 km from the city's center, with no specific growth direction.

With population increase, urban expansion becomes an inevitable phenomenon (Bagan & Yamagata, 2012). In order to increase the quality of life of all residents in a city, it is critical to keep a balance between population increasing, physical urban growth, economic development and other factors. The first step is to qualitatively and quantitatively determine how a city grows, which is provided by the result of my research.

Since China has experienced rapid urban growth only in recent decades (Bai et al., 2014), modern land use management systems in the cities of China is still in its infancy. From this perspective, the result of my research will help:

- land use management database generating;
- historical land use and land cover change monitoring;
- spatial pattern change prediction;
- comparative land use studying between cities;
- urban heat island effect study;
- urban public transportation planning;
- urban pollution mitigation or prevention;
- location selection of public service institutes.

From an integrated remote sensing and GIS technique perspective, the results further demonstrate the effectiveness of remote sensing and GIS in quantifying physical urban growth. It provides information such as:

- quantitive and qualitative change of land use type during the process of urbanization;
- urban landscape configuration change;
- different urban growth types within a study area.

The growth of a city is not simply reflected by physical expansion phenomenon. Along with the built-up area expansion, the population and the economy change at the same time. As with most human-induced landscapes, the shrinkage, shift or expansion of urban areas have strong relationships with the changes to urban environments and urban human behaviors. These relationships further impact urban ecological integrity and urban sustainability. Hence, in this study, the results of urban spatial pattern change provide valuable information for additional research in the future. This is the first step to gaining a better and comprehensive understanding of urban growth. In addition, the results can be useful for government and urban planners to examine if the current land use policy is reasonable, what the issues and options are and how the future land use planning can be made.

5.2 Limitations

In this study there are two main limitations. The first is the spatial resolution of available satellite imagery. It is a significant factor that limits the results' accuracy. The resolution of satellite imagery in this study is 30m*30m, but in some places there are multiple land use types within 900 square meters (one pixel), which makes the classification result less accurate. Imagery with higher spatial resolution (i.e. 10m*10m) would help to improve the classification result and the overall research results. However, the cost for such images was beyond this study's budget.

Second, in this study I only focused on urban expansion from the perspective of two-dimensional physical morphology. However, urban area expands not only outward, but also upward and downward. Obtaining the results from the third dimension would help to build a comprehensive understanding of urban expansion in the modern world. However, I was unable to get either the imagery that reflect three-dimensional change or the related data.

5.3 Future Research

Urban expansion often associates with not only environmental factors, but also many other socio-economic factors, such as population growth, economic development, traffic density, and commuting transition. In future studies, beside the aforementioned research area, researchers could also continue to find out the determinants of patterns of urban growth and the quality of urban growth in terms of effective use of land can be also considered. In addition, the environmental impact of the growth such as urban heat island effect study, the local climate change in regard in response to the growth and the extent to which it has the positive or negative effect on the quality of life can be also expanded as the future research.

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Appendix A: Landscape Metrics

A.1 Number of Patches (NP)

Distance (km)	Type	Number of Patches		Distance (km)	Type	Number of Patches	
		2003	2013			2003	2013
5	BA	5	48	30	BA	4152	7043
	WA	468	157		WA	1888	3148
	VE	410	268		VE	3837	5620
	FO	694	756		FO	11940	19931
	BL	469	309		BL	417	1826
10	BA	1163	542	35	BA	2683	6208
	WA	913	390		WA	1442	2791
	VE	2480	2631		VE	4485	5699
	FO	4299	2738		FO	7173	12335
	BL	2400	3388		BL	220	1583
15	BA	4442	2565	40	BA	1468	4743
	WA	1776	858		WA	802	2262
	VE	2141	4760		VE	2826	1853
	FO	10835	6891		FO	4342	8854
	BL	1674	5964		BL	95	835
20	BA	5726	5512	45	BA	290	1205
	WA	1899	1836		WA	222	782
	VE	1460	5903		VE	517	171
	FO	16350	11747		FO	1499	2994
	BL	940	7510		BL	30	37
25	BA	5776	7680	50	BA	5	54
	WA	2116	2988		WA	18	52
	VE	3705	5559		VE	167	43
	FO	16162	18069		FO	36	476
	BL	946	4933		BL	0	0

A.2 Mean Patch Size (MPS)

Distance (km)	Type	MPS (km^2) 2003	MPS (km^2) 2013	Distance (km)	Type	MPS (km^2) 2003	MPS (km^2) 2013
5	BA	1483.344	149.4975	30	BA	0.8129	1.7044
	WA	0.3006	0.6598		WA	0.4405	0.4933
	VE	0.1877	0.2445		VE	11.0277	7.6414
	FO	0.1608	0.5979		FO	2.1534	0.7904
	BL	0.2286	0.1817		BL	1.2699	0.2771
10	BA	13.0922	34.5294	35	BA	0.736	1.3605
	WA	0.4197	0.3942		WA	0.3923	0.4161
	VE	2.0482	0.7371		VE	6.1627	5.5521
	FO	0.36	0.4029		FO	3.5568	1.1293
	BL	0.5523	0.4873		BL	0.8971	0.4499
15	BA	2.3608	8.7624	40	BA	0.6971	0.9135
	WA	0.309	0.4987		WA	0.5218	0.4585
	VE	10.4773	2.2502		VE	5.6855	10.8925
	FO	0.467	0.3511		FO	3.3276	0.7159
	BL	0.4439	0.5428		BL	2.1704	0.3256
20	BA	1.1553	4.3684	45	BA	0.5987	0.5039
	WA	0.3146	0.3686		WA	0.3081	0.4021
	VE	26.7065	3.4851		VE	10.5237	43.2742
	FO	0.5188	0.4144		FO	2.3974	0.3614
	BL	0.3077	0.6366		BL	4.398	0.1265
25	BA	1.0833	2.7776	50	BA	0.144	0.3467
	WA	0.3298	0.3911		WA	0.19	0.315
	VE	12.7112	6.2462		VE	1.8846	20.5619
	FO	0.9979	0.6451		FO	25.395	0.6593
	BL	0.3847	0.3371		BL	0	0

A.3 Percentage of Landscape (PLAND)

Distance (km)	Type	PLAND (%) 2003	PLAND (%) 2013	Distance (km)	Type	PLAND (%) 2003	PLAND (%) 2013
5	BA	94.4429	91.3761	30	BA	4.6386	16.4976
	WA	1.7913	1.3191		WA	1.1429	2.1342
	VE	0.9799	0.8343		VE	58.1541	59.0219
	FO	1.4211	5.7554		FO	35.3366	21.6508
	BL	1.3649	0.7151		BL	0.7278	0.6954
10	BA	64.6216	79.4283	35	BA	3.5332	15.1112
	WA	1.6264	0.6524		WA	1.0122	2.0779
	VE	21.5576	8.2303		VE	49.4533	56.6137
	FO	6.5683	4.6822		FO	45.6482	24.9228
	BL	5.626	7.0068		BL	0.3531	1.2744
15	BA	26.7039	57.2317	40	BA	3.1818	13.4702
	WA	1.3975	1.0895		WA	1.3012	3.2246
	VE	57.1208	27.2744		VE	49.9549	62.7533
	FO	12.8857	6.1607		FO	44.921	19.7065
	BL	1.8921	8.2437		BL	0.6411	0.8453
20	BA	12.0328	43.7987	45	BA	1.8453	6.4541
	WA	1.0867	1.2311		WA	0.727	3.3423
	VE	70.9245	37.4205		VE	57.8287	78.6518
	FO	15.4298	8.8541		FO	38.1966	11.502
	BL	0.5262	8.6957		BL	1.4024	0.0497
25	BA	8.8701	30.2402	50	BA	0.0584	1.5181
	WA	0.9894	1.6564		WA	0.2774	1.3284
	VE	66.7618	49.2228		VE	25.5237	71.7028
	FO	22.8627	16.5231		FO	74.1406	25.4507
	BL	0.5159	2.3575		BL	0	0